Mining Optimization Laboratory

Report Twelve –2023/2024

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Executive Summary

This year, we have prepared a report including 23 papers under five main topics, as; 1) Strategic Mine Planning and Mine Design, 2) Implementation of In-pit Crushing and Conveying (IPCC) in Open Pit Mining, 3) Environmental Impacts and Sustainable Mining, 4) Operational Mine Planning, and 5) Other Topics. We continue to update all the research results on the MOL webpage https://sites.ualberta.ca/MOL/ on the members section. Sponsors have access to current and past research results and publications. Let's review the contributions in the MOL Report Twelve (2023/2024) by considering some of the main contributors.

The first group of papers in this year addressed the development and implementation of different mathematical programming frameworks for pit limit optimization, pushback design and strategic mine planning. The following four students have been the main contributors under this topic:

Emmanuel has proposed a stochastic MILP framework to optimize the open stope mine production scheduling, considering grade uncertainty and stockpiling strategy in **Paper 101**. He introduced a Stochastic Mixed Integer Linear Programming (SMILP) model, an advanced version of a previous Mixed Integer Linear Program (MILP). He enhanced the model to include various mining operations, such as decline development, ventilation, operational and ore pass development, stope design and extraction, backfilling, and stockpile management, all aimed at maximizing net present value (NPV). Emmanuel conducted six detailed case studies to assess and compare the economic and operational impacts of the SMILP model. Among these, the SMILP model with stockpile management (Case 4) achieved the highest NPV, demonstrating its superior performance and practical applicability in real-world mining operations.

Soroush conducted a comprehensive comparative analysis of mathematical and industrial approaches to long-term production scheduling in sublevel caving (SLC) mining. In **Paper 102**, he utilized an MILP model alongside the GEMS/PCSLC software. The MILP model integrated various operational constraints, such as active level limits, continuous mining, capacities, precedencies, and grade blending, to accurately represent the SLC method. The primary goal was to maximize the NPV of the mining project. Soroush developed and verified the model in a Jupyter Notebook environment, solving it with the CPLEX Python API. He compared the MILP model's performance with the Production Control System for Sublevel Caving (PCSLC) software, applying different mining strategies to assess project income over the mine's life. His analysis demonstrated the mathematical model's efficiency in optimizing production scheduling and highlighted its potential to improve decision-making and enhance economic outcomes in SLC mining.

Samaneh has focused on strategic mine planning, a crucial area in mining that aims to tackle long-term challenges while maximizing value within operational and financial limits. There are two main approaches to modeling mining problems: deterministic and stochastic optimization. Deterministic models, the traditional approach, use fixed input parameters but often overlook the uncertainties present in geological, economic, and operational factors. In real-world scenarios, addressing these uncertainties is vital, making stochastic optimization a preferred method. Unlike deterministic models, stochastic optimization accounts for uncertainties by considering multiple scenarios or probabilistic distributions for the parameters. In **Paper 103**, her study explores and compares these two approaches, highlighting that while stochastic optimization offers better solutions and enhances the sustainability of mining operations under uncertainty, it also introduces greater computational complexity. In **Paper 104**, she has focused on optimizing the economic value of a mining project through open-pit mine planning. Her work involves two key operations: ultimate pit and push-back design. She developed a method that integrates a maximum flow network problem while considering the precedence relationships between blocks in a block model. Using GEOVIA SURPAC, she created a block model with 26,162 blocks, each defined by various characteristics like volume and

gold grade. The data was then processed in Python to solve a Mixed-Integer Model for optimizing the ultimate pit and push-back design. For the push-back design, the model constrained the capacity of each push-back, assigning blocks accordingly. The block model was then used to generate pushbacks and implement a production schedule using Whittle software, with the Milawa Balanced algorithm providing a robust schedule. A comparative analysis showed that her proposed Mixed-Integer Programming approach achieved a higher NPV than the traditional Whittle implementation.

The second group of papers investigated the implementation of In-pit Crushing and Conveying (IPCC) systems in open pit mining. The following five students and researchers have been the main contributors under this topic:

Nasib explored the growing potential of IPCC system as an alternative to traditional truck-shovel methods in open-pit mines, motivated by rising fuel costs and environmental concerns. Recognizing that effective short-term planning in these mines must address operational and equipment uncertainties, he focuses on the under-researched area of integrating IPCC into short-term planning. To bridge this gap, in **Paper 201** he developed a simulation-optimization framework combining an MILP model and Monte Carlo simulation. The MILP model minimizes haulage costs while meeting long-term production goals, optimally allocating shovels to mining cuts to generate schedules. These schedules are then fed into the Monte Carlo simulation, which evaluates operational uncertainties and estimates key performance metrics, such as tonnes per gross operating hour (TPGOH), under scenarios with and without IPCC. Validated through a twelve-month case study in an iron ore mine, his model demonstrates the potential advantages of adopting semi-mobile IPCC systems over conventional truck-shovel operations.

Sandra reviewed state-of-the-art open pit mine planning methods involving IPCC systems, considering various time scales in **Paper 202**. She provided an overview of methods for both long and short-term mine planning through an extensive literature review, elaborating on the gaps and shortcomings in current research. Consequently, Sandra outlined a specific research agenda focused on long and short-term mine planning with IPCC. She proposed a research project aimed at addressing the identified research problems. She also discussed and evaluated the results and observations from the literature review, offering suggestions for further research along with a comprehensive summary of the findings.

Hongshuo's research demonstrated that conveyor operations had shown significant cost advantages over truck systems for long-distance transportation, which led to the adoption of the IPCC method as a superior alternative, especially at greater mining depths. Recently, the In-Pit Crushing and Stockpiling (IPCS) method, or near-face stockpile (NFS) mining, had emerged, separating the process into truck-to-stockpile and stockpile-to-crusher stages. This separation reduced the impact of mining rate fluctuations on milling and enhanced system resilience. Studies indicated that IPCS improved equipment utilization, stabilized the mining system, and increased production compared to traditional methods, though its specific advantages over IPCC in risk resistance had not been quantified. To address this gap, in **Paper 203** he developed an optimization model for IPCC using mixed integer linear programming and conducted a discrete event simulation with Arena to simulate operations and incorporate uncertainties. Comparative analysis with real mine data showed that IPCS increased equipment utilization, boosted annual output, and reduced truck utilization, highlighting its efficiency in managing operational uncertainties. In conclusion, he found that IPCS enhanced mining system efficiency and resilience compared to IPCC, particularly in managing uncertainty, warranting further research to refine and apply this framework across different mining environments.

Alireza integrated IPCC systems directly from the pit, reducing the need for extensive truck fleets and haulage infrastructure typically associated with Truck Shovel systems (TS). This approach minimized truck-related costs and environmental impacts while improving operational efficiency. In **Paper 204**, he optimized long-term scheduling in open-pit mining operations by comparing IPCC

with traditional TS systems. He employed a two-step mathematical optimization model to determine the optimal locations for crushers or crusher panels and to establish a practical long-term extraction sequence. Through a comprehensive case study involving pushbacks with roads and conveyor ramps, and by analyzing different road and conveyor network configurations, he examined the capital and operational costs across four scenarios for the in-pit crusher: without a crusher, with an ore crusher, with a waste crusher, and with both ore and waste crushers. His results included comparisons of NPV, tonne-kilometers traveled, total kilometers traveled, and the number of trucks required. Significant improvements in NPV were observed in scenarios with both ore and waste crushers, reflecting reduced hauling distances and operational costs. The waste crusher scenario also demonstrated substantial savings, while the ore crusher scenario showed moderate improvements compared to the base case without a crusher.

Vahid examined the cost-effectiveness and production efficiency of IPCC systems in mature open-pit mines. By integrating crushing with conveyor systems within the pit, these systems replaced part of the traditional Truck-Shovel haulage cycle, leading to significant haulage cost savings and improved operational efficiency. In **Paper 205**, he employed a robust methodology, including statistical analysis, data wrangling, and the development of a full-scale Discrete Event Simulation model using Simpy, which was validated against actual operational data. The simulation assessed various scenarios—pure Truck-Shovel, IPCC, and Out-Pit Crushing and Conveying (OPCC)—to evaluate their impacts on operational costs, production rates, and overall efficiency, providing valuable insights into the practical transition to IPCC systems.

The third group of papers consider elements of sustainable mining, specifically with a focus on quantifying and minimizing the Greenhouse Gas (GHG) emissions within the framework of mine planning optimization in different time horizons. The following students have contributed under this topic:

Bahar designed and coordinated mineral extraction systematically through mine planning, integrating exploration, production, and engineering considerations. Faced with growing pressure to incorporate environmental responsibility, her study addressed the precedence-constrained production scheduling problem (PCPSP) within green long-term mining planning. To optimize extraction processes while limiting carbon emissions, in **Paper 301** she introduced an adaptive large neighborhood search (ALNS) algorithm specifically tailored for long-term mine planning. This study involved parameter tuning for the ALNS algorithm, comparisons with an exact solver, and analysis of destroy-repair operators to identify key elements. The developed ALNS, evaluated through various benchmarks, showed optimality gaps of about 0.08, demonstrating the approach's effectiveness in enhancing mining operations while considering environmental impacts.

Cristina conducted a systematic review in **Paper 302**, addressing the critical challenge faced by the mining industry in reducing GHG emissions from mobile equipment. Her review examined recent technological advancements and techniques applied to mining mobile equipment aimed at mitigating GHG emissions. Through a thorough analysis of objectives, methodologies, results, production impacts, gaps, and limitations in various studies, she identified effective strategies for GHG reduction. The urgency of meeting the industry's commitments under the Paris Agreement for net-zero emissions by 2050 highlighted the significance of these advancements. Additionally, her review explored potential modifications and challenges in implementing these technologies to foster sustainable mining practices. Her study contributed valuable insights to the ongoing efforts of aligning mining operations with global climate goals, underlining the crucial role of mobile equipment in achieving a sustainable, low-carbon future for the mining sector.

Mohammad addressed the growing environmental impact of the mining industry amid rising global demand for mineral resources. He focused on the need for sustainable mining practices by integrating environmental considerations into planning and operations. In **Paper 303** he proposed an integrated

framework, termed LCA-MILP, which combined life cycle assessment (LCA) data with an MILP model to optimize mine planning processes. The framework aimed to reduce GHG and dust emissions while evaluating various economic scenarios. He validated the framework through a case study on an open-pit iron ore mine, demonstrating that GHG emissions could be reduced while achieving nearly the same original NPV. His findings underscored the importance of aligning environmental impact reduction with long-term mine planning to promote a more sustainable and socially responsible mining industry. In **Paper 304**, he presented an innovative framework for long-term open-pit mine planning that integrated economic and environmental considerations. By incorporating carbon pricing into the decision-making process, the framework addressed financial risks and explored two scenarios: one focused on minimizing environmental costs and the other on maximizing adjusted NPV. Applied to an open-pit iron ore mine, the framework evaluated its impact on block sequencing, greenhouse gas emissions, and financial outcomes. Sensitivity analyses showed the framework's adaptability to different carbon pricing scenarios. In **Paper 305**, he introduced a transformative multi-objective optimization (MOO) framework aimed at balancing economic and environmental aspects of open-pit mining, particularly focusing on GHG emissions. The same case study validated the framework's effectiveness. The results revealed that significant GHG emission reductions could be achieved with minimal impact on economic returns. Through detailed scenario analysis, he illustrated the trade-offs and synergies between maximizing NPV and minimizing ecological costs, emphasizing the need for integrating environmental considerations into mine planning to ensure a sustainable and economically viable mining industry. His research provided a sustainable approach to mine planning, balancing economic returns with ecological responsibility, and offered valuable insights for decision-makers in the mining industry.

Amir Abbas presented an integrated stochastic discrete-continuous simulation-based optimization framework in **Paper 306**, designed to address GHG mitigation in operational decision-making for open-pit mines. This framework aimed to minimize transportation costs while simultaneously reducing carbon dioxide emissions. A case study on a copper mine was conducted to determine the optimal size of the transportation fleet, balancing cost reduction with minimizing CO2-equivalent emissions. He also introduced a novel truck allocation method that improved cost efficiency, emission reduction, and performance indicators like tonnage hauled and cycle time. Sensitivity analysis was performed to evaluate the impact of various parameters on the objectives and performance, offering valuable insights for advancing GHG mitigation and sustainable mining practices.

Milad introduced a novel MILP model for short-term open-pit mine planning in **Paper 307**, which integrated GHG emissions, with economic objectives. The model addressed complex operational challenges such as block sequencing, multiple transport destinations, and stockpile management. It also evaluated the potential of IPCC systems as an innovative transport method to reduce haulage-related emissions, which account for over 35% of GHG emissions in open-pit mining. Applied to a case study at an iron ore mine, the model highlighted significant reductions in GHG emissions, haulage costs, and carbon tax liabilities, demonstrating that fixed IPCC systems offer substantial benefits and making a strong case for their broader adoption in the industry.

The fourth group of works this year investigated some aspects of operational mine planning, such as fleet allocation and dispatch optimization using simulation and Artificial Intelligence techniques. The following students have contributed under this group:

Khaleeq examined the substantial impact of material handling and transportation costs, which could constitute up to 50% of operating expenses in open-pit mining operations. The challenge of efficiently transporting extracted material to various destinations such as processing plants, dumps, or stockpiles highlighted the importance of optimizing truck dispatching and shovel allocation. Simulation-based optimization and mixed integer programming models had been used to improve dispatching efficiency. Despite the success of Reinforcement Learning (RL) in various industrial

processes over the past decade, deep Reinforcement Learning (DRL) had been relatively underutilized in mining. In **Paper 401**, he investigated the potential of DRL-based approaches for enhancing fleet management in mining operations, aiming to better understand current applications and future possibilities, as well as identifying any potential field constraints.

Yaa investigated the role of Discrete Event Simulation (DES) in optimizing mining operations and enhancing production. The review in **Paper 402** highlighted how DES addressed the complexities and variability inherent in mining systems, emphasizing its importance in improving operational efficiency, reducing costs, and supporting informed decision-making. Specific applications of DES in equipment usage were examined, demonstrating its capability to simulate mining processes, identify bottlenecks, evaluate alternate scenarios without disrupting real-world operations, and optimize resource allocation. Key benefits included the ability to forecast the impacts of operational and strategic changes, as well as predict environmental factors such as energy prices and resource depletion. The integration of DES with optimization methods, like mixed integer programming, was noted for creating comprehensive decision support systems that merge strategic, operational, and environmental considerations. Despite its advantages, challenges such as modeling complexity, data collection issues, and integration with existing management systems remained. This review aimed to provide a deeper understanding of DES's potential to improve mining operations and productivity. In **Paper 403**, she presented a structured guideline for designing, implementing, and validating a simulation model for optimizing mining operations using HaulSim. The study began by defining the conceptual framework, system boundaries, and key performance criteria, followed by thorough data collection and preprocessing to ensure reliable input parameters. HaulSim was employed to simulate various aspects of mining operations, including resource allocation, equipment utilization, and process flow. The research demonstrated HaulSim's effectiveness in predicting and enhancing mining operations, offering valuable insights for strategic planning and decision-making.

Ehsan developed a hybrid Discrete Event Simulation-Genetic Algorithm (DES-GA) approach to create an AI-driven Decision Support System (DSS) for optimal fleet assignment in open-pit mining operations. As presented in **Paper 404**, this approach utilized Graph Neural Networks (GNNs) to improve resource assignment decisions, addressing complexities such as fleet diversity, multiple dig and dump points, and process uncertainties. The DES-GA model generated a dataset for GNN training, incorporating key features like road networks, fleet availability, and shovel-to-dig point and truck-to-shovel allocations. The study demonstrated that this method significantly enhanced real-time dispatching, reduced costs, and minimized environmental impacts in mining operations.

Finally, the last group of works this year includes the following three papers about floating plant, blast analysis and rock excavation process.

In **Paper 501**, ***Khaleeq*** explored the application of machine learning models in mining processes, focusing on predicting output quality in flotation plants. He utilized the Extreme Gradient Boost Regressor (XGBR) and Long Short-Term Memory (LSTM) networks to predict the concentration purities of iron and waste silica. To achieve this, data from 23 variables reflecting a flotation plant were monitored every two minutes over six months, processed, and restructured for model use. The results demonstrated that while both XGBR and LSTM were effective, XGBR outperformed LSTM in predicting iron and silica concentrations. This research laid the groundwork for automating flotation plant control and highlighted the potential of both traditional and deep learning models in mineral processing engineering.

Magreth conducted a study on rock blasting, as reported in **Paper 502**, examining how the intact rock properties and the presence of structures influenced the intensity and distribution of fractures in the rock mass. Through field blasts and numerical simulations using the Riedel–Hiermaier–Thoma (RHT) material model in LS-DYNA, she found that structures did not necessarily stop the fracturing of the rock mass. Depending on their geometry and mechanical properties, the extent of damage

could either develop or be halted by these structures. She also discovered that the material properties and location of the structures relative to the blasthole, free face, and pit wall significantly affected the size and distribution of fractures on the bench and the formation of the pit wall. When comparing the results to field measurements, she observed a general consistency in stress wave pressure, peak particle velocity attenuations, fracture distribution, and pit wall formation.

Pedro demonstrated how the production rate in mining operations was significantly influenced by the physical properties of the rock, such as density, compressive strength, and abrasiveness. These properties directly impacted the extent of fracturing and extraction, which in turn affected the overall production rate. To highlight the importance of measuring these rock features, he used neural network models in **Paper 503** to estimate two key properties: density and point load strength. He collected experimental data from rock samples with varying compositions, dividing them into training and testing sets. After data preparation, he built and trained neural network models with several dense layers and non-linear functions, incorporating techniques to prevent overfitting. The models performed well in predicting density and point load strength, achieving low error rates on the test sets. By integrating these predictions into production rate models, he quantified how factors like density and strength influenced excavation productivity, allowing for optimization by relating controllable parameters to the target production rate while considering site-specific rock characteristics. His study demonstrated how machine learning techniques, such as neural networks, could improve predictive models used in rock excavation operations.

We extend our gratitude to all the contributors who played a crucial role in preparing the 2024 MOL Report. This includes the dedicated faculty members from four universities, the graduate students, postdoctoral fellows, and alumni from nine universities, and two industrial/consultant affiliates. Special thanks to Dr. ***Hongshuo Gong*** for his review of the submitted papers and to ***Liane Tse Tse*** for her tireless efforts as the administrative assistant in proofreading and editorial revisions, ensuring the highest quality of this report. Your collective contributions have been invaluable.

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Following are researchers and students affiliated with Mining Optimization Laboratory in September 2024.

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Open Stope Mine Production Scheduling Optimization with Stochastic Mixed Integer Linear Programming: Considering Grade Uncertainty and Stockpiling Strategy

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ABSTRACT

Conventional geostatistical techniques, like ordinary kriging, can produce biased and overly smoothed estimates, leading to unrealistic production schedules. In contrast, simulation-based methods offer a more effective approach by generating multiple equiprobable models of the orebody, allowing for better assessment and management of grade uncertainty risks in mine planning. The study presents a Stochastic Mixed Integer Linear Programming (SMILP) model, which is an advanced version of an initial Mixed Integer Linear Program (MILP). This enhanced model encompasses a variety of mining operations, including primary (decline) development, ventilation development, operational development, ore pass development, stope design and extraction, as well as backfilling and stockpile management, all aimed at maximizing the net present value (NPV). Six comprehensive case studies were conducted. These case studies aimed to analyze and compare the economic and operational outcomes when employing the SMILP model. Among the case studies presented, the SMILP model with stockpile management (Case 4) exhibited superior performance, reporting the highest NPV when compared to the other five cases. Case 4achieved a 25-year mine life production schedule with a generated NPV amounting to $8,077.86M, while the MILP model with stockpile management (Case 2) yielded $7,801.20 M, indicating a4% increment in financial gain by the SMILP model. These findings underscore the effectiveness and practical applicability of the developed model in real-world mining scenarios.

1. Introduction

Mine planning can be conducted using two distinct approaches: deterministic and stochastic. The deterministic approach relies on historical data from past mining activities, if future trends will mirror previous patterns [1-3] . In contrast, the stochastic approach acknowledges the uncertainty inherent in mining processes by incorporating variability into the planning model, based on historical data. Unlike deterministic methods, which overlook fluctuations, stochastic mine planning recognizes the inherent unpredictability of mining activities, making it a more comprehensive and realistic approach [1-6].

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1.1. Stochastic Integrated Mine Planning Approaches in Underground Mining

Stochastic mine planning is a complex scheduling process due to its ability to incorporate uncertainties such as geological, technical, and economic, inherent in mining operations [7, 8]. Researchers have analyzed risks associated with geological and grade uncertainty to considerably help the decision makers in better understanding various cases and conditions associated with the optimization process [2, 9, 10]. The authors [11-13] concluded that uncertain attributes other than grade and geology should be added to the optimization problem. Hence, subsequent models should be extended to take stochastic variables into account during optimization.

The application of stochastic mine planning in production scheduling has been reported by various researchers in open pit mining taking into consideration grade uncertainty and associated risk [3, 4, 14] , orebody uncertainty, in situ grade and geological uncertainty [3, 5, 15-17] , geological and market uncertainty [18] and NPV [19] to mention a few. Conceptual developments in open pit mining have gradually led to the application of stochastic mine planning in underground mine planning notwithstanding the intricate nature of underground mine planning. The uncertainty related to orebody is a critical aspect affecting the forecasted performance of designs and is linked to the failure of meeting production targets and project financial expectations in mine planning [8,13, 20] .

The essence of accounting for uncertainty and risk which leads to an improvement in decision making was introduced in mine evaluation though the Integrated Valuation Optimization Framework (IVOF) [21] . The author asserts that the complexity of mine projects makes it a business that requires constant assessment of risk because the value of a mine project is typically influenced by many underlying economic and physical uncertainties, including metal prices, metal grades, costs, schedules, quantities, and environmental issues, among others, which are not known with absolute certainty. In underground mining, the use of stochastic variables like grade uncertainty and predefined levels of acceptable risk [13] were developed and explored in a probabilistic Mixed Integer Programming (MIP) model to optimize stope designs, including size, location, and number of stopes. The application of the proposed approach was based on the ability to stochastically simulate equally probable representations of the deposit. This approach forms the basis of the model presented in this paper.

The advent of Stochastic Integer Programming (SIP) [22] adopted risk-based concepts developed in open pit mining to the underground stoping environment and showcased how conventional technologies cannot quantify risk since they are unable to foresee a significant upside potential/or downside risk for the conventionally produced designs. The work quantified risk in terms of the uncertainty a conventional stope design has in expected contained ore tones, grade, and economic potential. Evidently, the model could not achieve the set goals and recommendations from the authors led to the development of a new model which incorporates uncertainties from both the geological and economic factors while minimizing cost [23] . The model integrated two elements: stochastic simulation and stochastic optimization. These elements provided an extended mathematical framework that allows modelling and direct integration of orebody uncertainty to mine design, production planning, and evaluation of mining projects and operations. This stochastic framework increases the value of production schedules by 25%. Further improvements of SIP models [2, 9, 24, 25] indicated that stochastic solution maximizes the economic value of a project and minimizes deviations from production targets in the presence of ore/metal uncertainty because SIP models account and manage risk in ore supply despite the difficulties surrounding creating such planning process [7] .

As the need to incorporate multiple components of the mining value chain increased several methods were developed over the past decades. Efforts have been made in new models to incorporate more decisions and flexibility to the mining optimization of a mining complex. However, they either ignored such realities needed to be considered in the presence of uncertainties associated with the

underground mining process or consider decisions taken before optimization commenced with simultaneously optimizing mining, blending, processing, and transportation decision variables while accounting for geological uncertainty [1]. The expansion of SIP led to the introduction and use of Stochastic Mixed integer Programming (SMIP) which permitted the use of both continuous and integer variables for multiple constraints including primary development, ventilation, and operational development [11]. The SMIP model allowed the optimization of mining complexes in open-pit, underground operations, and processing destinations [1].

1.2. Stockpiling in Underground Optimization

The adoption of stockpiling in mining operations is an approach used in situations where ore materials mined exceeds the plant requirement. In this regard, the best grades are allowed to be processed directly while lower grades are stockpiled for a future date. It is possible to use one or more grade stockpiles, were there could be a low grade and a medium-low grade stockpile [26]. In many cases, such stockpiles may not get processed for years, possibly until: a) the mine is depleted b) the mined grades are lower than those in the stockpile. Such stockpiles can grow to enormous size if accumulated over many years. In some instances, oxidation and processability may be a concern for reactive materials with long term stockpiles [26, 27]. In long-term open-pit production planning (LTOPP), non-linear stockpiling constraints were incorporated for a problem-specific solution method [28]. The formulation helped to track material flow from aggregate to stockpile and plant. This concept [28] forms the foundation of the stockpiling strategy adopted in the stochastic underground formulation approach in this paper.

A goal programming model for a surface iron ore processing plant blending requirement was presented [29]. The model illustrated blending material from two high grade and a low-grade stockpile. The proposed model provided an optimal reclamation schedule by dividing the stockpiles into blocks and subsequently assigning grade values to each block. However, the proposed model did not include decisions on material flow from the mine and stockpile but solely focused on reclamation decisions. A proposed production scheduling model with uncertain supply that includes stockpiling was also presented [30]. The model used a predetermined constant grade for reclaiming material from the stockpile and allow blocks into the stockpile based on the probability of block grade being within the acceptable range for the stockpile. However, the authors do not compare the actual grade of material in the stockpile to the predefined grade.

A Mixed Integer Programming (MIP) for medium-term production planning with stockpiling was presented [31]. The authors divided ore into different categories based on low, high grade and recovery of the main two elements and defined a stockpile for rehandling low-grade ore when needed. However, they avoid nonlinearity by not keeping track of elements grades going to and reclaimed from the stockpile. The cost of uncertainty in a long term mine production plan presented for a Mixed Integer Linear Programming (MILP) model [32] which considers stockpiles. The model finds the mining sequence of blocks from a predefined pit shell and their respective destinations, with two objectives: to maximize the net present value of the operation and to minimize the cost of uncertainty. The presence of stockpile in the model allowed the optimization to extract extra ore at early stages of the mine-life which helped to reduce the chance of short falls at later years.

A multi-step approach to long-term open-pit production planning that determined pushbacks based on a hybrid binary programming-heuristic method were presented [33, 34]. The authors introduced stockpiling to the model with non-linear objective function and later illustrated the benefit of developing a linear objective function and constraints. The linearized model improved reducing the error as the number of stockpiles increased. However, it became evident that the number of stockpiles and grade ranges will depend heavily on the characteristics of the deposit and operations due to homogenous reclamation and other important stockpiling assumptions with respect to multiple element grades.

Subsequent mathematical programming models [35-37] also considered stockpiling with a predetermined fixed grade. They compared their results against solutions obtained, showed how close to the optimum solution their solutions were, and showed that the observed element head grades are within the required boundaries [36]. However, they did not report the errors caused by assuming a fixed reclamation grade for the stockpile

1.3. Summary of Gaps in Literature

Majority of studies so far illustrate the benefits of incorporating grade uncertainty in open-pit production scheduling optimization. Notwithstanding the complexities associated with the development and implementation of underground mining methods, some efforts have been made in incorporating grade uncertainty in underground mining production scheduling optimization [2, 11, 13, 38]. However, the application of stochastic optimization is relatively recent in underground mining and the methods used in the literature remains to be verified when applied to different types of deposits and underground mining methods.

Generally, stockpiles can be considered as buffers of material for future use for controlling capacity and blending requirements. Again, the presence of a stockpile allows optimization to extract extra ore at early stages of the mine-life and the extra ore reduce the chances of short falls at later years [32, 34, 39]. The use of stockpiling in the optimization process has been extensively used in open pit mining but less considered in underground mining [28, 30, 33-35, 37]. The proposed optimization approach is to consider grade uncertainty for underground open stope extraction with primary development, ventilation development, operational development, ore pass development, backfilling, and stockpiling management [40].

This research, therefore, seeks to develop a risk-based optimization framework using stochastic mixed integer linear programming (SMILP) that effectively integrates grade uncertainty into the optimization of long-term production scheduling in open stope underground mining, by developing a stochastically simulated equally probable representations of a deposit for underground production scheduling optimization. The objective function of the proposed SMILP model is to maximize the net present value and balance the risk associated with grade uncertainty simultaneously, while meeting all technical and operational requirements.

2. Methodology

An assessment of the proposed approach and results will be illustrated through a case study corresponding to a gold deposit. Figure 1 is a schematic representation of the proposed approach.

Studies on the effect of grade uncertainty on NPV in long-term production plans have been reported for underground mining projects. It has been identified that there are differences between the actual and expected production targets especially in the early years of production [9, 10, 13]. To address the issue of grade uncertainty, instead of using a single estimated block model for production scheduling, 50 simulated realizations, that are representative of ore grade variability will be used as input to the SMILP model. A conventional model which was based on Ordinary Kriging (OK) estimation was considered as the base case model. Both models in addition to the E-type model were then compared to illustrate the impact of grade uncertainty on the integrated mine development and production scheduling problem.

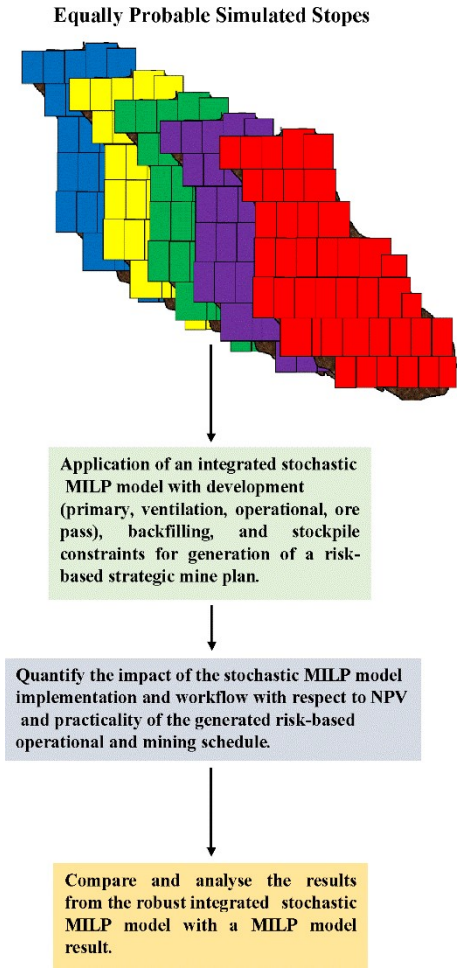

Figure 1. Illustration of proposed approach.

The proposed workflow used in this study to generate production schedule under grade uncertainty from the SMILP framework are as follows:

a. Design stopes from an economic gold block model using Promine AutoCAD [41]. The gold grades in the block model are estimated using OK and serves as the base case model.
b. Implement geostatistical modelling using Sequential Gaussian Simulation (SGS) algorithm to map out gold ore grade uncertainty in the designed stopes, utilizing. Stanford Geostatistical Modeling Software (SGeMS) [42].
c. Select all the stopes for all the realizations, E-type, and Ordinary Kriging. Save the selected stopes in ASCI file format.
d. For each case study, define the input scheduling parameters in MATLAB to formulate the problem.
e. Implement the developed mathematical programming formulations in MATLAB. TOMLAB/CPLEX [43] is used as the solver for the defined optimization problem.
f. Perform production scheduling optimization and comparative analysis based on the generated results from the OK, E-type and SGS block models.

3. Statistical analysis of gold data

To start geostatistical modelling, it is necessary to perform preliminary statistical analysis including compositing, recognizing outliers, identifying trends, and data transformation. This is necessary because data collection practices in general focuses on portions of the study area that are most important. For this reason, the element of interest is gold grades since its variability in estimation creates uncertainty which potentially impacts the overall net present value of the mining project [11]. Presented in Figure 2 is a 3D map of the 120 stopes with gold grades.

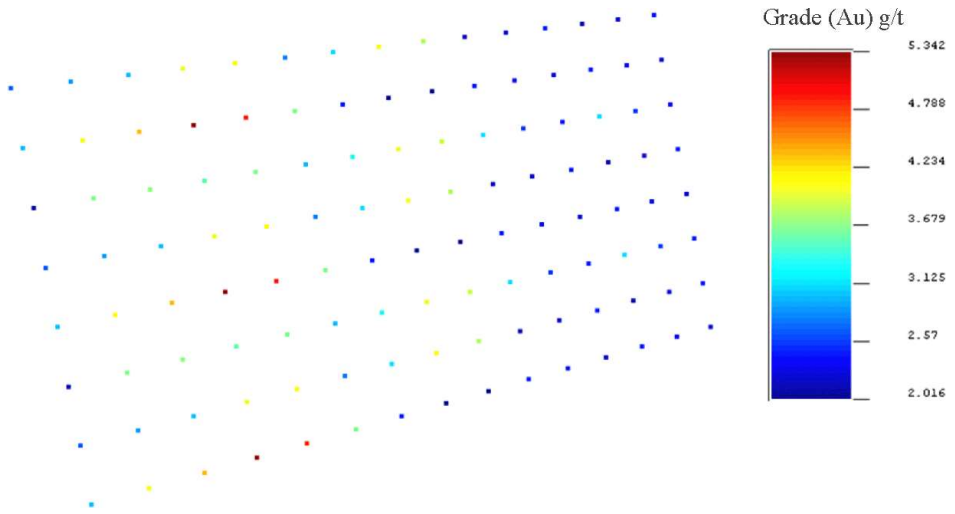

Figure 2. Location of stopes with gold grade distribution.

3.1. Spatial Correlation Analysis Using Variogram

The measurement of spatial continuity was employed to understand the correlation between the observations of the univariate sample at different locations. This analysis is useful to detect the presence of general trends in the data. Geostatistical techniques were used to analyze spatial variability and distribution of sample data to estimate parameters at unsampled locations in three main steps [44]:

1. Assumption of stationarity,
2. Spatial modelling of sample data, and
3. Estimation of variable value at unsampled location.

The analysis of spatial correlation can be undertaken using Stanford Geostatistical Modeling Software, (SGeMS) [42].

The original data set containing gold grades for 120 stopes were transformed to a gaussian space using standard normal score transformation applied in geostatistical analyses. Transformation of data to normal score distribution satisfies the assumption of stationarity of data. The transformed normal score data is also useful as input data in the stochastic gaussian simulation technique [45] as shown in Figure 3 for the gold grades.

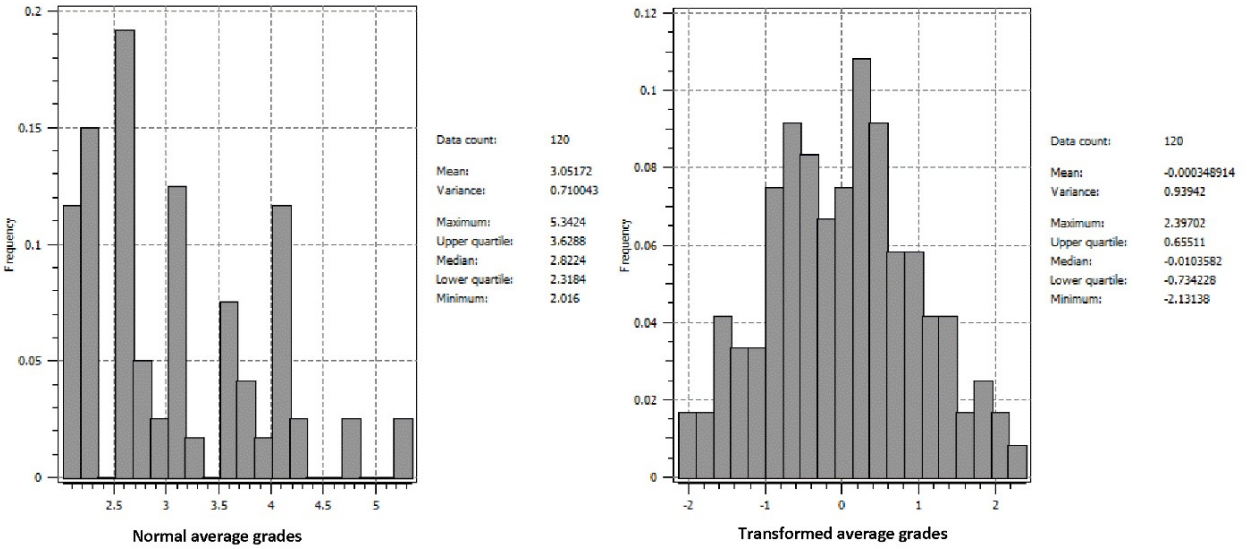

Figure 3. Histogram and transformed normal score for gold grades.

Variogram analysis, which allows for examination of data correlation with respect to distance, was done for gold grades. Omnidirectional variogram for the grades was first computed to identify the sill while vertical variograms were used to identify the nugget effect. Primary variogram maps were calculated to determine the orientation of the major axis in the presence of anisotropy. Directional experimental variograms were calculated and theoretical variogram models were fitted to the experimental variograms. The parameters used to model the experimental variogram are presented in Table 1.

Table 1. Parameters used for variogram modelling.

Direction	Azimuth (°)	Variogram model	Sill contribution	h_{min} (m)	h_{max} (m)	Nugget
Vertical	0.0	Gaussian	0.5	3.5	5.9	0.5
Minor	112.5	Gaussian	0.5	3.5	5.9	0.5
Major	67.5	Gaussian	0.5	3.5	5.9	0.5

A gaussian variogram model was fitted to the experimental variograms in the horizontal major direction and the horizontal minor direction. Figure 4 shows the experimental and fitted variogram models in the major and minor directions, and in the vertical direction. The general equation for gaussian variogram model is as shown in Eq. (1).

$$\gamma(h) = C.\left(1 - \exp\left(\frac{-3h^2}{a^2}\right)\right) \quad (1)$$

Where C is the structure variance and a is the effective range.

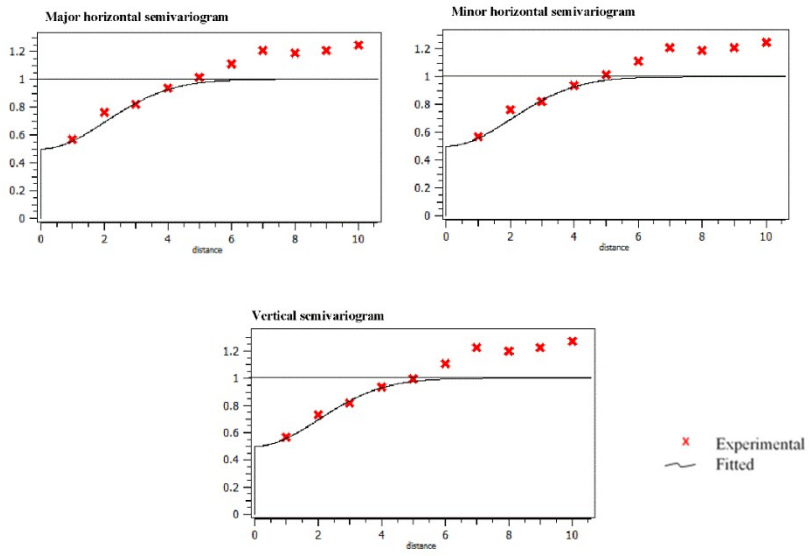

Figure 4. Experimental directional variogram and fitted variogram models for gold grades (distance in meters).

4. Assumptions

It is assumed that the mineral reserve will be extracted using underground mining techniques with a predetermined classical optimum design for stope limits. The optimum stope outline represents reserve discretization units that will maximize the profit from the project. For the open stope underground mining method in this research, ore extraction is achieved by an advancement method with a top-down approach. In addition:

1. The ore pass bin is considered in the mining system as the primary point from where all material mined (ore and waste) exit the mine.
2. Materials from the ore pass bin are managed on a first-in first-out basis with no mixing.
3. Material from the ore pass bin can be sent directly to the processing plant or stockpiled at the surface ore stockpile.
4. The surface ore stockpile is adopted to store ore that exceeds the current processing plant capacity and is reclaimed in the future.
5. There are no physical or chemical modifications should ore stay longer in the surface stockpile.

It is also assumed that grade uncertainty will be the only stochastic variable considered during the geologic block modelling. It is also assumed that the future cost and price data used for the economic block models are constant. This assumption implies that as cost and price changes in the future, there is a need for re-optimization of the production schedules based on prevailing economic conditions and current industry practice. Ore extraction is achieved by open stoping and includes either retreating or advancement methods. Caving mining methods will not be evaluated.

Activities involved in collecting drilling and sampling data for developing the geologic block model will not be considered. Other geotechnical properties of the deposit will not be modeled or considered

during optimization aside stope sequencing. No stability analysis of the development and stope designs will be undertaken. Figure 5 is a representation of the material flow from the mine to the processing plant through the ore pass bin and/or surface ore stockpile. As illustrated in Figure 5, material extracted, from stope y_k^t can be sent directly to processing plant x_k^t through the ore pass. Alternatively, material extracted from stope $y_{k,}^t$ can be sent to the stockpile $u_{k,si}^t$ and material from the stockpile $u_{k,so}^t$ can be reclaimed to the processing plant.

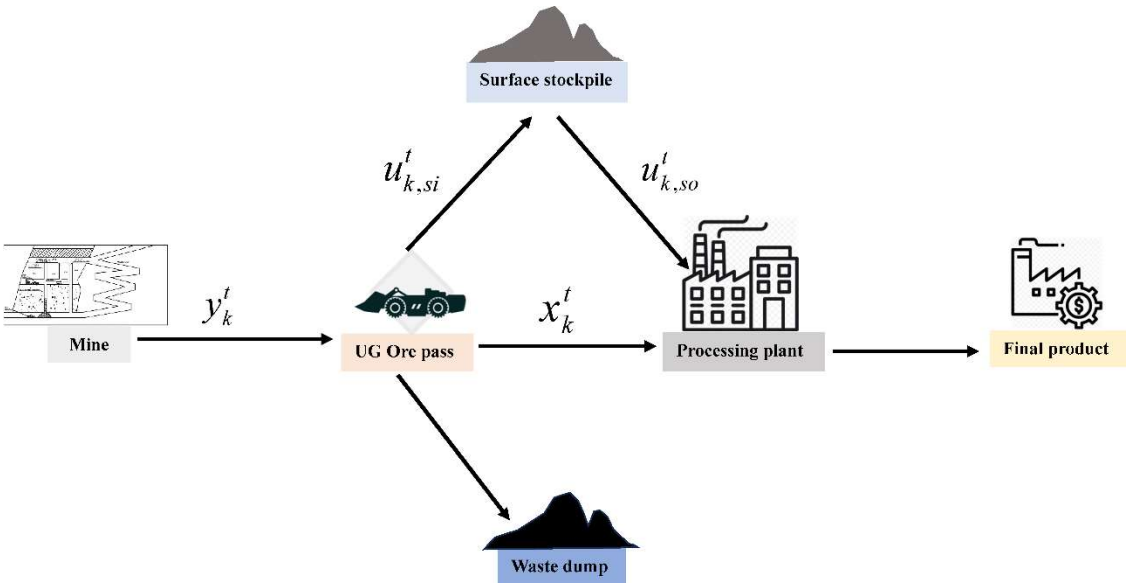

Figure 5. Material flow diagram from mine to final product

4.1. Notation

We present a SMILP formulation for the open stope underground mining production scheduling problem. The notation for indices, decision variables, sets and parameters are as follows:

t index for schedule time periods: $t = 1, 2, 3, \ldots, T,$ where *T* is the schedule duration.

k index for stope identification: $k = 1, 2, 3, \ldots, K,$ where *K* is the total number stopes.

l index for level identification: $l = 1, 2, 3, \ldots, L$, where *L* is the total number of levels.

s index for realization identification: $s = 1, 2, 3, \ldots, S$, where *S* is the total number of realizations.

4.2. Sets

$K = \{1,...,K\}$ set of all stopes in the model

$K_l = \{1,...,K_l\}$ set of all stopes on level *l* in the model

$S = \{1,...,S\}$ set of all equally probable stope realizations in the model

$C = \{1,...,C\}$ set of all primary development in the model

$C_l = \{1,...,C_l\}$ set of all primary development on level *l* in the model

$A = \{1,..., A\}$ set of all operational development in the model

$A_l = \{1,..., A_l\}$ set of all operational development on level *l* in the model

$V = \{1,..., V\}$ set of all ventilation development in the model

$V_l = \{1,..., V_l\}$ set of all ventilation development on level *l* in the model

$P = \{1,..., P\}$ set of all ore pass development in the model

$P_l = \{1,..., P_l\}$ set of all ore pass development on level *l* in the model

$A_k(J)$ for each stope *k*, there is a set $A_k(J) \subset K$ defining the adjacent stopes that cannot be mined simultaneously with the extraction or backfilling of stope *k*; where *J* is the total number of stopes in the set $A_k(J)$.

$G_k(S)$ for each stope *k*, there is a set $G_k(S) \subset K$, defining the immediate predecessor stopes that must be extracted prior to stope *k*; where *S* is the total number of stopes in the set $G_k(S)$.

$D_a(L)$ for each level *l*, there is a set $D_a(L) \subset OD_l$, defining the number of operational development on that level that must be completed before a stope and an ore pass can be extracted; where *L* is the total number of operational development on that level in the set $D_a(L)$.

$D_c(L)$ for each level *l*, there is a set $D_c(L) \subset CD_l$, defining the number of primary development that must be completed before operational development on that level can be started; where *L* is the total number of primary development on that level in the set $D_c(L)$.

$D_v(L)$ for each level *l*, there is a set $D_v(L) \subset VD_l$, defining the number of ventilation development that must be completed before operational development on that level can be started; where *L* is the total number of ventilation development on that level in the set $D_v(L)$.

$L_l(M)$ for each level l , there is a set $L_l(M)$ defining all stopes on this level; where M is the total number of stopes in the set $L_l(M)$.

$L_l(D)$ for each level l , there is a set $L_l(D)$ defining all operational development on this level; where D is the total number of operational development activities in the set $L_l(D)$.

4.3. Parameters

$R^t_{k,p,s}$	revenue generated by selling the final mineral commodity in stope *k* of realization *s* in period *t* from the ore pass.
$R^t_{k,so,s}$	revenue generated by selling the final mineral commodity in stope *k* of realization *s* in period *t* from the stockpile.
i	discount rate.
o_k	ore tonnage in stope *k.*
$o_{k,so}$	ore tonnage in stope *k* sent from stockpile to plant.
$o_{k,so,s}$	ore tonnage in stope *k* for realization *s* sent from stockpile to plant.
$o_{k,s}$	ore tonnage in stope *k* of realization *s.*
w_k	waste tonnage in stope *k.*
$w_{k,s}$	waste tonnage in stope *k* of realization *s.*
$g_{k,s}$	average grade of mineral in ore portion of stope *k* for realization *s.*
$g^t_{k,so}$	average grade of mineral in ore portion of stope *k* sent from stockpile to plant.
$g^t_{k,so,s}$	average grade of mineral in ore portion of stope *k* for realization *s* sent from stockpile to plant.
r^t	processing recovery: the portion of mineral recovered in stope in period *t.*
sp^t	selling price in present value terms obtainable per unit of mineral commodity.
sc^t	selling cost in present value terms per unit of mineral commodity.
mp^t_k	extra cost in present value terms per tonne of ore for mining and processing of stope *k* in period *t*.
rc^t	mining recovery of stope in period t.
$di_{k,s}$	mining dilution of stope k of realization *s*.
C^t_k	total cost in present value terms of primary development for stope *k* in period *t.*
c^t_k	variable cost in present value terms per length of primary development for stope *k* in period *t.*

H_k^t total cost in present value terms of ventilation development for stope *k* in period *t.*

h_k^t variable cost in present value terms per length of ventilation development for stope *k* in period *t.*

E_k^t total cost in present value terms of operational development for stope *k* in period *t*

e_k^t variable cost in present value terms per length of operational development for stope *k* in period *t.*

Q_k^t total cost in present value terms of mining from stope *k* in period *t.*

q_k^t variable cost in present value terms per tonne of mining from stope *k* in period *t*.

F_k^t total cost in present value terms of backfilling stope *k* in period *t.*

cf_k^t variable cost in present value terms per unit volume of backfilling stope *k* in period *t.*

Z_k^t total cost in present value terms of ore pass development for stope *k* in period *t.*

z_k^t variable cost in present value terms per length of ore pass development for stope *k* in period *t.*

cs_k^t variable cost in present value terms per tonne for stockpiling ore from stope *k* in period *t.*

$L_{c,lb}^t$ lower bound on primary development length (decline) in period *t.*

$L_{c,ub}^t$ upper bound on primary development length (decline) in period *t.*

d_{cl} primary development length cl.

$L_{v,lb}^t$ lower bound on ventilation development length in period *t.*

$L_{v,ub}^t$ upper bound on ventilation development length in period *t*

d_{vl} ventilation development length vl.

$L_{a,lb}^t$ lower bound on operational development length for period *t.*

$L_{a,ub}^t$ upper bound on operational development length for period *t.*

d_a	operational development length a .
$L^t_{p,lb}$	lower bound on ore pass development length in period *t.*
$L^t_{p,ub}$	upper bound on ore pass development length in period *t.*
d_p	ore pass development length p .
$T^t_{m,lb}$	lower bound on available mining capacity in period *t* (tonnes).
$T^t_{m,ub}$	upper bound on available mining capacity in period *t* (tonnes).
$T^t_{pr,lb}$	lower bound on ore processing capacity in period *t* (tonnes).
$T^t_{pr,ub}$	upper bound on ore processing capacity in period *t* (tonnes).
$T^t_{si,ub}$	upper bound on stockpile capacity in period *t* (tonnes).
$gr^t_{pr,lb}$	lower bound on acceptable average grade of ore at the processing plant in period *t.*
$gr^t_{pr,ub}$	upper bound on acceptable average grade of ore at the processing plant in period *t.*
$gr^t_{si,lb}$	lower bound on acceptable average grade of ore at the stockpile in period *t.*
$gr^t_{si,ub}$	upper bound on acceptable average grade of ore at the stockpile in period *t.*
$V^t_{f,lb}$	lower bound on backfilling volume in period *t.*
$V^t_{f,ub}$	upper bound on backfilling volume in period *t.*
d_{fv}	backfilling volume fv .
N^t_{lc}	the maximum number of active levels available for operational development in period *t.*
N^t_{le}	the maximum number of active levels available for stope extraction in period *t.*
N_{xd}	the maximum length of extraction duration for stopes.
GDR	geological discount rate.

$pntCT^t_{o,+}$ penalty cost in terms of the upper ore tonnage target deviation in period *t.*

$pntCT^t_{o,-}$ penalty cost in terms of the lower ore tonnage target deviation in period *t.*

$pntCT^t_{g,+}$ penalty cost in terms of the upper ore grade target deviation in period *t.*

$pntCT^t_{g,-}$ penalty cost in terms of the lower ore grade target deviation in period *t.*

$SPpntCT^t_{g,+}$ penalty cost in terms of the stockpile upper grade target deviation in period *t.*

$SPpntCT^t_{g,-}$ penalty cost in terms of the stockpile lower grade target deviation in period *t.*

4.4. Decision variables

$x^t_k \in [0,1]$ continuous variable representing the portion of stope *k* to be extracted as ore and processed in period *t*

$y^t_k \in [0,1]$ continuous variable representing the portion of the stope *k* to be mined in period *t*; fraction of *y* characterizes both ore and waste in the stope

$f^t_k \in [0,1]$ continuous variable representing the portion of stope k to be backfilled in period *t*.

$u^t_{k,si} \in [0,1]$ continuous variable representing the portion of stope k sent to stockpile in period *t*.

$u^t_{k,so} \in [0,1]$ continuous variable representing the portion of stope k sent from stockpile to the plant in period *t*.

$d^t_c \in [0,1]$ continuous variable representing the portion of primary development length c to be completed in period t.

$d^t_a \in [0,1]$ continuous variable representing the portion of operational development length a to be completed in period t.

$d^t_v \in [0,1]$ continuous variable representing the portion of ventilation development v to be completed in period t.

$d^t_p \in [0,1]$ continuous variable representing the portion of ore pass development p to be completed in period t.

$d^t_{a,l} \in [0,1]$ continuous variable representing the set of operational development activities a to be completed on level l in period t.

$odev^t_{s,+} \in [0,1]$ continuous variable representing the excess from the ore tonnage upper bound in period *t* for realization *s*.

$odev^t_{s,-} \in [0,1]$ continuous variable representing the shortage to the ore tonnage lower bound in period *t* for realization *s*.

$gdev^t_{s,+} \in [0,1]$ continuous variable representing the excess from the grade upper bound in period *t* for realization *s*.

$gdev^t_{s,-} \in [0,1]$ continuous variable representing the shortage to the grade lower bound in period *t* for realization *s*.

$jgdev^t_{s,+} \in [0,1]$ continuous variable representing the excess from the stockpile grade upper bound in period *t* for realization *s*.

$jgdev^t_{s,-} \in [0,1]$ continuous variable representing the shortage to the stockpile grade lower bound in period *t* for realization *s*.

$b^t_k \in \{0,1\}$ b^t_k is a binary integer variable controlling the precedence of extraction of mining stope *k;* b^t_k is equal to one if extraction of stope *k* has started in period *t,* otherwise it is zero

$bf^t_k \in \{0,1\}$ bf^t_k is a binary integer variable controlling the precedence of backfilling of stope *k;* bf^t_k is equal to one if backfilling of stope *k* has started in period *t,* otherwise it is zero

$b^t_{c,l} \in \{0,1\}$ $b^t_{c,l}$ is a binary integer variable controlling the precedence of operational developments $b^t_{c,l}$ is equal to one if primary development c on level l has started by or in period t, otherwise it is zero.

$b^t_{a,l} \in \{0,1\}$ binary integer variable controlling the precedence of operational developments. $b^t_{a,l}$ is equal to one if operational development a on level l has started by or in period t, otherwise it is zero.

$b^t_{p,l} \in \{0,1\}$ binary integer variable controlling the precedence of ore pass development. $b^t_{p,l}$ is equal to one if ore pass development p on level l has started by or in period t, otherwise it is zero.

$b^t_{v,l} \in \{0,1\}$ binary integer variable controlling the precedence of ventilation development (installations). $b^t_{v,l}$ is equal to one if ventilation development (installation) v on level l has started by or in period t, otherwise it is zero.

$lc_l^t \in \{0,1\}$ binary integer variable: when it is equal to one, it implies operational development activities are in progress on level l in period t.

$le_l^t \in \{0,1\}$ binary integer variable: when it is equal to one, it implies stope extraction activities are in progress on level l in period t.

5. Stochastic Mixed Integer Linear Programming (SMILP) Model Formulation

The SMILP optimization framework for generating long-term production schedule in the presence of grade uncertainty was modeled using multiple realizations from Sequential Gaussian Simulation (SGS) of the orebody. Revenue is calculated for each stope in each realization. The revenue of a stope is generated by selling the final product less all the costs involved in developing, extracting, and processing the stope. The mining cost per stope is a function of the distance between its location and its destination (processing plant and stockpile). Since the long-term production plan isa multi-period optimization problem and stopes are extracted in different periods, a discount rate is applied to calculate the present value of the revenue and the costs. Grade uncertainty causes shortfall from target production levels.

The application of geological discount rate referred to as GDR [14] in this work helps to control the grade and ore tonnage risk distribution over time and ensures the extraction of lower-risk and higher-grade stopes in the early periods, leaving higher-risk stopes for later periods when more information becomes available from mining. It is essential for the operation to mine less risky parts of the deposits in the early stages with limited geological information. As more geological information becomes available in the form of operational data, new schedules can be produced for later periods.

Penalty cost parameters are financial consequences for deviations from desired outcomes, that make simulation exercises more realistic and reveals the impact of decisions made. By incorporating penalty costs, simulations can effectively evaluate different strategies, manage risks, and promote optimal performance. Therefore, the penalty cost can be altered to prioritize the most critical operational targets according to the optimization requirements in the mining complex.

Penalty cost parameters $pntCT_{o,+}^t$, $pntCT_{o,-}^t$, $pntCT_{g,+}^t$, $pntCT_{g,-}^t$, $SPpntCT_{g,+}^t$ and $SPpntCT_{g,-}^t$ are defined and used for minimizing deviations from ore tonnage and ore grade production targets.

The objective function of the SMILP model in Eq. (2) is to maximize the expected NPV and minimize deviations from production targets. The first part of the objective function comprises of the total discounted cashflow from ore material from direct mining and stockpile to the processing plant for all realizations. The second part of the objective function minimizes the costs associated with deviating from the processing plant ore tonnage operating targets for all realizations. The third and fourth part minimizes the total costs associated with deviating from the processing plant and stockpile ore grade operating targets for all realizations respectively. Thus, the second, third, and fourth parts aim to control grade uncertainty by minimizing the variability from the ore tonnage and ore grade targets. Deviations are discounted in terms of geological discount rate (GDR) to implement a time dependent risk profile [14]. The concept presented in Appianing et al. [46] was used as the starting point of this work.

The objective function expressed in Eq. (2) is composed of the discounted revenues considering ore recovery rc^t and mining dilution $di_{k,s}$ factors in Eqs. (3) and (4), discounted cost of stope extraction

Eq. (5), discounted cost of primary development Eq. (6), discounted cost of ventilation development Eq. (7), discounted cost of operational development Eq. (8), discounted cost of ore pass development Eq. (9) and discounted cost of backfilling Eq. (10). Therefore, to obtain an optimum schedule, NPV must be maximized and the deviation from target productions must be minimized simultaneously among all simulation realizations. Therefore, the revenue for the stochastic model is calculated using Eqs. (3) and (4). By this uncertainty integrated objective function, the SMILP model can reduce the risk of not meeting the planned production targets and provide a feasible schedule.

$$Max \frac{1}{S}\sum_{s=1}^{S}\sum_{t=1}^{T}\sum_{k=1}^{K}\left[\frac{\begin{array}{l}(R^t_{k,p,s}\times x^t_k)+(R^t_{k,so,s}\times u^t_{k,so})-(Q^t_k\times y^t_k)-(C^t_k\times d^t_c)\\ -(H^t_k\times d^t_v)-(E^t_k\times d^t_a)-(Z^t_k\times d^t_p)-(F^t_k\times f^t_k)\end{array}}{(1+i)^t}\right] - \left[\begin{array}{l}\frac{1}{s}\sum_{s=1}^{S}\sum_{t=1}^{T}\left[\frac{(pntCT^t_{o,+}\times odev^t_{s,+})+(pntCT^t_{o,-}\times odev^t_{s,-})}{(1+GDR)^t}\right]\\ +\frac{1}{s}\sum_{s=1}^{S}\sum_{t=1}^{T}\left[\frac{(pntCT^t_{g,+}\times gdev^t_{s,+})+(pntCT^t_{g,-}\times gdev^t_{s,-})}{(1+GDR)^t}\right]\\ +\frac{1}{s}\sum_{s=1}^{S}\sum_{t=1}^{T}\left[\frac{(SPpntCT^t_{g,+}\times jgdev^t_{s,+})+(SPpntCT^t_{g,-}\times jgdev^t_{s,-})}{(1+GDR)^t}\right]\end{array}\right] \quad (2)$$

$$R^t_{k,p,s}=(g_{k,s}\times o_{k,s}\times r_k\times rc^t\times(sp^t-sc^t))-(o_{k,s}\times(1+di_{k,s})\times(mp^t_k+cstp^t_k)) \quad (3)$$

$$R^t_{k,so,s}=(g_{k,s}\times o_{k,s}\times r_k\times rc^t\times(sp^t-sc^t))-(o_{k,s}\times(1+di_{k,s})\times mp^t_k) \quad (4)$$

$$Q^t_k=q^t_k\times(o_k+w_k) \quad (5)$$

$$C^t_k=c^t_k\times d_c \quad (6)$$

$$H^t_k=h^t_k\times d_v \quad (7)$$

$$E^t_k=e^t_k\times d_a \quad (8)$$

$$Z^t_k=z^t_k\times d_p \quad (9)$$

$$F^t_k=cf^t_k\times d_{fv} \quad (10)$$

5.1. Constraints

Constraints considered for the formulation follow the underground mining sequence of operation. Thus, for a typical underground mining system, capital development precedes ventilation development before operational development. Extraction then precedes operational development and finally backfilling. Illustrated in Figure 6 are the constraint dependencies for the open stope mining production schedule formalism. In summary, the primary contribution of this research is the integration of mine development, grade uncertainty, stockpiling and production schedules in a stochastic optimization framework that generates a practical mine-plan.

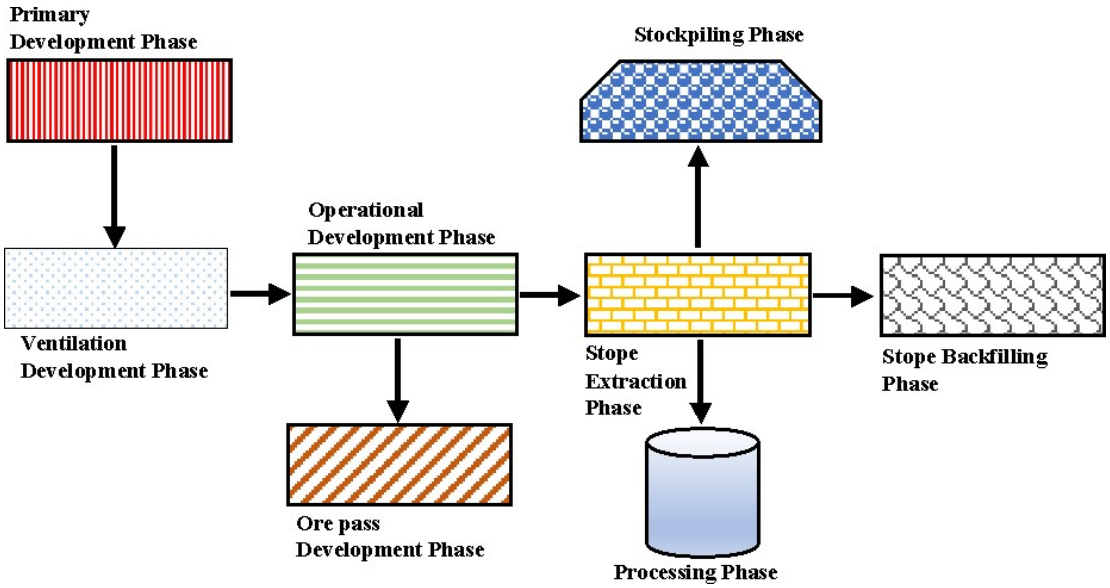

Figure 6. Constraints dependencies.

5.1.1. Primary Development Constraints

Eqs. (11) and (12) define the primary development upper and lower limits capacity constraints for the mine. These inequalities ensure that the total length of primary development required in a period is within the stated lower and upper limits of the total available equipment capacity for developing the mine. Eqs. (13) to (16) control the precedence relations between sections of primary development leading to each mining level and the ventilation development on each level.

Specifically, Eqs. (13) to (15) ensure that the set of primary development representing a section above a level must be completed before the primary development $d_{c,l}^{t}$ of the level commences. Eq. (16) ensures that the ventilation development $b_{v,l}^{t}$ on a level linking the primary development can only commence after completion of a set of required primary development $\sum_{t=1}^{t} d_{c,l}^{t}$ above and on that level.

$$\sum_{c=1}^{C}\left(d_{c,l}\times d_{c}^{t}\right)\le L_{c,ub}^{t},\ \forall t\in\{1,...,T\};\tag{11}$$

$$\sum_{c=1}^{C}\left(d_{c,l}\times d_{c}^{t}\right)\ge L_{c,lb}^{t},\ \forall t\in\{1,...,T\};\tag{12}$$

$$b_{c,l}^{t}-\sum_{t=1}^{t} d_{s,l}^{t}\le 0,\ \forall l\in(1,...,L), s\in D_{c}(L);\tag{13}$$

$$\sum_{t=1}^{t} d_{c,l}^{t}-b_{c,l}^{t}\le 0,\quad \forall l\in\{1,...,L\}, c\in\{1,...,C\};\tag{14}$$

$$b_{c,l}^{t}-b_{c,l}^{t+1}\le 0,\quad \forall l\in\{1,...,L\}, t\in\{1,...,T-1\}, c\ \in\{1,...,C\};\tag{15}$$

$$b_{v,l}^{t}-\sum_{t=1}^{t} d_{c,l}^{t}\le 0,\quad \forall l\in\{1,...,L\}, c\in D_{c},(L), v\in D_{v}(L);\tag{16}$$

5.1.2. Ventilation Development Constraints

Ventilation is required to provide airflow into development and workings for the comfort of workers and functioning of equipment. Eqs. (17) to (22) present the set of constraints defining the ventilation requirements to enhance stope extraction. Eqs. (17) and (18) define the ventilation development upper and lower limits capacity constraints for the mine. These inequalities ensure that the total length of ventilation development required in a period is within the stated lower and upper limits of the total available equipment capacity for ventilation development. Eqs. (19) to (22) control the precedence relationships between the sections of ventilation development leading to each mining level and the operational development on each level.

Specifically, Eqs. (19) to (21) ensure that the set of ventilation development representing a section above a level must be completed before the ventilation development $d_{v,l}^t$ of the level commences. Eq. (22) ensures that the operational development $d_{a,l}^t$ on a level linking the ventilation development $b_{v,l}^t$ can only commence after completion of a set of required ventilation development $\sum_{t=1}^{t} d_{v,l}^t$ above and on that level.

$$\sum_{v=1}^{V}\left(d_{vl} \times d_v^t\right) \le L_{v,ub}^t, \quad \forall t \in \{1,...,T\}; \tag{17}$$

$$\sum_{v=1}^{V}\left(d_{vl} \times d_v^t\right) \ge L_{v,lb}^t, \quad \forall t \in \{1,...,T\}; \tag{18}$$

$$b_{v,l}^t - \sum_{t=1}^{t} d_{s,l}^t \le 0, \quad \forall l \in \{1,...,L\}, s \in D_v(L); \tag{19}$$

$$\sum_{t=1}^{t} d_{v,l}^t - b_{v,l}^t \le 0, \quad \forall l \in \{1,...,L\}, v \in \{1,...,V\}; \tag{20}$$

$$b_{v,l}^t - b_{v,l}^{t+1} \le 0, \quad \forall l \in \{1,...,L\}, t \in \{1,...,T-1\}, v \in \{1,...,V\}; \tag{21}$$

$$b_{a,l}^t - \sum_{t=1}^{t} d_{v,l}^t \le 0, \quad \forall l \in \{1,...,L\}, a \in D_a(L), v \in D_v(L); \tag{22}$$

5.1.3. Operational development constraints

If a stope is scheduled to be mined in a period, a set of operational development must be completed ahead or in that period. Eqs. (23) to (28) present the set of constraints defining the operational development and lateral precedence relations for stope extraction sequence. This includes the type and length of each operational development (level drives and crosscuts). Eqs. (23) and (24) define the operational development upper and lower limits capacity constraints for the mine. These equations ensure that the total length of operational development required in each period is within the defined lower and upper limits of the total available equipment capacity for developing the mine. Eqs. (25) to (27) control the lateral precedence relation of the operational development required for each stope. Eq. (28) ensures that for each stope, there is a set of operational development $\sum_{t=1}^{t} d_{a,l}^t$ that must be completed before mining the stope $b_{k,l}^t$.

$$\sum_{a=1}^{A}\left(d_a \times d_a^t\right) \le L_{a,ub}^t, \quad \forall t \in \{1,...,T\}; \tag{23}$$

$$\sum_{a=1}^{A}\left(d_a \times d_a^t\right) \ge L_{a,lb}^t, \quad \forall t \in \{1,...,T\}; \tag{24}$$

$$b_{a,l}^t - \sum_{t=1}^{t} d_{s,l}^t \le 0, \quad \forall l \in \{1,...,L\}, s \in D_a(L); \tag{25}$$

$$\sum_{t=1}^{t} d_{a,l}^t - b_{a,l}^t \le 0, \quad \forall l \in \{1,...,L\}, a \in \{1,...,A\}; \tag{26}$$

$$b_{a,l}^t - b_{a,l}^{t+1} \le 0, \quad \forall l \in \{1,...,L\}, t \in \{1,...,T-1\}, a \in \{1,...,A\}; \tag{27}$$

$$b_{k,l}^t - \sum_{t=1}^{t} d_{a,l}^t \le 0, \quad \forall l \in \{1,...,L\}, k \in \{1,...K_l\}, a \in D_a(L); \tag{28}$$

5.1.4. Ore Pass Development Constraints

Eqs. (29) and (30) define the ore pass development upper and lower limits capacity constraints for the mine. These inequalities ensure that the total length of ore pass developed in a period is within the stated lower and upper limits of the total available equipment capacity for developing the ore pass for the mine. Eqs. (31) to (34) control the precedence relations between the sections of ore pass development leading to each mining level and the operational development on the level.

Specifically, Eqs. (31) to (33) ensure that the set of ore pass development representing a section above a level must be completed before the ore pass $d_{p,l}^t$ of the level commences. Eq. (34) ensures that the development of the ore pass $d_{p,l}^t$ linking the operational level can only commence after completion of a set of required operational development $\sum_{t=1}^{t} d_{a,l}^t$ above and on that level.

$$\sum_{p=1}^{P}\left(d_p \times d_p^t\right) \le L_{p,ub}^t, \quad \forall t \in \{1,...,T\}; \tag{29}$$

$$\sum_{p=1}^{P}\left(d_p \times d_p^t\right) \ge L_{p,lb}^t, \quad \forall t \in \{1,...,T\}; \tag{30}$$

$$b_{p,l}^t - \sum_{t=1}^{t} d_{s,l}^t \le 0, \quad \forall l \in \{1,...,L\}, s \in D_p(L); \tag{31}$$

$$\sum_{t=1}^{t} d_{p,l}^t - b_{p,l}^t \le 0, \quad \forall l \in (1,...,L), p \in \{1,...,P\}; \tag{32}$$

$$b_{p,l}^t - b_{p,l}^{t+1} \le 0, \quad \forall l \in (1,...,L), t \in \{1,...,T-1\}, p \in \{1,...,P\}; \tag{33}$$

$$b_{p,l}^t - \sum_{t=1}^{t} d_{a,l}^t \le 0, \quad \forall p \in \{1,...,P\}, a \in D_a(L), l \in (1,...,L); \tag{34}$$

5.1.5. Mining Capacity Constraints

The total material mined is expressed as the sum of ore tonnage, and waste tonnage. Though the total material may not be extracted all together in a specific period, the fractional extraction of material is

controlled using the continuous decision variable y_k^t. The mining capacity constraints are expressed in Eqs. (35) and (36).

$$\sum_{k=1}^{K}\left[(o_{k,s}+w_{k,s})\times y_k^t\right]\le T_{m,ub}^t,\ \ \forall t\in\{1,...,T\},\forall s\in\{1,...,S\}; \tag{35}$$

$$\sum_{k=1}^{K}\left[(o_{k,s}+w_{k,s})\times y_k^t\right]\ge T_{m,lb}^t,\ \ \forall t\in\{1,...,T\},\forall s\in\{1,...,S\}; \tag{36}$$

5.1.6. Processing Capacity Constraints

To complete the SMILP formulation, Eqs. (37) and (38) are the processing capacity constraints that control the quantity of mill feed for the mine in each period for all realizations. We introduce continuous variables $odev_{s,+}^t$ and $odev_{s,-}^t$ which serve as buffers to allow for deviations from the processing targets. They are however penalized in the objective function. Penalizing such deviations ensure that the tonnage of ore processed at the plant is close to the required targets as much as is feasible.

$$\sum_{k=1}^{K}\left[((o_{k,s}\times x_{k,\mathrm{m}}^t)+\sum_{so=1}^{SO}(o_{k,so,s}\times u_{k,so}^t)-odev_{s,+}^t\right]\le T_{pr,ub}^t,\forall t\in\{1,...,T\},\forall s\in\{1,...,S\}; \tag{37}$$

$$\sum_{k=1}^{K}\left[((o_{k,s}\times x_{k,\mathrm{m}}^t)+\sum_{so=1}^{SO}(o_{k,so,s}\times u_{k,so}^t)+odev_{s,-}^t\right]\ge T_{pr,lb}^t,\forall t\in\{1,...,T\},\forall s\in\{1,...,S\}; \tag{38}$$

5.1.7. Grade Blending Constraints

Eqs. (39) and (40) define the upper and lower limit of the grade to be sent to the plant in each period. The deviation decision variables $gdev_{s,+}^t$ and $gdev_{s,-}^t$ are introduced to serve as buffers to the ore grade targets. Eqs. (41) and (42) also define the upper and lower limit of grade delivered to the stockpile. The deviation decision variables $jdev_{s,+}^t$ and $jdev_{s,-}^t$ are introduced to serve as buffers to the stockpile ore grade targets. Similar to the processing quantity constraints, the excess and shortage of the desired grade range in each period across all geological realizations are penalized as indicated in the objective function(Eq. (2)). These constraints are controlled by the continuous decision variables $x_{k,m}^t, u_{k,si}^t, u_{k,so}^t, gdev_{s,+}^t, gdev_{s,-}^t, jgdev_{s,+}^t$ *and* $jgdev_{s,-}^t$ in each period.

$$\sum_{k=1}^{K}\left[(g_{k,s}-gr_{pr,ub}^t)\times(o_{k,s}\times x_{k,m}^t)+\sum_{so=1}^{SO}(g_{k,so,s}^t-gr_{pr,ub}^t)\times(o_{k,so,s}\times u_{k,so}^t)-gdev_{s,+}^t\right]\le 0, \tag{39}$$
$$\forall t\in\{1,...,T\},\forall k\in\{1,...,K\},\forall s\in\{1,...,S\};$$

$$\sum_{k=1}^{K}\left[(gr_{pr,lb}^t-g_{k,s})\times(o_{k,s}\times x_{k,m}^t)+\sum_{so=1}^{SO}(gr_{pr,lb}^t-g_{k,so,s}^t)\times(o_{k,so,s}\times u_{k,so}^t)+gdev_{s,-}^t\right]\le 0, \tag{40}$$
$$\forall t\in\{1,...,T\},\forall k\in\{1,...,K\},\forall s\in\{1,...,S\}$$

$$\sum_{k=1}^{K}((g_{k,s}-gr_{si,ub}^t)\times(o_{k,s}\times u_{k,si}^t)-jgdev_{s,+}^t)\le 0, \tag{41}$$
$$\forall t\in\{1,...,T\},\forall k\in\{1,...,K\},\forall s\in\{1,...,S\}$$

$$\sum_{k=1}^{K}((gr_{si,lb}^{t} - g_{k,s}) \times (o_{k,s} \times u_{k,si}^{t}) + jgdev_{s,-}^{t}) \leq 0, \quad \forall t \in \{1,...,T\}, \forall k \in \{1,...,K\}, \forall s \in \{1,...,S\}; \tag{42}$$

5.1.8. Stope Extraction Precedence Constraints

Eqs. (43) to (45) control the lateral precedence relations of stope extraction on each level of the mining operation. The stoping sequence for the deposit is implemented in an advancing and top-down approach. Thus, mining generally starts from the upper level to the lower level exploiting the deposit from the center of the mine towards to the periphery of the mine.

$$b_k^t - \sum_{t=1}^{t} y_s^t \leq 0, \quad \forall s \in G_k(S), k \in \{1,...,K\}; \tag{43}$$

$$\sum_{t=1}^{t} y_k^t - b_k^t \leq 0, \quad \forall k \in \{1,...,K\}; \tag{44}$$

$$b_k^t - b_k^{t+1} \leq 0, \quad \forall t \in \{1,...T-1\}, k \in \{1,...,K\}; \tag{45}$$

5.1.9. Backfilling Management Constraints

The backfilling constraints include backfilling capacity and sequencing constraints, and stope status constraints. Eqs. (46) and (47) present the upper and lower limit backfilling capacity constraints. The total volume of material backfilled in each period cannot exceed the capacity of the backfill plant and equipment in the period.

The stope status constraints are defined to monitor geotechnical and ground quality conditions. These constraints control where to start operational development and extraction for a level and progress sequentially. Eq. (48) ensures that each active stope can only be in either extraction or backfilling phase during any specific period. The two activities cannot be in progress at the same time for a stope. Eq. (49) ensures that stope ore extraction precedes backfilling. Eq. (50) ensures that each stope is in either the extraction or backfilling phase immediately after a non-zero stope extraction period. The stope status and backfilling sequencing constraints work together to ensure each stope progresses through discrete mining activities sequentially from operational development to extraction and then backfilling. These constraints indirectly limit the exposure time of the void area after mining to reduce potential excessive geotechnical stresses prior to backfilling.

$$\sum_{k=1}^{K}\left(d_{fv} \times f_k^t\right) \leq V_{f,ub}^t, \quad \forall t \in \{1,...,T\}; \tag{46}$$

$$\sum_{k=1}^{K}\left(d_{fv} \times f_k^t\right) \geq V_{f,lb}^t, \quad \forall t \in \{1,...,T\}; \tag{47}$$

$$b_k^t + f_k^t \leq 1, \quad \forall t \in \{1,...,T\}, k \in \{1,...,K\}; \tag{48}$$

$$f_k^t - \sum_{t=1}^{t}(x_{k,\mathrm{m}}^t + u_{k,si}^t) \leq 0, \quad \forall t \in \{1,...,T\}, k \in \{1,...,K\}; \tag{49}$$

$$b_k^t \leq b_k^{t+1} + bf_k^{t+1}, \quad \forall t \in \{1,...,T-1\}, k \in \{1,...,K\}; \tag{50}$$

5.1.10. Non-Adjacent Stope Extraction Constraints

These are geotechnical constraints that focus on limiting the size of unsupported void areas. To demonstrate the functioning of these constraints, the nine adjacent stopes depicting the two kinds of

spatial constraints required to facilitate geotechnical stability of the stoping area in extraction and backfilling scenarios can be seen in Figure 7. When a stope is being extracted or backfilled, the adjacent stopes cannot be active. As illustrated in Figure 7, if the central stope Sp5 is in the extraction state, all operational activities are forbidden in the near adjacent stopes (Sp2, Sp4, Sp6, Sp8). Similarly, when a stope is being backfilled, the adjacent stopes cannot be exploited. Eqs. (51) and (52) ensure that all forms of adjacent stope extraction or backfilling activities are avoided to prevent excessively large unsupported voids.

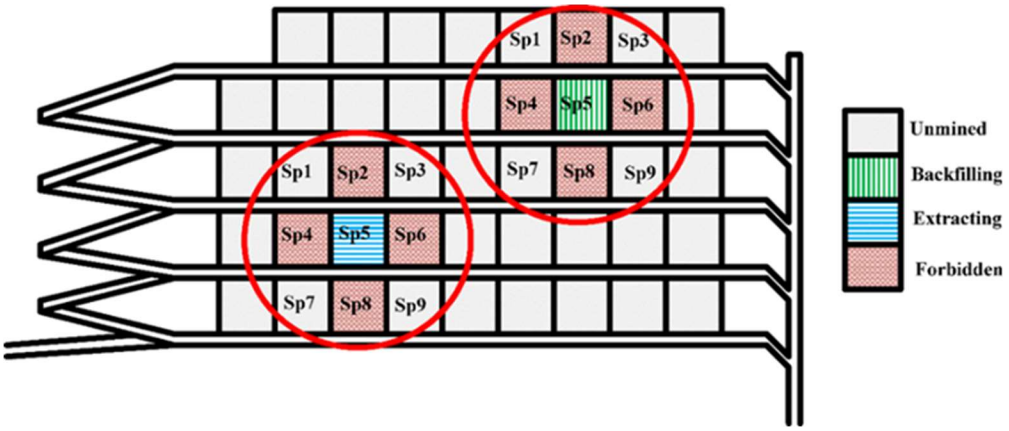

Figure 7. A schematic illustration of non-adjacent stope extraction and backfilling activities modified after Huang et al. [11].

$$b_k^t + b_j^t \le 1, \ \forall t \in \{1,...,T\}, k \in \{1,...,K\}, j \in A_k(J); \tag{51}$$

$$bf_k^t + b_j^t \le 1, \ \ \forall t \in \{1,...,T\}, k \in \{1,...,K\}, j \in A_k(J); \tag{52}$$

5.1.11. Active Levels Control Constraints

Many active levels in a mine might lead to serious operational problems. A controlled maximum number of simultaneous active levels allow mine planners to adjust extraction to different application scenarios depending on available infrastructure, production rates, equipment capacities, and the stability of the surrounding rocks. The constraints expressed in Eqs. (53) to (56) control the maximum number of simultaneous active levels in each period. In Eqs. (53) and (54), when operational development activity is ongoing, or a portion of a stope is being extracted in period *t,* on level l, the relevant binary variable lc_l^t and le_l^t must be equal to one. In Eqs. (55) and (56), N_{lc}^t and N_{le}^t are provided as allowable input in the formulation for which the maximum number of simultaneous active levels must not exceed in each period. The active levels control constraints guide the model to generate a more operationally feasible mining pattern, thus ensuring a practical maximum NPV.

$$\sum_{t=1}^{t}\left(\frac{1}{D}\sum_{d=1}^{D} d_{a,l}^t - lc_l^t\right) \le 0, \ \ \forall t \in \{1,...,T\}, l \in \{1,...,L\}, \ \mathrm{a} \in L_l(D); \tag{53}$$

$$\sum_{t=1}^{t}\left(\frac{1}{M}\sum_{m=1}^{M} x_m^t - le_l^t\right) \le 0, \ \ \forall t \in \{1,...,T\}, l \in \{1,...,L\}, \ \mathrm{m} \in L_l(M); \tag{54}$$

$$\sum_{l=1}^{L} lc_l^t \le N_{lc}^t, \ \ \forall t \ \in \{1,...,T\}; \tag{55}$$

$$\sum_{l=1}^{L} le_l^t \le N_{le}^t, \quad \forall t \in \{1,...,T\}; \tag{56}$$

5.1.12. Stope Extraction Duration Constraints

The length of stope extraction depends on notably, stope size, rate of production, and mining plan. Eq. (57) ensures that the period of extraction of a stope cannot exceed a pre-defined number of periods. This inequality enables the model to implement continuous stope extraction, mirror the mining environment, and regulate the allowed extraction period. This adds practicality and strengthens the functionality of the formulation.

$$\sum_{t=1}^{T} y_k^t \le N_{xd}, \quad \forall t \in \{1,...,T\}; \tag{57}$$

5.1.13. Stockpile Management Constraints

The stockpile capacity constraint that control the quantity of ore material sent to the stockpile is presented in Eq. (58). This constraint also ensure that the capacity of stockpile does exceed predefined limit. To control ore sent to the stockpile, the decision variable is used. Since the stockpile is primarily grade controlled, there is no additional requirement to introduce a deviational variable to minimize ore tonnage deviation from the stockpile capacity target. An additional stockpile ore tonnage deviation variable adds to the complexity of the optimization problem and extends the solution time. Eq. (59) ensures that the cumulative quantity of ore sent to the stockpile exceeds the cumulative quantity of ore sent out of the stockpile to the plant. Thus, at the end of the mine-life, there could be some ore left in the stockpile. Eq. (60) accumulates the metal content of ore sent to the stockpile and ensures that the cumulative metal content must not exceed the cumulative metal content sent out from the stockpile to the plant.

$$\sum_{k=1}^{K}\left[(o_{k,s} \times u_{k,si}^t)\right] \le T_{si,ub}^t, \forall t \in \{1,...,T\}, \forall s \in \{1,...,S\}; \tag{58}$$

$$\sum_{i=1}^{t}\sum_{k=1}^{K}(o_{k,so,s} \times u_{k,so}^i) \le \sum_{i=1}^{t-1}\sum_{k=1}^{K}(o_{k,s} \times u_{k,si}^i), \forall t \in \{1,...,T\}, \forall s \in \{1,...,S\}; \tag{59}$$

$$\sum_{i=1}^{t}\sum_{k=1}^{K}(o_{k,so,s} \times g_{k,so,s}^t \times u_{k,so}^i) \le \sum_{i=1}^{t-1}\sum_{k=1}^{K}(o_{k,s} \times g_{k,s} \times u_{k,si}^i), \forall t \in \{1,...,T\}, \forall s \in \{1,...,S\}; \tag{60}$$

5.1.14. Variables Control Constraints

Eq. (61) defines the relations between mining, ore extraction, and stockpiling variables controlling the stope mining, ore stockpiling, and waste decisions. Thus, the continuous variables x_k^t and $u_{k,so}^t$ representing ore extraction and stockpiling plus amount of the waste dilution should always be smaller than or equal to the continuous variable y_k^t representing stope mining in each period. Eq. (62) show the relation between stockpiling variables controlling material that goes to stockpile and out of stockpile to processing plant. Thus, the sum of the continuous variables must be smaller than or equal to 1. Eqs. (63) and (64) ensure that the total fractions of stopes and backfilling volumes over the scheduling periods sum up to one. Eqs. (65) to (66) ensure that the total fractions of ore sent to stockpile from the mine and sent from stockpile to processing plant from stockpile over the scheduling periods sum up to one. Thus, ore in each circumstance may be scheduled once. Eqs. (67) to (70) ensure that all developments (primary, ventilation, operational, and ore pass) are going to be constructed once in the life of the mine. The variable control constraints define the logics and inter-relations of the binary and continuous variables that define extraction, backfilling, and primary, ventilation, operational, and ore pass development to ensure they are within desired ranges.

$$x_k^t + u_{k,so}^t \le y_k^t, \forall t \in \{1,...,T\}, k \in \{1,...,K\}; \quad (61)$$

$$u_{k,si}^t + u_{k,so}^t \le 1, \forall t \in \{1,...,T\}, k \in \{1,...,K\}; \quad (62)$$

$$\sum_{t=1}^{T} f_k^t \le 1, \forall k \in \{1,...,K\}; \quad (63)$$

$$\sum_{t=1}^{T} x_k^t \le 1, \forall k \in \{1,...,K\}; \quad (64)$$

$$\sum_{t=1}^{T} u_{k,si}^t \le 1, \forall k \in \{1,...,K\}; \quad (65)$$

$$\sum_{t=1}^{T} u_{k,so}^t \le 1, \forall k \in \{1,...,K\}; \quad (66)$$

$$\sum_{t=1}^{T} d_c^t \le 1, \forall c \in \{1,...,C\}; \quad (67)$$

$$\sum_{t=1}^{T} d_v^t \le 1, \forall v \in \{1,...,V\}; \quad (68)$$

$$\sum_{t=1}^{T} d_a^t \le 1, \forall a \in \{1,...,A\}; \quad (69)$$

$$\sum_{t=1}^{T} d_p^t \le 1, \forall p \in \{1,...,P\}; \quad (70)$$

5.1.15. Non-Negativity Constraints

Eq. (71) ensures that all continuous decision variables are non-negative. Eq. (72) defines all binary variables as non-negative and integers. Eq. (73) defines the additional non-negativity constraints for deviational decision variables for processing tonnes and ore grade targets. These constraints enforce that none of these variables can take on negative values during the optimization process.

$$x_k^t, u_{k,si}^t, u_{k,so}^t, y_k^t, f_k^t, d_c^t, d_v^t, d_a^t, d_p \ge 0 \quad (71)$$

$$b_k^t, b_{c,l}^t, b_{v,l}^t, b_{a,l}^t, b_{p,l}^t \ge 0 \text{ and integers} \quad (72)$$

$$odev_{s,+}^t, odev_{s,-}^t, gdev_{s,+}^t, gdev_{s,-}^t, jgdev_{s,+}^t, jgdev_{s,-}^t \ge 0, \forall_t \in \{1,...T\}, \forall_s \in \{1,...S\}; \quad (73)$$

6. Results and discussions of Case studies

This section presents the implementation of the SMILP optimization models for a gold deposit. Six Case studies are presented. For Cases 1 and 2, a single orebody model which was based on Ordinary Kriging (OK) was used as the input block model. Cases 3 and 4 were implemented based on stochastic block models represented by 50 SGS realizations. The SGS realizations generate a set of equally probable block models used to capture and assess uncertainty in the deposit and production schedule. Cases 5 and 6 were based on the E-type block model which is the average simulated block model generated by post-processing of the SGS realizations. The E-type estimates showed slight differences from the Ordinary Kriging model. However, in theory, the E-type model is identical to the kriging results in Gaussian space [47, 48] . For Case 1, the MILP model is implemented without the grade controlled stockpile management strategy and for Case 2, the MILP model is implemented with the grade controlled stockpile management strategy. For Case 3, the integrated SMILP model

is also implemented without the grade-controlled stockpile management strategy and finally for Case 4, the SMILP model is implemented with the grade-controlled stockpile management strategy. Similarly, for Case 5 was implemented without the grade-controlled stockpile management and Case 6 implemented with the grade-controlled stockpile management. Grade uncertainty is incorporated into the mine planning by using multiple simulated orebody realizations as inputs for the SMILP model. The SMILP model optimizes on a block-by-block basis to account for the consistent variation in ore grades across different blocks in each realization. Thus, this chapter documents the implementation of the uncertainty-based SMIL model, which integrates stockpiling management into production planning optimization under conditions of grade uncertainty and further presents the comparison between the MILP and SMIL models' performance, and the identified indicators needed to achieve desired production levels. The effects of the identified indicators like risk factors and deviational parameters on the production schedules are also presented through sensitivity analysis. Additionally, the advantage of incorporating a grade-controlled stockpile management strategy is presented. This chapter also documented.

Table 2 provides details about the gold deposit's characteristics and the designed stopes. Figure 8 displays a cross-section of the block model, illustrating the distribution of gold grades within the deposit. Figure 9 shows the section of the block model, some designed stopes, and development layout created using Promine software [41]. IBM CPLEX Optimization Studio V12.6.3 [43] was integrated within a MATLAB 2023a [49] environment to define the modelled framework and solve the optimization problem at a gap tolerance of 1%. The model was tested on an Intel (R) Core™ i7-6500U CPU at 2.50 GHz with 64 GB of RAM.

Table 2. Characteristics of gold deposit and designed stopes.

Description	Value
Total mineralized material (Mt)	2.88
Maximum grade value of Au (g/t)	5.34
Minimum grade value of Au (g/t)	1.40
Average grade value of Au (g/t)	3.05
Number of levels	8
Stope height (m)	30
Stope length (m)	25
Stope width (m)	10-12

The orebody exhibits scattered high-grade mineralization throughout the deposit, while certain areas in the upper region contain prominent low-grade sections. The surrounding waste rock is composed of medium to low strength rock, making open stoping with backfilling the preferred mining method. 120 stopes were designed from the block model with 8 operational levels. Each level had 15 stopes (numbering from left to right) and continue on the level below following same pattern from left to right. Thus, the decending and advancing method of extracton was adopted where stope extraction starts from the first level continues downwards while exploiting stopes sequentially on each level towards the end of each level before moving to the next level downwards.

Table 3 contains the economic and technical criteria used to assess the case study. On the basis of the total amount of material to be extracted and the proposed plant capacity, respectively, annual capacities for mining and processing were established. Cost projections in Canadian dollars were gathered from industry professionals and technical mining company reports [50-52].

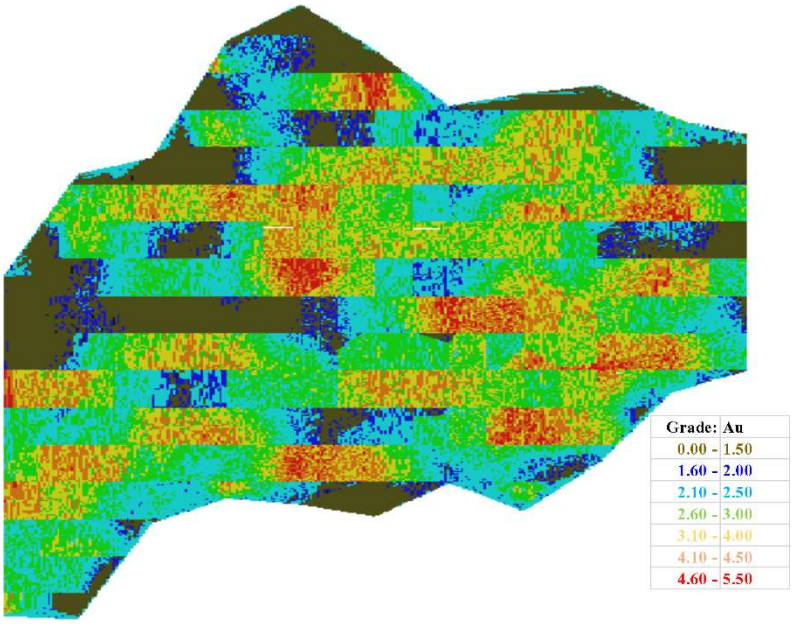

Figure 8. Cross-section of the block model depicting the distribution of gold grades (Not drawn to scale).

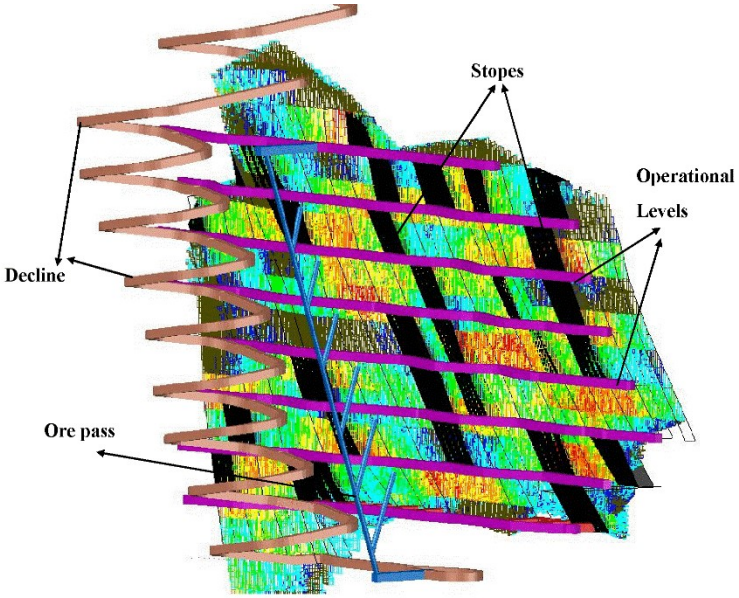

Figure 9. A pictorial illustration of the block model with some designed stopes and development.

Table 3. Technical data used.

Parameter	Value
UG mining cost ($/t)	96.04
Processing cost ($/t)	15.21
Backfilling cost ($/t)	15.00
Operational development cost ($/m)	4,500
Capital development cost ($/m)	6,500
Ventilation cost ($/m)	3,000
Selling price of gold ($/oz)	2,000
Discount rate (%)	8.00
Mining recovery (%)	93.00
Variable Mining dilution* (%)	5.00 / 10.00
Maximum mining capacity (Kt/period)	140.0
Maximum processing capacity (Kt/period)	110.0
Maximum backfilling capacity (m^3/period)	50,000
Maximum operational development (m/period)	200
Maximum capital development (m/period)	500
Maximum ventilation development (m/period)	500
Maximum stope extraction duration (Period)	2
Maximum ore pass development (m/period)	143
Maximum active levels	7

*Mining dilution of 10% was applied to stopes at the orebody's periphery, while mining dilution of 5% was applied to the remaining stopes. For our case studies, all the lower boundaries of the mining productivity data were set to zero. The optimizer was allowed to operate on multiple active mining levels due to the incorporation of stope backfilling, which improves ground control and increases operational flexibility.

The risk factors indicated in Table 4 were designed largely for Cases 3 and 4 to reduce the risk associated with processing plant and stockpile ore tonnage and ore grade deviations from predetermined targets during production scheduling. These risk parameter values were used for Cases 3 and 4 optimization runs, and were adopted from Huang, Li [11] to assess their impact on the SMILP model solution. In Table 5 are the parameters used for all stockpile implementation cases.

Table 4: Risk parameters for SMILP case studies.

Parameter	Cases 3 and 4
Number of realizations (#)	50
Geological risk discount rate (%)	20
Cost of shortage in ore production ($/tonne)	1500
Cost of excess in ore production ($/tonne)	1500
Cost of shortage in grade ($/g)	500
Cost of excess in grade ($/g)	500
Cost of shortage in stockpile grade ($/g)	500
Cost of excess in stockpile grade ($/g)	500

Table 5: Stockpile parameters.

Stockpile	Value
Maximum grade value of Au (g/t)	1.40
Minimum grade value of Au (g/t)	0.10
Rehandling cost ($/t)	0.5

6.1. Summary Results of Cases 1 and 2

Cases 1 and 2 which involves the MILP model formulation without stockpiling and with stockpiling respectfully benefited from optimized schedules for primary, ventilation, operating, and ore pass development, as well as mining, processing, and backfilling production schedules for a 25-year mine-life. Presented in Table 6 presents the summary of results from Cases 1 (MILP without stockpiling management) and 2 (MILP with stockpiling management). From Table 6, Case 2 achieved more ore tonnage even though it recoded a lower average grade. The high ore tonnage enabled Case 2 to record a higher metal content. These results made Case 2 record a higher metal content which subsequently caused Case 2 to record the highest NPV which is approximately 13% higher than that of Case 1.

Table 6: Summary of cases 1 and 2 results.

Case	Ore tonnage (Mt)	Average grade (g/t)	Au metal (t)	NPV (M$)
Case 1	2.19	2.98	6.53	7344.00
Case 2	2.52	2.87	7.23	7801.20

6.2. Case 3 – SMILP without Stockpile Management

In Figure 10, the primary, ventilation, and ore pass development schedules are presented. The NPV of the SMILP model was $7,601.30 M. Throughout the mine life, 2.64 Mt of material was mined, and 2.37 Mt of material was processed. Aside ore pass development which had the last schedule occurring in Year 23, primary and ventilation development occurred within the first 5 periods. Figure 11 shows the operational development schedule with varying capacities from Year 1 to Year 25 per production requirements.

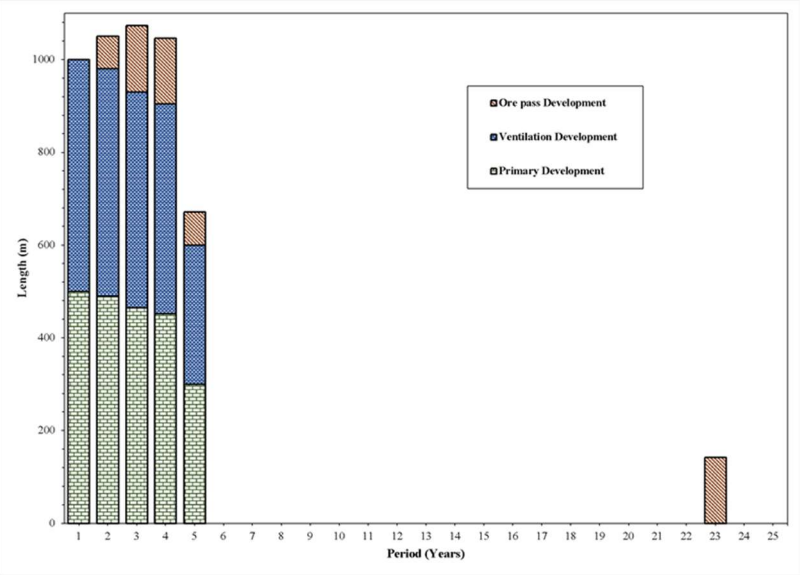

Figure 10. Primary, ventilation, and ore pass development schedule for Case 3.

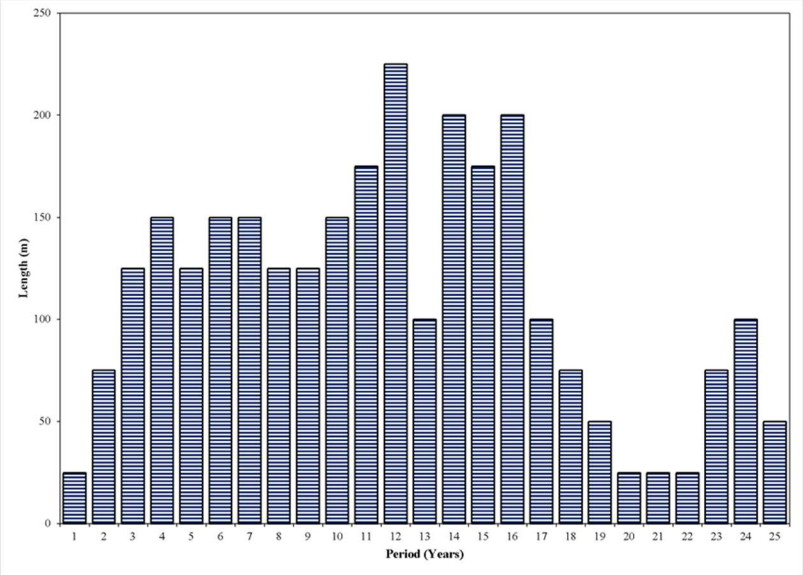

Figure 11. Operational development schedule for Case 3.

The material mined schedule presented in Figure 12 includes waste dilution. The mining operation commenced in Year 1 ramping up following the completion of primary, ventilation, and some initial operational development. The mining output gradually increases from Year 1 to a maximum capacity of 140 Kt in Year 9 and gradually decreases from Year 14 to the end of mine life in Year 25.

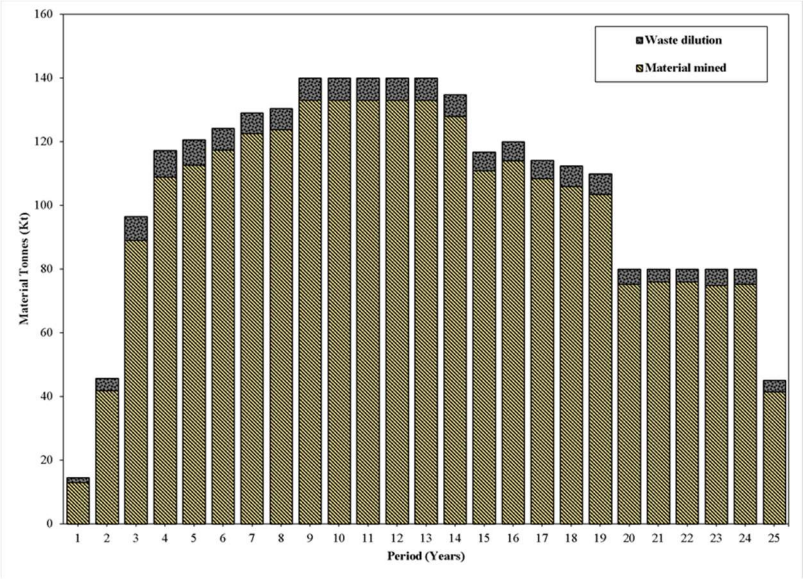

Figure 12. Mined material with estimated waste dilution for Case 3.

Figure 13 shows the material processing schedule and average grade curve from the SMILP model without stockpile management consideration. The plant's operation started in Year 1 ramping up to full plant capacity of 110 Kt in Year 4, and gradually ramping down to 80 Kt from Year 20 to Year 24. The SMILP model emphasizes targeting high-grade locations during the early years of mining based on the average grade profile to optimize the project's Net Present Value (NPV). However, due to development constraints, only a limited number of stopes are available for extraction during the first three years. As a result, the mining system is limited to lower grades that are instantly accessible on the upper levels. As development advances and more stopes become accessible for extraction, the

processing plant's head grade improves from Year 1 to Year 7. In general, medium to high-grade ores are largely extracted during the first ten years of mining, from Year 1 to Year 10. As the higher-grade areas become depleted, the mining operation turns to extracting medium to lower -grade ores from Year 11 to Year 25. This facilitates strategic resource management and effective extraction of higher-grade material when it contributes most to the project's overall financial performance.

The schedule illustrated in Figure 14 shows the order in which each of the three underground mining production phases is completed, ensuring a systematic mining process.

- Operational Development: This phase entails the development of drives and crosscuts within the mine to provide access to the various sections of the orebody. Before proceeding to stope extraction, operational development is prioritized and completed to facilitate ventilation.
- Stope Extraction: After the operational development phase is completed, the stope extraction phase begins. During this phase, accessing and removing of valuable ore material takes place while maintaining the structural integrity of the surrounding rock is mined from the stope
- Backfilling: This phase constitutes the structural integrity of stope extraction. It entails filling the voids left after ore extraction with prescribed material. Backfilling helps to maintain ground stability, reduce surface subsidence and managing of waste material

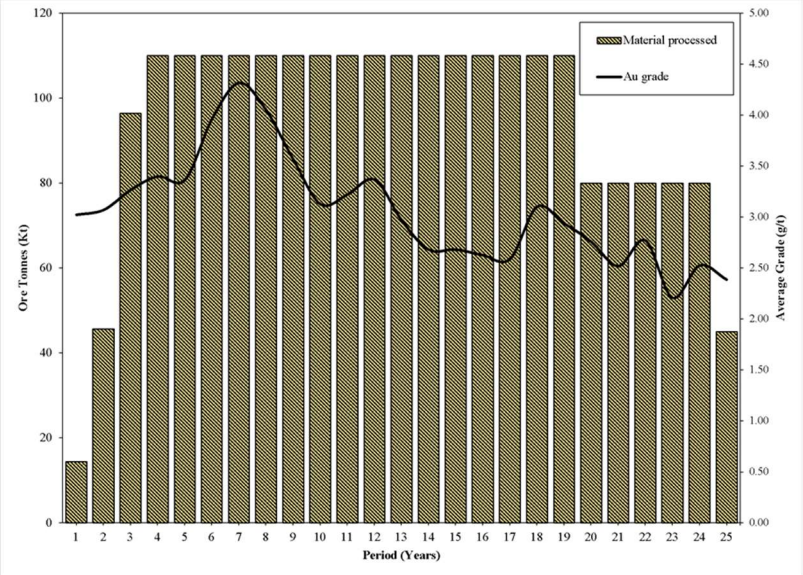

Figure 13. Material processed with average grade curve for Case 3.

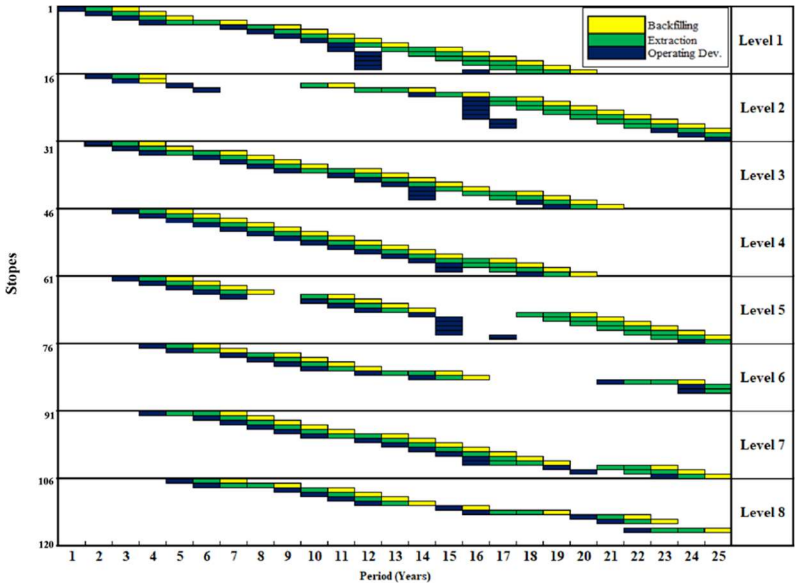

Figure 14. Annual operational development, stope extraction and backfilling schedule for Case 3.

There were certain unique instances in the mining operation where some levels become inactive after mining has started on them due to the availability of higher-grade stopes elsewhere. These extraction variations can be seen on Level 2 from Period 7 to Period 9 and on Level 6 from Period 17 to Period 20.

On Level 2, after the operational development in Periods 6 and 7 for Stopes 18 and 19, there were no immediate extraction and backfilling activities. On Level 6, no immediate operational development, extraction, and backfilling activities occurred from Period 17 to Period 20 before operational development of Stope 84 started. As mentioned earlier, these mining variations were caused by the presence of higher-grade stopes on Level 7, which were prioritized for extraction.

On Levels 6 and 8, some stopes were not extracted by the end of mine life. Specifically, Stopes 87 to 90 on Level 6, and Stopes 116, 118, and 119 on Level 8 respectively. The optimizer made these decisions based on the availability of varied ore grades in the deposit, with the goal of maximizing the project's NPV while maintaining efficient resource governance and safety considerations.

6.3. Case 4 – SMILP with Stockpile Management

The optimized primary, ventilation, operational and ore pass development schedules, and mining, stockpiling, processing, and backfilling schedules allowed for efficient resource utilization and a resulting NPV of $8,077.86 M, which is approximately 10% higher than MILP Case. Figure 15 indicates that primary and ventilation development follow the same timeline as in Case Studies 1, 2 and 3. However, ore pass development, which directly connects to ore extraction and stockpiling, occurred in three separate times; in Years 2 to 4, in Year 16, and in Years 18 and 21.

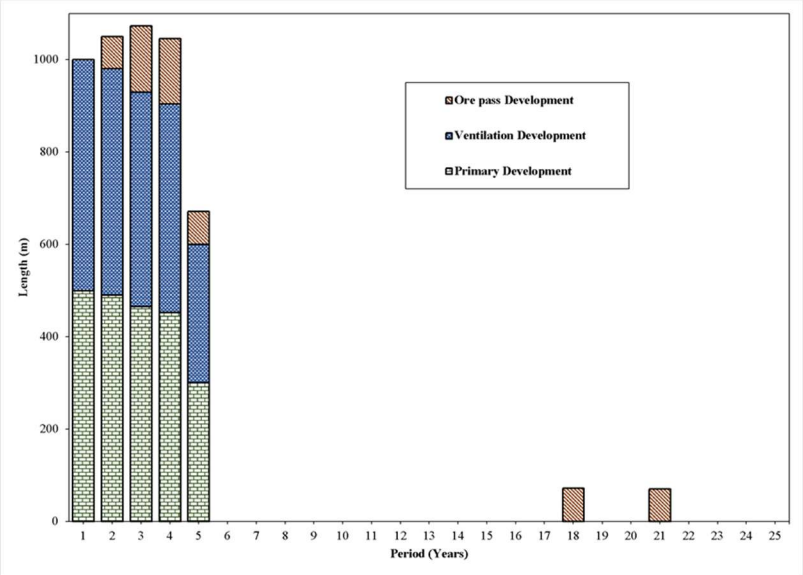

Figure 15: Primary, ventilation and ore pass development schedules for Case 4.

Except for Year 24, operational development occurred at variable rates based on production requirements throughout the mine life as presented in Figure 16.

Figure 17 shows the schedule for material mined with estimated waste dilution. During the first twelve years of the mine life, the planned maximum mining capacity of 140 Kt was achieved from Year 5 to Year 12. The mining operation started ramping down from Year 13 to the end of mine life. This Case resulted in the extraction of 2.5 Mt of material from the open stopes.

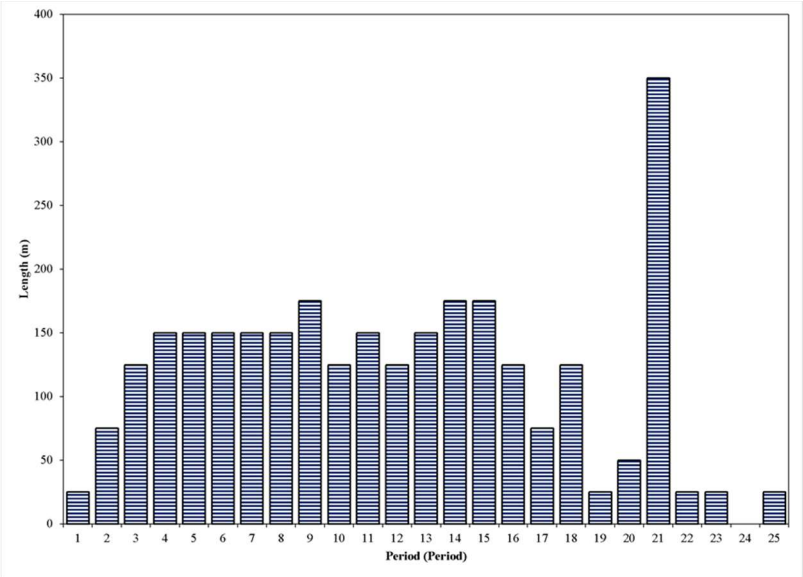

Figure 16: Operational development schedule for Case 4.

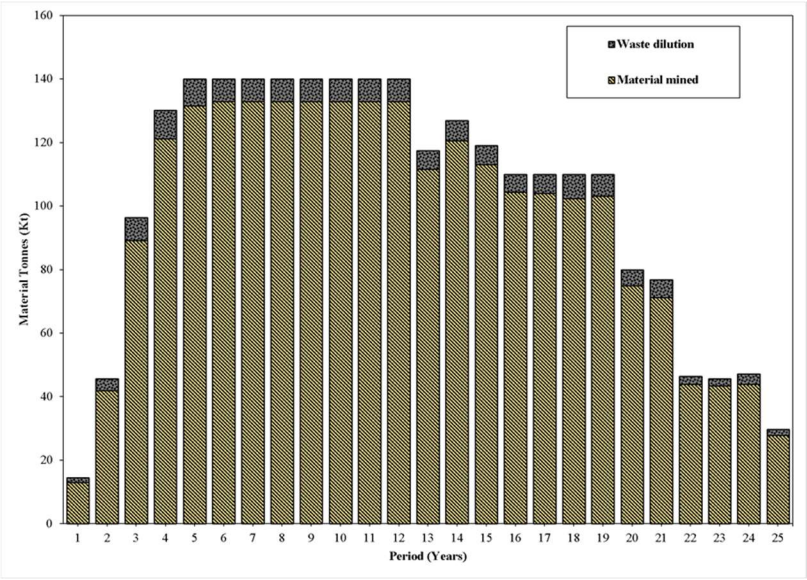

Figure 17: Material mined schedule with estimated waste dilution for Case 4.

Figure 18 depicts a detailed schedule that includes both material processed directly from the mine and material processed from the stockpile. The application of the grade controlled stockpiling strategy, and selective material blending guarantees a steady supply of high-quality ore to the processing plant in the initial stages of the mining operation, optimizing the overall financial returns of the project. Generally, the stockpile inventory profile indicates how the optimizer effectively controlled material storage, strategically utilizing the stockpile to ensure steady plant operations and enhance total material processed. By carefully regulating the stockpile and using it to supplement the direct ore extraction, the project adapts to varying ore grades.

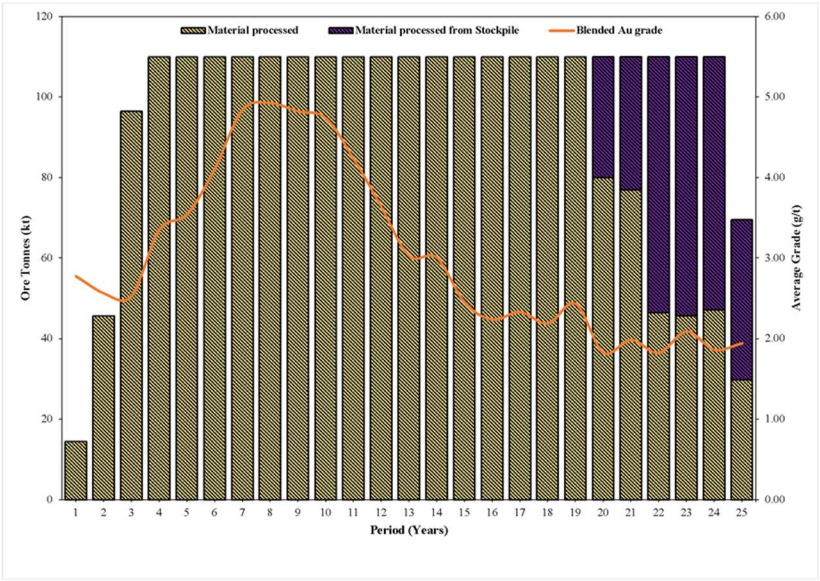

Figure 18: Processed material schedule with blended grade curve for Case 4.

The schedule of material sent to the stockpile and from the stockpile to the processing facility is shown in Figure 19. This schedule demonstrates the execution of the grade control technique. Low-grade material was transported to the stockpile at certain times; from Years 4 to 15. This enabled the extraction of higher-grade material while accumulating lower-grade material for future use. Grade-

blended stockpiled material was reclaimed from the stockpile to the processing plant as needed from Year 20 until the end of mine life. This demonstrates how the stockpile was effectively used to deliver a continual supply of ore to the processing plant, ensuring efficient processing and resource management in the later stages of the mining operation. Approximately 294 Kt of material was stored and reclaimed, adding to the project's overall strategic planning and grade control.

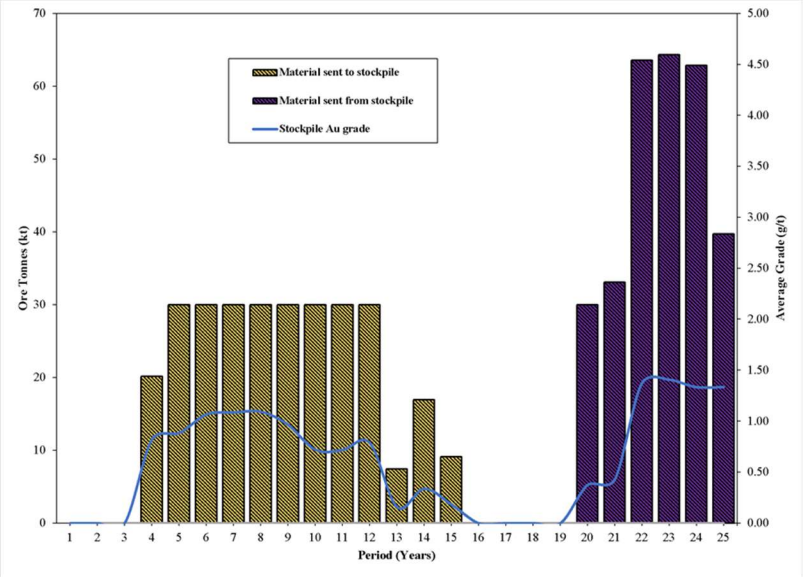

Figure 19: Stockpiled material schedule and grade curve for Case 4.

The stockpile inventory profile is shown in Figure 20 demonstrating material buildup and depletion over the mine life. The stockpile inventory gradually builds up from Year 4 to Year 15. Strategically, lower-grade material is preferentially delivered to the stockpile during these times, while higher-grade material is processed directly from the mine. This stockpiling strategy guarantees a stable supply of material to the processing facility, allowing for a consistent output rate. The stockpile inventory decreases from Year 20 to the end of mine life.

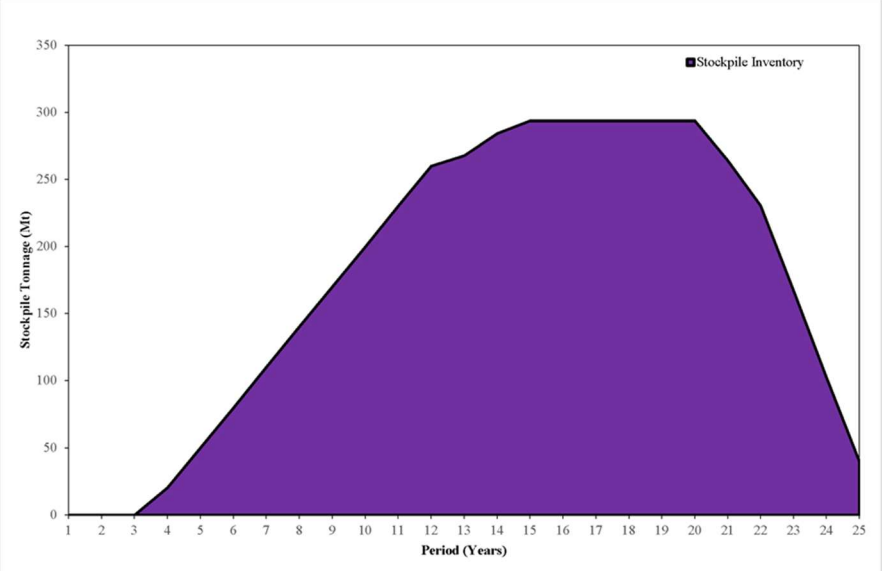

Figure 20: Stockpile inventory profile for Case 4.

Figure 21 depicts the stope production steps. On Levels 6, 7, and 8 during Period 24, there was no operational development work due to extraction and backfilling activities already taking place on these levels. In Period 21 on Level 8, a series of operational advancements and extraction occurred for Stopes 110 to 119. However, the optimizer did not initiate backfilling activity since these stopes constitute the last set of stopes on this level prior to the end of mine life. Subsequently, Stopes 110 to 119 on Level 7 were backfilled from Periods 22 to 25.

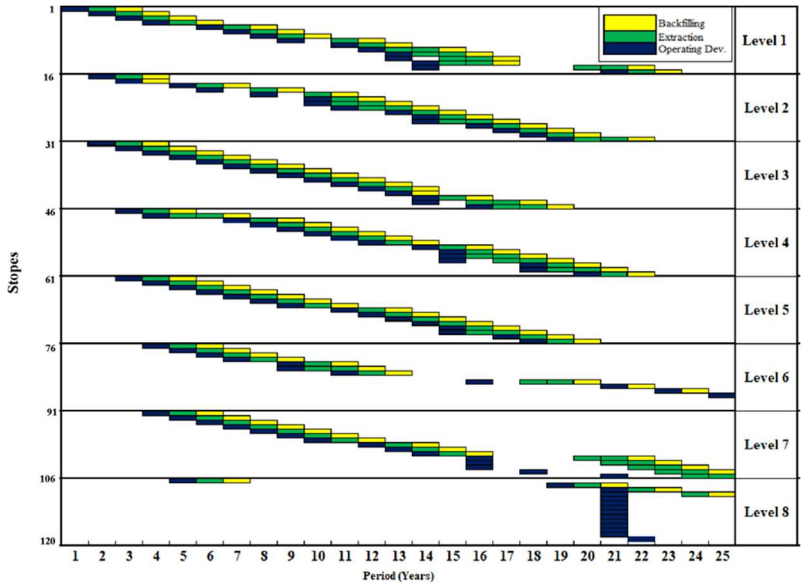

Figure 21: Annual operational development, stope extraction and backfilling schedules for Case 4.

6.4. Case 5 – E-type without Stockpile Management

The E-type block model is the average block model of all generated realizations. This is the expected block model representing a conservative risk profile. Similarly, this experiment was designed to create a consistent processing feed over the course of the mine's existence. 2.29 Mt of material was extracted and total NPV realized was $7,036.10 M. Figure 22 indicate the yearly development schedules for primary, ventilation and ore pass and Figure 23 shows the operational development schedule.

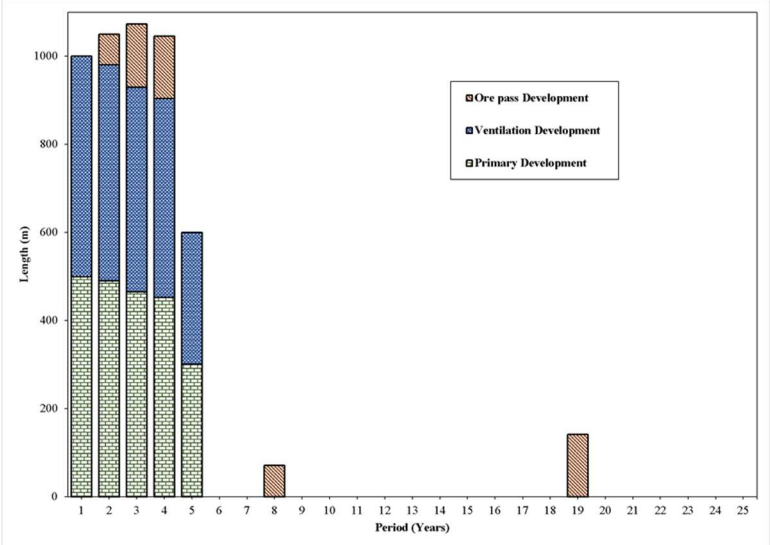

Figure 22: Primary, ventilation and ore pass development schedules for Case 5.

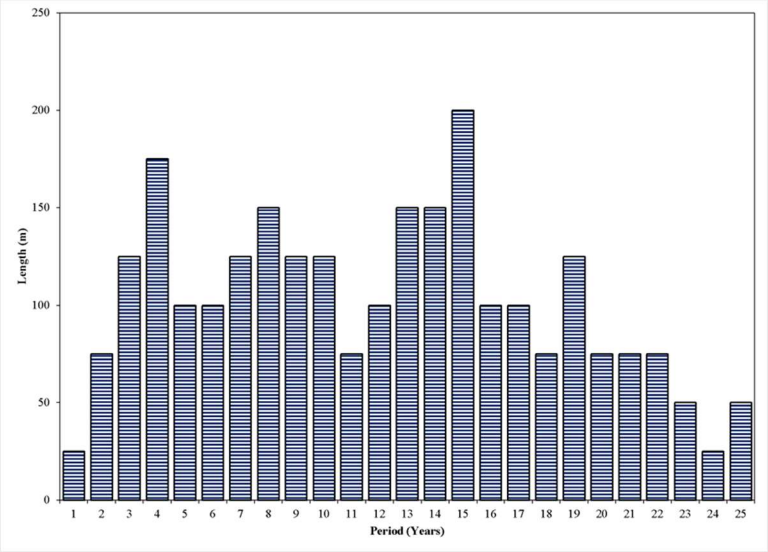

Figure 23: Operational development schedule for Case 5.

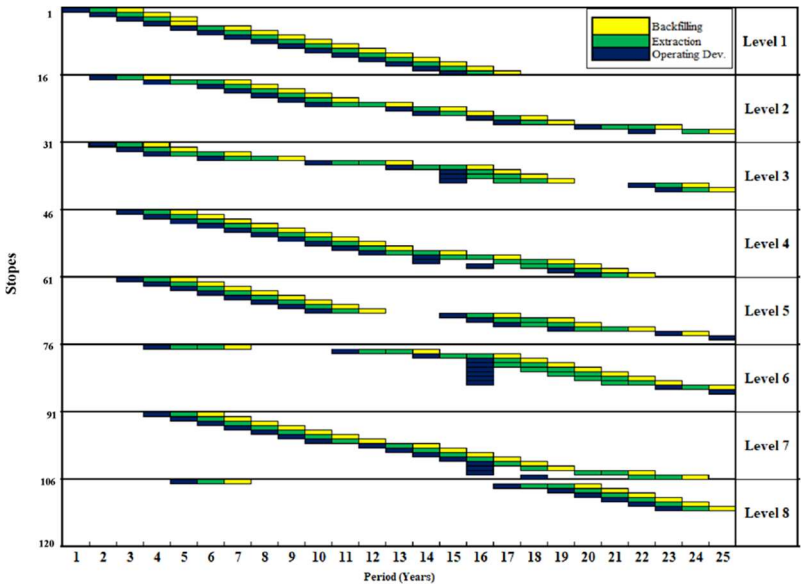

Figure 24 to

Figure 26 presents the mining schedule, processing schedule with grade curve, and operational phases schedules. Case 5 equally met all operating restrictions, and material quality and quantity requirements. It can be seen from Figure 24 that due to development activities, little access was gained to the ore during the first 3 years of the production plan. Gradually as more development were completed, stopes become accessible in subsequent years and the processing plant operate at maximum capacity from Period 4 until Period 16 (Figure 25) when the mine begins a ramping down phase due to limited available stopes. The

annual operational development, stope extraction and backfilling schedules are presented in

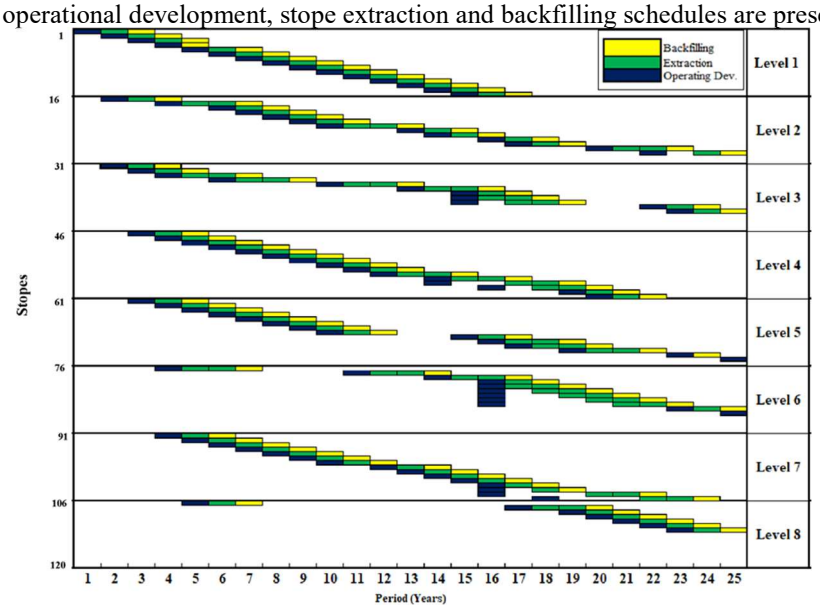

Figure 26.

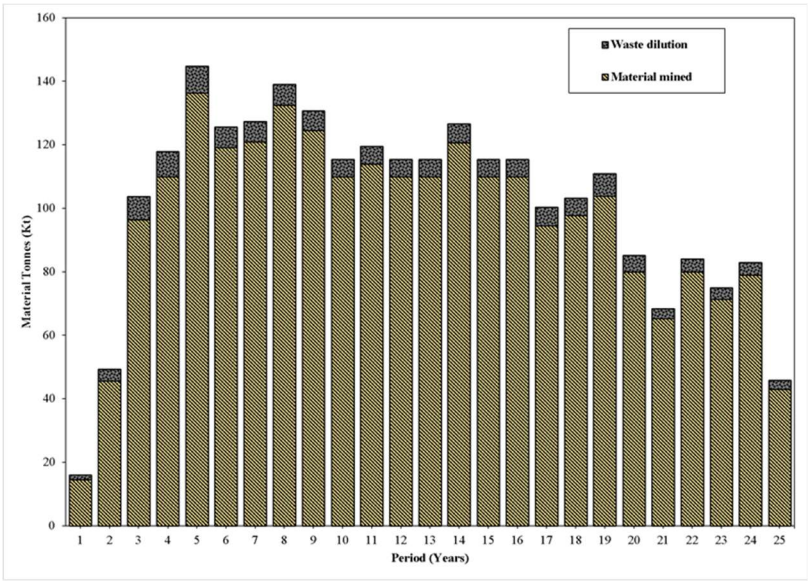

Figure 24. Material mined schedule with estimated waste dilution for Case 5.

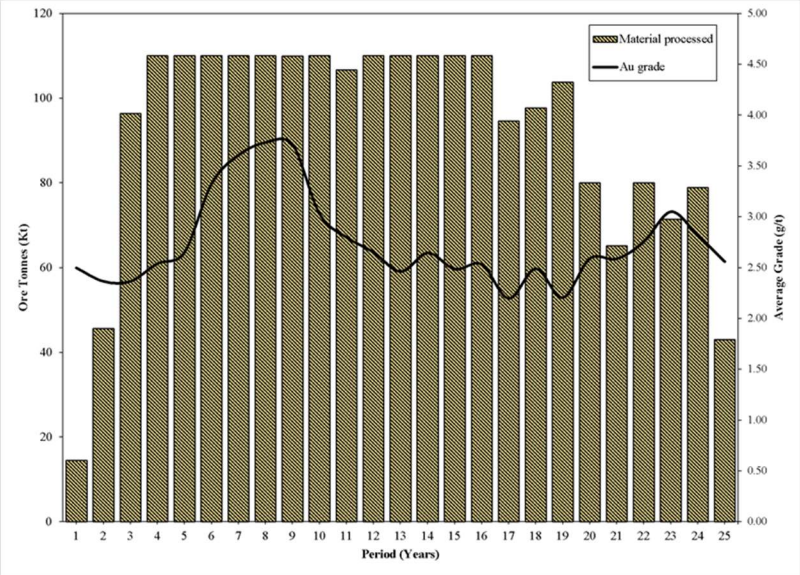

Figure 25. Material processed schedule with average grade curve for Case 5.

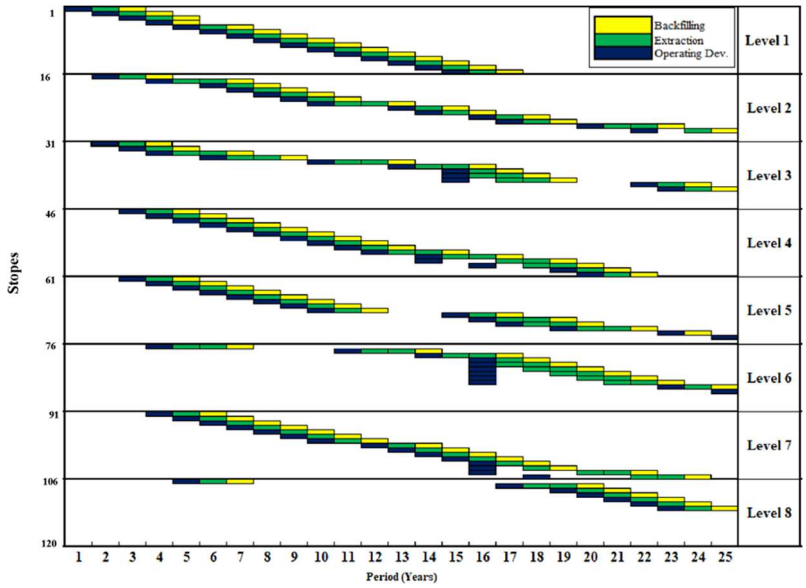

Figure 26. Annual operational development, stope extraction and backfilling schedules for Case 5.

6.5. Case 6 – E-type with Stockpile Management

The optimal primary, ventilation, operational, and ore pass development schedules, and mining, stockpiling, processing, and backfilling schedules allowed for efficient resource utilization generating a NPV of $7,360.52 M, approximately 8% lesser than Case 4 because of the conservative grades in the E-type block model. Figure 27 shows the yearly development schedules for primary, ventilation, and ore pass, whereas Figure 28 highlights the operational development schedule.

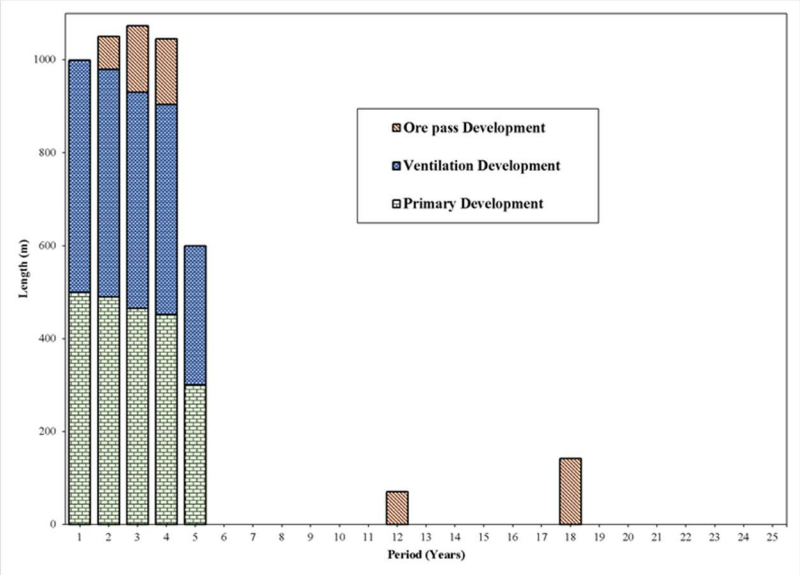

Figure 27. Primary, ventilation and ore pass development schedules for Case 6.

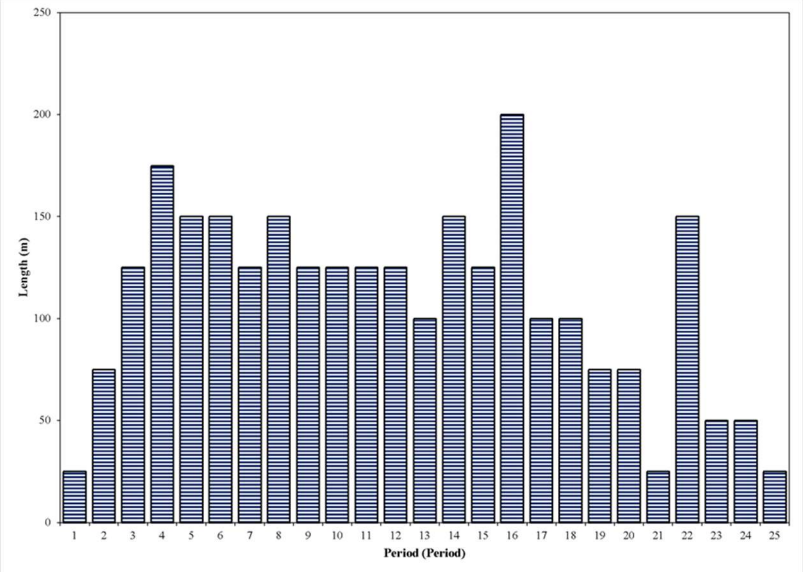

Figure 28. Operational development schedule for Case 6.

Figure 29 presents a graphical representation of the mining material schedule. This schedule outlines the tonnage of material to be mined over the life of the mining operation, including stockpiling. By controlling the capacity of the stockpile, it can be seen in Figure 30 that the mining operation was able to maintain control over ore accumulation and reclamation for processing. Thus, the management of stockpiling (Figure 31) was critical in maintaining control over ore accumulation and reclamation resulting in 2.4 Mt of material being processed from open stopes during the mine life.

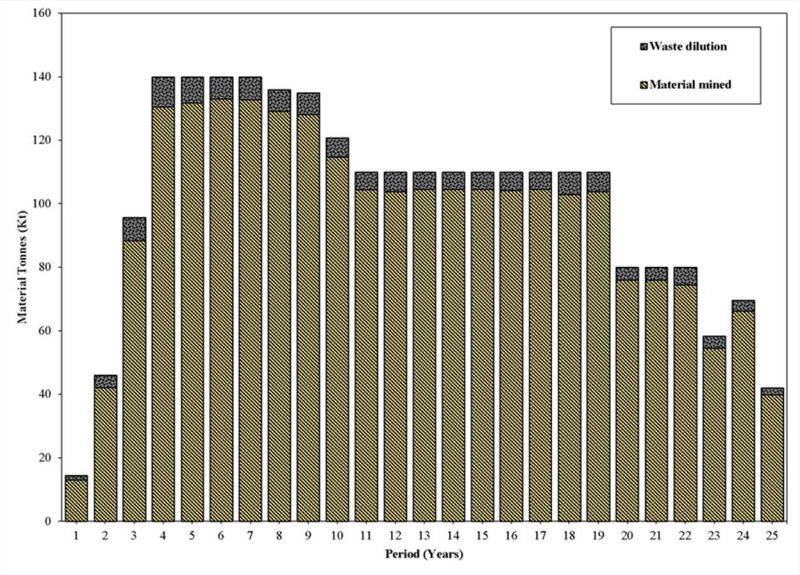

Figure 29: Material mined schedule with estimated waste dilution for Case 6.

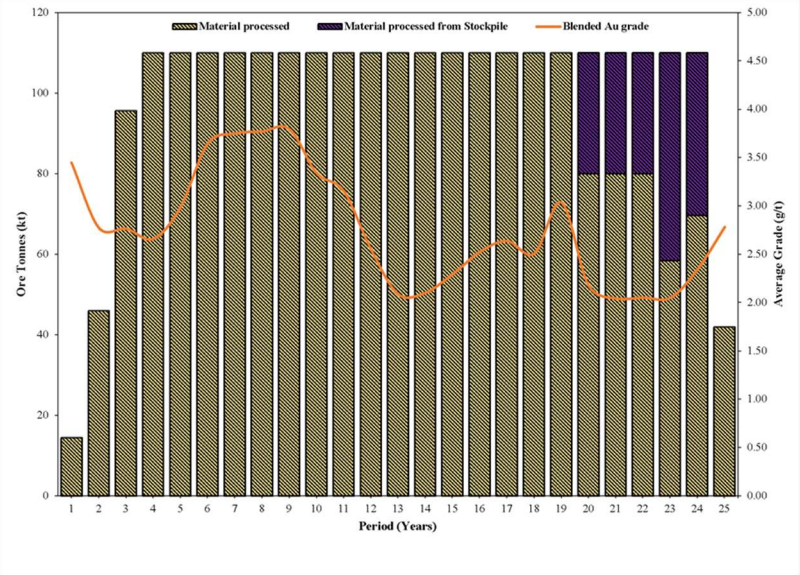

Figure 30: Processed material schedule with blended grade curve for Case 6.

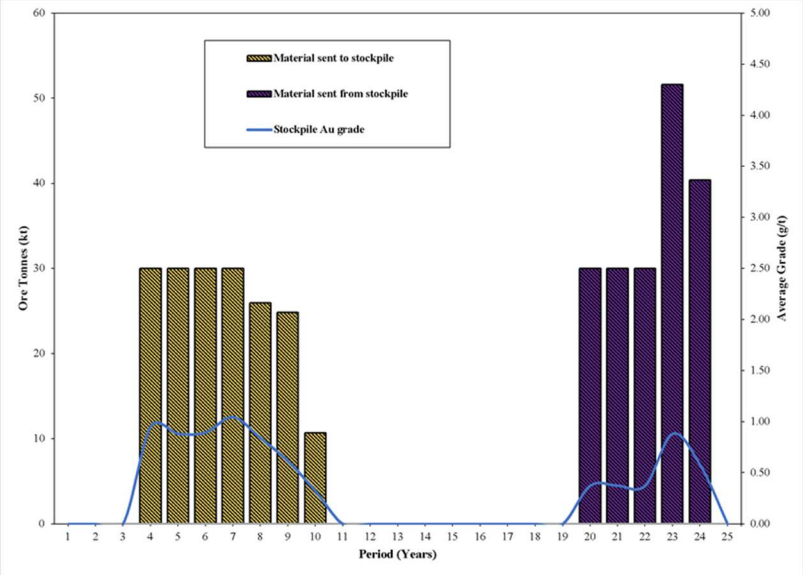

Figure 31: Stockpiled material schedule and grade curve for Case 6.

The stockpile inventory profile is presented in Figure 32. Illustrated in Figure 33 is the progression of stope production phases. During Periods 11 to 13 on Level 5, Periods 8 to 11 on Level 6, and Periods 9 to 12 on Level 8, there was inactivity on these levels due to higher grades in other areas including Levels 3, 4 and 7.

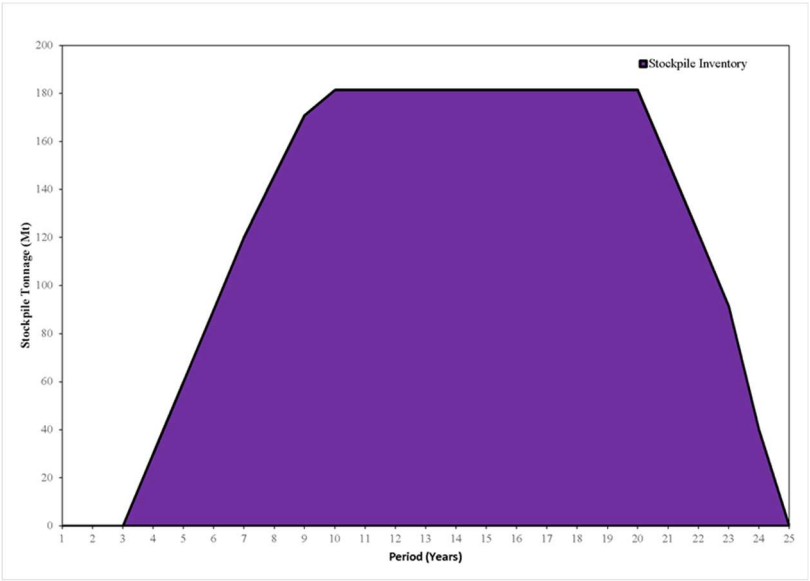

Figure 32: Stockpile inventory profile for Case 6.

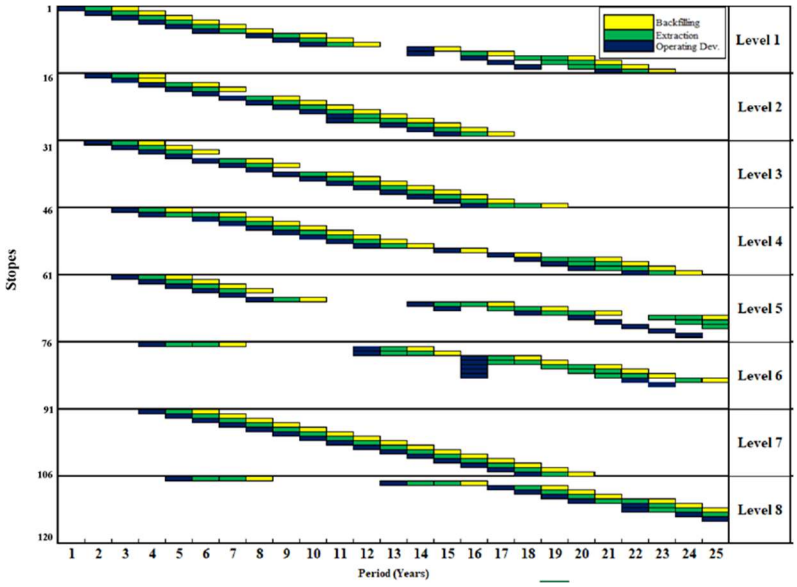

Figure 33: Annual operational development, stope extraction and backfilling schedules for Case 6.

6.6. Summary of results and findings on case studies

The study used the same set of constraints and parameters to compare the results and test the robustness of the model under different scenarios. This criterion of analysis was adopted to ensure consistency while examining the impact of data and constraint variations. It enables direct comparison of results when the same input data and restrictions are utilized for different scenarios, making it easier to identify the consequences of specific changes or improvements. Presented in Table 7 is the summary of results produced from the implementation of the MILP and SMIL formulations. In Table 7, Case 4 which incorporates the SMILP with a stockpile management strategy stands out as the superior performer among the five other case studies. It processed more ore tonnage at a higher grade and achieved the best NPV. Therefore, Case 4, which incorporates stockpiling in a SMILP framework to generate a risk-based production schedule provides the best NPV in the presence of grade uncertainty.

Table 7: Summary of case study results.

Case	Ore tonnage (Mt)	Average grade (g/t)	Au metal (t)	NPV (M$)
Case 1	2.19	2.98	6.53	7344.00
Case 2	2.52	2.87	7.23	7801.20
Case 3	2.33	3.05	7.11	7601.30
Case 4	2.54	3.02	7.67	8077.86
Case 5	2.29	2.77	6.34	7036.10
Case 6	2.51	2.93	7.35	7360.52

7. Conclusions

A comprehensive literature review revealed limitations that exist in the current body of knowledge in underground mining production scheduling optimization. Despite numerous works in underground production scheduling optimization, the literature review exposed that there has never been any previous attempt to formulate a stochastic underground mining mathematical programming

framework with integrated stockpile management and grade uncertainty considerations. In effect, such limitations affect the practicality and optimality of the generated underground mine plan. This research therefore pioneers the effort to employ a stochastic mathematical programming framework to contribute to the body of knowledge and provide a novel understanding in uncertainty-based integrated mine planning optimization for underground mining operations.

An integrated SMILP theoretical framework has been developed. The research objectives have been successfully achieved within the research scope. The following conclusions were drawn from the research:

1. The multi-objective SMILP optimization framework with stockpile management maximizes the NPV of the mining project while generating underground development, extraction and processing schedules in the presence of grade uncertainty.
2. The SMILP model minimizes the geological risk cost by placing higher penalties for ore grade and ore tonnage deviations from production targets in the early years of mine life and deferring production deviations to later years when more geological information becomes available to update the block model and mine plan.
3. The SMILP optimization framework with SGS block model realizations performed better in terms of NPV and total ore tonnage processed compared to a similar MILP optimization framework implementation with Kriged and E-type block models.
4. Grade uncertainty influences the ore tonnage and input ore grade sent to both the stockpile and plant at different periods. The implementation of the SMILP model contributes significantly to decrease the effect of grade uncertainty during mining. The uncertainty-based integrated production schedule with stockpile management generates better profitability with a higher chance of success during implementation.
5. The proposed SMILP framework was verified in terms of both feasibility and risk assessment using six case studies while providing a systematic workflow towards promoting robust risk-based strategic underground mine planning with stockpile management.

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A Comparative Analysis of Mathematical and Industrial Approaches for Sublevel Caving Long-Term Production Scheduling Optimization

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ABSTRACT

Efficient production scheduling is critical for optimizing the performance and profitability of sublevel caving (SLC) mining operations. This paper presents a comprehensive comparative analysis of mathematical and industrial SLC long-term production scheduling approaches, utilizing a mixed-integer linear programming (MILP) optimization model and the GEMS/PCSLC software. The MILP model incorporates various operational constraints, including the maximum number of active levels, continuous mining, mining and processing capacities, vertical and horizontal precedencies, and grade blending, ensuring a robust and realistic representation of the SLC mining method. The model's primary objective is to maximize the net present value (NPV) of the mining project. The formulations are developed, implemented, and verified in the Jupyter Notebook environment and solved using the CPLEX Python API. The production scheduler aims to maximize the NPV of the mining operation while it has control over defined constraints. To benchmark and validate the performance of the MILP model, Production Control System for Sublevel Caving (PCSLC)- the only available software designed for SLC production scheduling- has been employed. By applying different mining directions and strategies to the MILP model and PCSLC, this study provides an in-depth understanding of the project's income over the mine's life. Application and comparison of the models for production scheduling using 541 mining units over 22 periods are presented. The comparative analysis demonstrates the mathematical model's efficiency in optimizing production scheduling and highlights potential improvements in decision-making processes for SLC mining operations. The findings underscore the advantages of the mathematical model to enhance the economic outcomes of sublevel caving projects.

1. Introduction

The sublevel caving (SLC) mining method involves blasting all material for extraction, unlike block cave mining which relies on natural fragmentation through gravity and stresses. This necessitates a systematic network of tunnels due to the blasting requirement [1, 2]. A significant challenge in SLC project design is to create an accurate scheduling plan that considers the complexities of SLC mining, such as cave initiation and propagation, minimizing dilution, and preventing undermining. Conventional mathematical models often struggle to model these aspects effectively [3].

The complexities and technological advancements inherent to SLC necessitate comprehensive mine planning approaches that optimize SLC operation’s performance and encompass critical SLC mine

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components. A robust SLC mine plan integrates all technical facets strategically, with production scheduling playing a pivotal role in determining the most cost-effective mining sequence over the mine's life [4].

Underground production scheduling involves discrete and continuous decisions regarding extraction location, timing, mining unit allocation over the mine's life, and vertical and horizontal precedence relationships [5]. The objective of a production schedule is to optimize the extraction sequence to meet market specifications efficiently while satisfying operational constraints and demand requirements [6]. Mathematical programming models offer precise algorithms that can optimize multi-time-period schedules operationally, providing superior alternatives to manual and heuristic methods [7]. In SLC scheduling, the MILP models are effective in capturing both the continuous and discrete nature of decision variables, ensuring a detailed and accurate approach to managing the complexities of sublevel caving operations [8].

The GEMS/PCSLC software is specifically designed for sublevel caving projects, making it the only commercial scheduling software for this type of mining operation. The PCSLC module employs powerful engines to optimize the production scheduling of SLC operations. This software ensures that the extraction sequence is efficient and meets operational and market requirements. By leveraging advanced algorithms, the PCSLC module enhances the ability to plan and execute complex mining schedules, reducing the reliance on traditional manual and heuristic approaches. This makes PCSLC an invaluable tool for mining engineers seeking to maximize productivity and operational efficiency in SLC projects [2, 9].

This paper introduces a comparative analysis of long-term SLC production scheduling using both theoretical and industrial approaches. In the theoretical part, the MILP method is employed, which is powerful as a deterministic approach to finding the optimal solution and maximizing the NPV of the entire operation. PCSLC software is used as a benchmark to validate the developed mathematical model. This dual approach is highly beneficial for analyzing the results of both methods, gaining insights into SLC mining aspects, and understanding industry practices.

2. Summary of Literature Review

Sublevel caving is a widely used underground mining method known for its high production rates and operational flexibility. Recent research highlights the application of advanced mathematical programming models, particularly mixed-integer programming (MIP), to optimize production scheduling in sublevel caving. These models address unique challenges such as material flow complexity and ore-waste mixing during blasting. Studies by Khazaei and Pourrahimian [10] and Shenavar et al [11, 12] emphasize maximizing net present value (NPV) through refined technical constraints and block model processing.

Innovative tools and algorithms have also been developed to enhance scheduling efficiency. Villa and Diering [13] introduced an application for planning sublevel caving projects, focusing on ore recovery and dilution modeling, while Diering and Breed [14] developed the Footprint Finder tool for rapid layout evaluation and draw factor optimization. Case studies, particularly at LKAB's Kiruna Mine, demonstrate the practical benefits of these approaches, with research by Kuchta, Newman, and

Topal [15], Newman et al. [16], and Martinez and Newman [17] showcasing significant cost savings and improved production target adherence. Overall, integrating advanced mathematical models and innovative tools is crucial for optimizing sublevel caving production scheduling, promising enhanced efficiency and economic outcomes.

While all mentioned studies have explored methods to present SLC production scheduling, few have explicitly validated their developed models against real-world data. These studies have primarily focused on developing and optimizing mathematical models rather than validating them through practical application in mining operations. In this study, the PCSLC is leveraged to create the input data for the MILP model. A comparative analysis of both the model and PCSLC schedules is then conducted to evaluate the capabilities and advantages of using the model in real-world SLC scenarios. This approach aims to bridge the gap between theoretical model development and practical application, providing a robust validation of the scheduling models in operational environments.

3. Problem Statement

Manual planning methods and heuristic algorithms in commercial software often fail to ensure optimal production schedules for sublevel caving (SLC) mines. Although mathematical models for SLC optimization have been developed to address these issues, previous studies primarily focus on production sequencing without incorporating a validation process. This gap limits the reliability of these models for real-world mining applications.

This study aims to bridge this gap by developing an SLC scheduling model that optimizes the extraction sequence while meeting the head grade requirements of the processing plant. The model captures all complexities of SLC operations, including cave propagation control and undermining prevention. The goal is to generate a strategic long-term production schedule that maximizes net present value (NPV) while addressing all operational and technical constraints. These constraints include mining and processing capacities, continuous extraction, the number of active levels in each period, grade blending, and the sequencing of mining units.

To achieve this, PCSLC (Production Control System for Sublevel Caving) has been utilized to create the input data for the Mixed-Integer Linear Programming (MILP) model. A comparative analysis has been conducted between the MILP model and PCSLC schedules to evaluate the capabilities and advantages of the MILP model in real-world SLC scenarios. This approach aims to validate the model's effectiveness in practical applications, enhancing SLC operations' overall efficiency and economic viability. Through this validation, the study seeks to provide a robust and reliable framework for optimizing SLC production schedules in actual mining environments.

4. Methodology

This paper introduces a comprehensive MILP model for long-term production scheduling in SLC mines. The model includes all facets of mining operations, focusing on providing optimal production schedules while efficiently addressing all technical and operational constraints. The employment of MILP as a precise algorithm enables the determination of maximum NPV and optimal mining sequences.

The study includes a rigorous verification and validation process. The verification step involves calibrating the model on a small-scale SLC case to ensure that constraints such as mining and processing plant capacities, continuous mining, the number of active levels, and vertical and horizontal precedencies are functioning correctly. It also involves analyzing NPV for different gap tolerance values to assess financial impacts and conducting sensitivity analysis by varying key parameters to confirm the model's robustness under different scenarios and assumptions.

Following verification, the validation process involves comparing the MILP model schedules with those generated by the PCSLC. This comparative analysis evaluates the capabilities and advantages of the MILP model in real-world SLC scenarios. This approach aims to validate the model's effectiveness, improve the efficiency and profitability of SLC operations, and provide a reliable framework for optimizing production schedules in real mining environments. The methodology and workflow, including the steps for model development, verification, and validation, is illustrated in Figure 1.

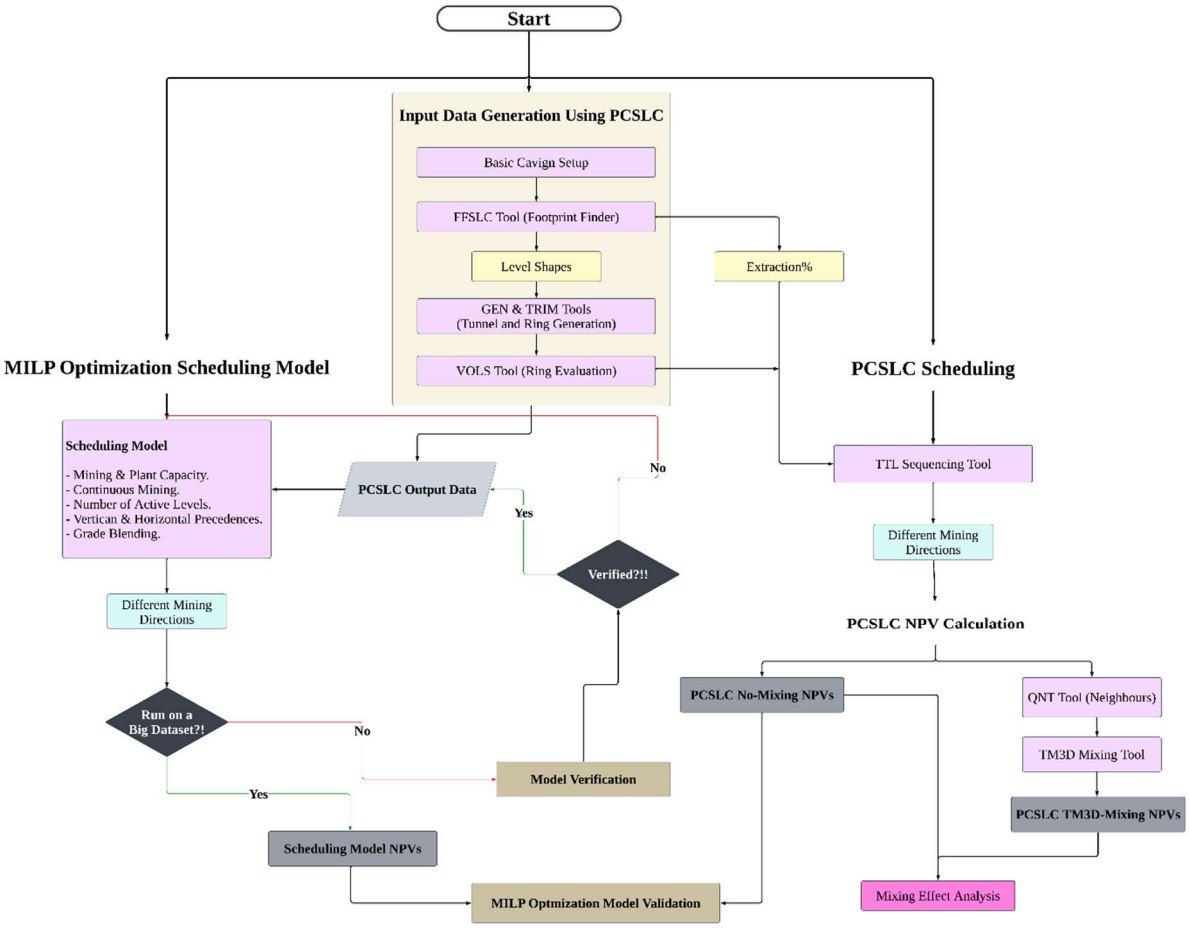

Figure 1. The workflow of the research.

4.1. Key Terminology

Production drift: A horizontal underground excavation serves as a primary pathway for ore extraction and transporting mined ore from the mining unit to the orepasses through a perimeter drift that connects several production drifts within a specific production area and level (see Figure 2).

Ring: A production ring is the quantity of the in-situ ore that will be fired at any one time by a blasted ring (see Figure 2).

Mining unit: A mining unit is where the Load-Haul-Dump unit (LHD) operates, which contains one production drift and several production rings along that drift (see Figure 2).

Level (or sublevel): Levels represent the successive horizontal sublevels situated at different depths, including multiple production drifts driven along the orebody's strike. The sublevel height is generally measured as the vertical floor-to-floor distance between the levels (see Figure 2).

Both mining units and rings consist of attributes like coordination, tonnage, grade, percentage of dilution, and economic data. The model determines which mining unit starts being mined in each period over the horizon to maximize the NPV. Furthermore, the model satisfies constraints such as development activities, mining, stockpile inventory management, processing capacities, continuous mining of scheduling units, restrictions on the allowable number of active production faces, grade blending, and vertical and horizontal sequencing.

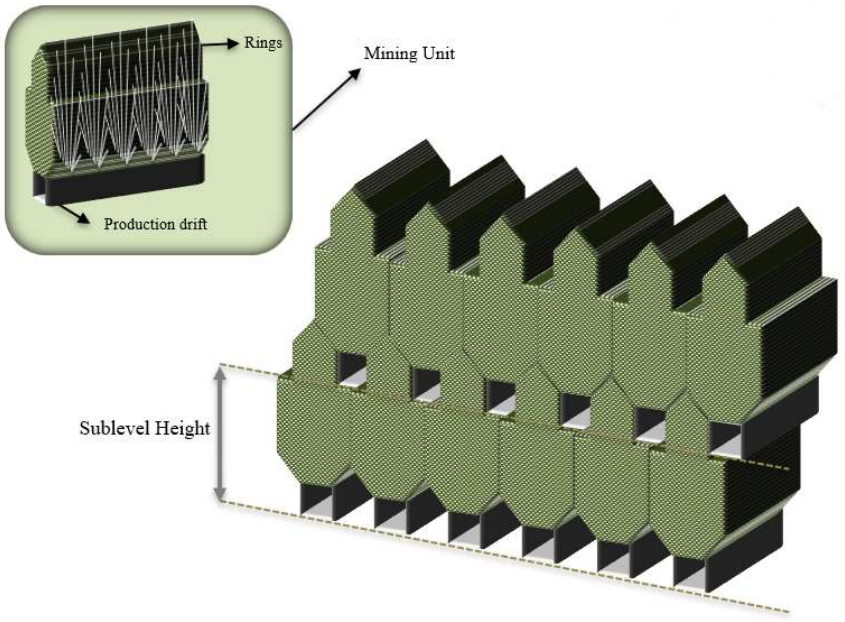

Figure 2. Typical view of mining unit, production ring, and sublevel in an SLC mine.

4.2. GEMS/PCSLC Scheduling

The Geovia GEMS software, especially the PCSLC module, was employed to prepare the input data for the model by generating tunnels and rings [18]. This process ensures that all quantitative parameters like tonnage, grade, and density are transferred from the block model level to the MU level. Figure 3 illustrates all the steps from data preparation to scheduling in the software.

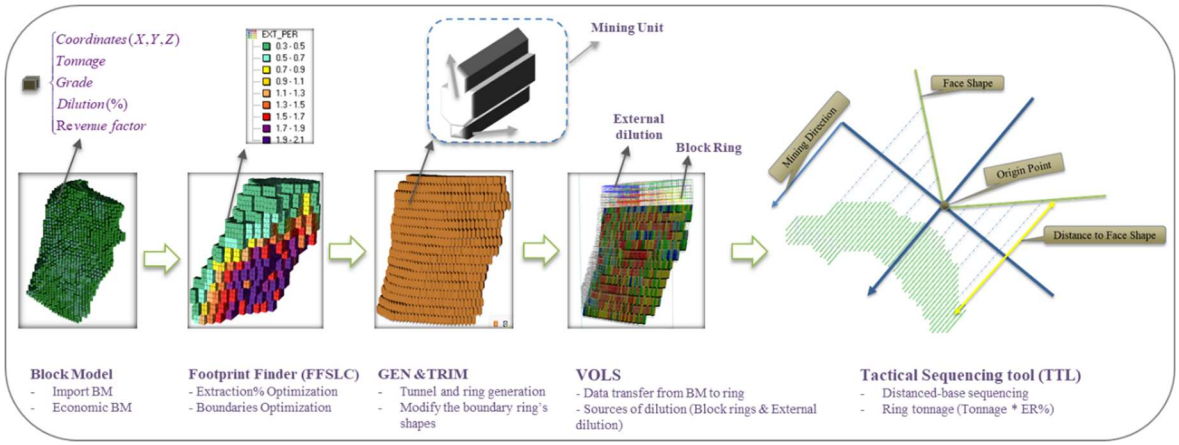

Figure 3. All steps from data preparation to scheduling in GEMS/PCSLC.

4.3. Mathematical Model Scheduling

The scheduling MILP model aims to provide a production schedule that represents the various limitations of an SLC operation. This includes constraints on mining and processing plant capacities, meeting the processing plant's head grade requirements common among all mathematical scheduling models, and SLC-specific constraints. These constraints involve controlling the continuity of mining unit extraction due to the nature of caving, determining the number of active levels to manage cave propagation, imposing the vertical and horizontal precedence rules to manage the lead-lag rules between adjacent mining units and the units in the levels above to prevent undermining and minimize the impact of stress and explosive damage on neighbouring units.

Continuous decision variables track development activities and mined material for each mining unit in each period, while binary variables govern the starting extraction time of mining units and whether a mining unit is being mined in a specific period.

The SLC production scheduling formulation involves defining sets, parameters, and decision variables for V production areas, L levels, and M mining units to be mined over T periods.

4.4. Indices

$m = \{1, 2, ..., M\}$ Index for mining units, where M is the total number of MUs.

$l = \{1, 2, ..., L\}$ Index for levels, where L is the total number of levels.

$t = \{1, 2, ..., T\}$ Index for periods, where T is the scheduled time horizon.

4.5. Sets

S_{M_l} Set of MUs in all production areas on the level l.

$S^V_{M_m}$ Set of MUs whose start period is restricted vertically by MU m.

$S^H_{M_m}$ Set of MUs whose start period is forced by adjacency to MU m.

4.6. **Parameters**

P	Profit (Selling price minus selling cost) per ton of metal ($/ton).
C^P	Processing cost per ton of ore material ($/ton).
C^M	Mining cost per ton of ore material ($/ton).
δ^t	Discount factor at period t.
o_m	Ore tonnage in mining unit m.
M_m	Metal obtained after mining and processing mining unit m (ton).
$\underline{Q_m^t}$	Lower bound on mining capacity at period t.
$\overline{Q_m^t}$	Upper bound on mining capacity at period t.
$\underline{Q_p^t}$	Lower bound on ore processing capacity at period t.
$\overline{Q_p^t}$	Upper bound on ore processing capacity at period t.
$\underline{g_p^t}$	Lower bound on an acceptable average grade by processing plant at period t.
$\overline{g_p^t}$	Upper bound on an acceptable average grade by processing plant at period t.
n_l	Number of mining units at the level l.

4.7. Decision Variables

$x_m^t \in [0,1]$	Continuous variable represents the mining unit's portion to be mined at period t.
$x_{m,p}^t \in [0,1]$	Continuous variable represents the portion of mining unit m sent directly to the processing plant at period t.
$bs_m^t \in \{0,1\}$	Binary integer variable equals one if extraction of the mining unit m is started at period t; otherwise, it is zero.
$as_m^t \in \{0,1\}$	Binary integer variable equals one if the mining unit m is active at period t otherwise, it is zero.

4.8. Objective Function

The optimization model maximizes the NPV of caving operations in Eq. (1), subtracting the cost of all development activities from the revenue obtained from ore extraction.

$$Max \quad \sum_{t=1}^{T} \delta_t \left[P(\sum_{m=1}^{M} M_m \times x_{m,p}^t) - C^P(\sum_{m=1}^{M} O_m \times x_{m,p}^t) - C^M \sum_{m=1}^{M} O_m \times x_m^t \right] \quad (1)$$

4.9. Mining and Processing Capacity

Eq. (2) enforces the mining capacity, using continuous decision variable x_m^t, between the acceptable lower and upper limits of the total available equipment capacity in each period. Eq. (3) controls the quantity of mill feed using continuous decision variable $x_{m,p}^t$.

$$\underline{Q_m^t} \le \sum_{m=1}^{M}\left[(o_m \times x_m^t)\right] \le \overline{Q_m^t} \qquad \forall t \in \{1,2,...,T\} \tag{2}$$

$$\underline{Q_p^t} \le \sum_{m=1}^{M}\left[(o_m \times x_{m,p}^t)\right] \le \overline{Q_p^t} \qquad \forall t \in \{1,2,...,T\} \tag{3}$$

4.10. Active Number of Levels

Eq. (4) to Eq. (6) determine the number of active levels (λ^t) which is controlled by adding the decision variables L_l^t. This is critical for effective cave initiation and propagation. Multiple levels help redistribute stress, promote consistent caving, and ensure smooth ore flow, reducing blockages and hang-ups. They also improve ore recovery, minimize dilution, and manage subsidence more evenly, enhancing overall safety and operational flexibility. This balance ensures successful and efficient SLC operations.

$$(1/n_l) \times \sum_{m \in S_{M_l}} as_m^t \le L_l^t \qquad \forall l \in \{1,2,...,L\}, t \in \{1,2,...,T\} \tag{4}$$

$$\sum_{m \in S_{M_l}} as_m^t \ge L_l^t \qquad \forall l \in \{1,2,...,L\}, t \in \{1,2,...,T\} \tag{5}$$

$$\sum_{l=1}^{L} L_l^t \le \lambda^t \qquad \forall t \in \{1,2,...,T\} \tag{6}$$

4.11. Continuous Mining Constraints

Each mining unit must be continuously extracted after opening until closing. Eq. (7) forces variable as_m^t to be zero if no portion of the mining unit m is extracted at period t, while Eq. (8) changes the value as_m^t to 1 when a portion of the mining unit m is extracted at period t. Eq. (9) ensures that if extraction from the mining unit m is started during or after period two, at least a portion of the mining unit is extracted until all of the material within that mining unit has been extracted; otherwise, the mining unit must be closed. Eq. (10) ensures that if extraction from the mining unit m is started in period one, the related variable as_m^t for the mining unit is equal to 1.

$$as_m^t \le M \times x_m^t \qquad \forall t \in \{1,2,...,T\}, m \in \{1,2,...,M\} \tag{7}$$

$$x_m^t \le as_m^t \qquad \forall t \in \{1,2,...,T\}, m \in \{1,2,...,M\} \tag{8}$$

$$as_m^t - as_m^{t-1} \le bs_m^t \qquad \forall m \in \{1,2,...,M\}, t \in \{2,...,T\} \tag{9}$$

$$as_m^1 - bs_m^1 \le 0.5 \qquad \forall m \in \{1,2,...,M\} \tag{10}$$

4.12. Processing Plant Grade Control Constraint

Eq. (11) meets the ore quality specification of the processing plant within the predefined limits.

$$\underline{g_p^t} \le \frac{\sum_{m=1}^{M} M_m \times x_{m,p}^t}{\sum_{m=1}^{M} O_m \times x_{m,p}^t} \le \overline{g_p^t} \qquad \forall t \in \{1,2,...,T\} \tag{11}$$

4.13. Vertical and Horizontal Sequencing Constraints

In SLC mining, strict operational rules govern ore extraction. According to Figure 4, vertical sequencing mandates that MU10 extraction begins only after MU6 and MU7 reach a specified extraction percentage. Additionally, horizontal sequencing dictates that MU10 extraction starts after MU9 sufficiently retreats past its neighbouring level.

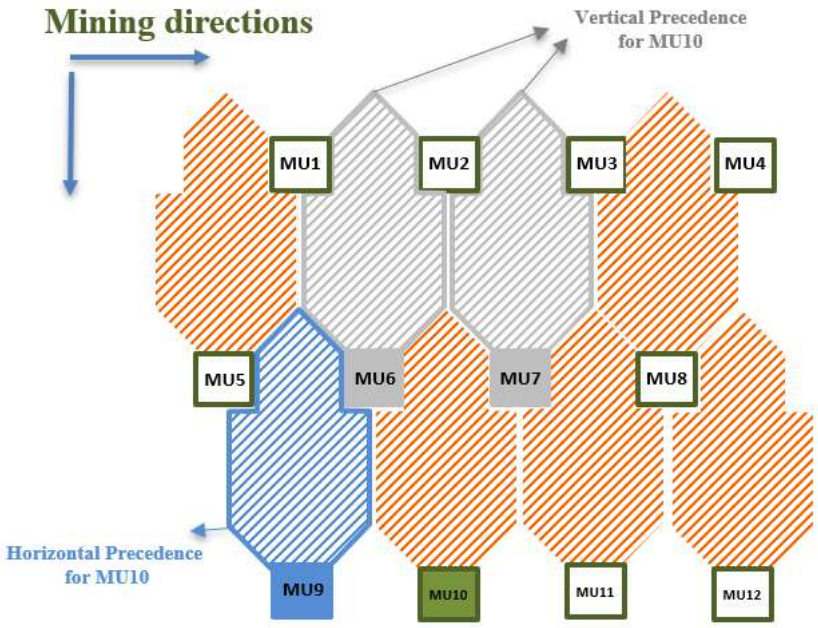

Figure 4. A vertical cross-section of eight MUs in two sublevels.

Eq. (12) and (13) ensure vertical and horizontal sequencing between mining units in the long-term resolution. Vertical and horizontal precedencies and required extraction percentages for predecessor MUs enforce these operational rules. Eq. (14) and (15) ensure that mining operations in both the MU and its precedencies occur, with production in precedencies ahead of the MU. Eq. (16) and (17) prevent further mining of horizontal and vertical precedence positioned at the upper level and the back of mining unit m once extraction in mining unit m is completed. This prevents re-mining precedencies due to caving propagation. Eq. (18) encourages extracting the maximum feasible quantity from mining unit m in each period to minimize vehicle relocation and improve ore blending.

$$bs_m^t - \sum_{t'=1}^{t} x_{m'}^{t'} \le \delta_m\% \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T\}, \forall m' \in S_{M_m}^V \tag{12}$$

$$bs_m^t - \sum_{t'=1}^{t} x_{m'}^{t'} \le \delta_m\% \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T\}, \forall m' \in S_{M_m}^H \tag{13}$$

$$\sum_{t' \le t} x_{m'}^{t'} - \sum_{t' \le t} x_m^{t'} \ge as_{m'}^t + as_m^t - 2 \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T\}, \forall m' \in S_{M_m}^V \tag{14}$$

$$\sum_{t' \le t} x_{m'}^{t'} - \sum_{t' \le t} x_m^{t'} \ge as_{m'}^t + as_m^t - 2 \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T\}, \forall m' \in S_{M_m}^H \tag{15}$$

$$(as_m^{t+1} - as_m^t) + 1 \ge as_{m'}^{t+1} \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T-1\}, \forall m' \in S_{M_m}^V \tag{16}$$

$$(as_m^{t+1} - as_m^t) + 1 \ge as_{m'}^{t+1} \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T-1\}, \forall m' \in S_{M_m}^H \tag{17}$$

$$x_m^t - x_m^{t+1} \ge 1 - as_m^t \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T-1\} \tag{18}$$

4.14. Variable Control Constraints

Eq. (19) enforces the extracted material from each mining unit to be sent to the processing plant in each period. Eq. (20) to Eq. (21) ensure that the total fraction of material mined and sent to the processing plant is less than one over the scheduling periods. Eq. (22) prevents a mining unit from being mined more than once. Eq. (23) ensures that all continuous decision variables in the model are between zero and one. Eq. (24) guarantees that all binary variables are non-negative and integers.

$$x_{m,p}^t = x_m^t \qquad \forall t \in \{1,2,...,T\}, m \in \{1,2,...,M\} \tag{19}$$

$$\sum_{t=1}^{T} x_m^t \le 1 \qquad \forall m \in \{1,2,...,M\} \tag{20}$$

$$\sum_{t=1}^{T} x_{m,p}^t \le 1 \qquad \forall m \in \{1,2,...,M\} \tag{21}$$

$$\sum_{t \in T_m} bs_m^t \le 1 \qquad \forall m \in \{1,2,...,M\} \tag{22}$$

$$x_m^t, x_{m,p}^t \in [0,1] \tag{23}$$

$$bs_m^t, as_m^t \in \{0,1\} \tag{24}$$

5. Case Study- Implementation of the MILP Model on a Real SLC Mine

The SLC method was selected for mining an iron ore underground mine after evaluating various qualifying factors, including ore strength, host rock strength, deposit shape, size, orientation, ore

grade, uniformity, and deposit depth. The ore tonnage is approximately 137 Mt at an average grade of 47% Fe.

Figure 5(a) presents a 3D view of the orebody extended in an NW-SE direction with an azimuth of 130. All MUs have been conducted perpendicularly to the strike of the orebody, following the azimuth of NE-40 (Figure 5(b)). The orebody has a maximum length (along the strike) of 900 m and a width of 437 m.

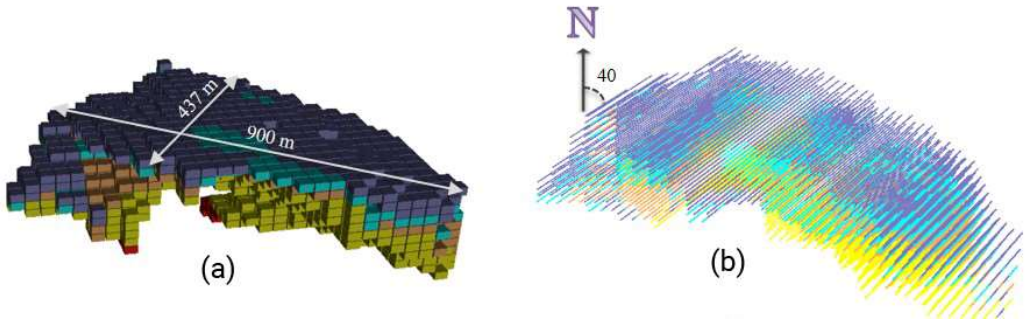

Figure 5. a) Plan view of the orebody; b) Mining units in different levels.

The orebody is situated 500 m below the surface with a 198 m thickness. The analysis includes eleven levels with 541 MUs, each having a production drift of 4.6 m width and 4.3 m height. MUs are spaced at 16 m intervals and have a height of 18 m, matching the sublevel height. The staggered placement of MUs across levels optimizes drilling coverage and material flow. The orebody includes eleven levels, with MUs allocated based on their coordinates to respective levels (Figure 6).

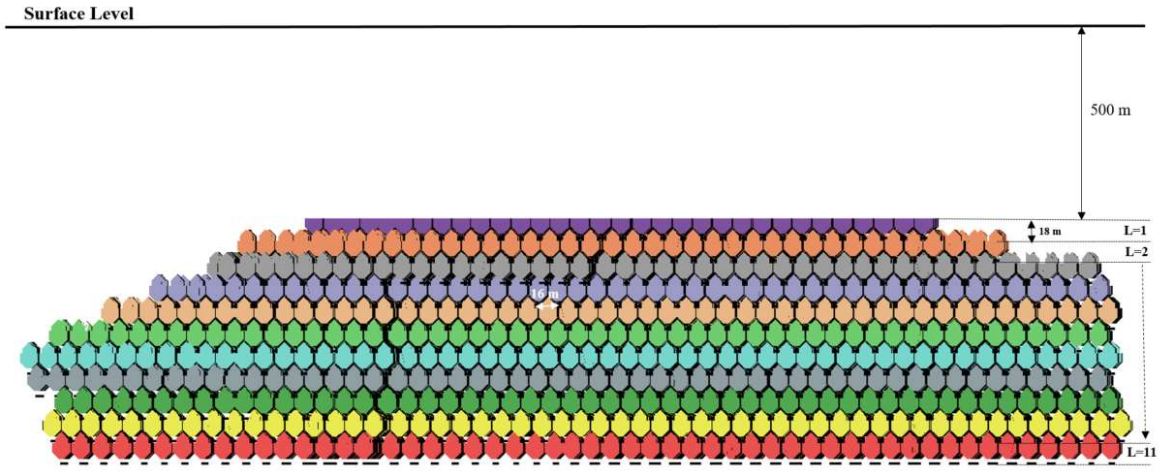

Figure 6. Cross-section view of MUs across 11 levels in the SLC mine.

The SLC mine was organized as follows: eleven horizontal levels, which are horizontal cuts positioned progressively deeper in the earth's surface. In each level, the LHDs load and haul the blasted ore from the production face to the ore passes, where the ore is transported directly to the main haulage level and then hoisted to the surface through the vertical shaft.

In the implemented model, once an LHD starts to mine an MU, that unit must be continuously mined; otherwise, the scheduling unit will be shut down, and the unextracted portion will be left behind. The

vertical and horizontal precedence relationships among MUs control the schedule of each MU. The initiation of new MUs extraction in each period is managed to align with mine production requirements, the permissible number of active levels in each period, and the average production grade. Table 1 provides a detailed value of input data used in the model.

Table 1. List of Input data for scheduling model implementation.

Parameters	**Values**
Mine layout	Transverse
Production drifts azimuth	NE-40^0
Mining direction	SW-220^0
Number of MUs	541
Number of levels	11
Mining capacity (first two years of production)	4.5 and 5.5 Mt/year
Mining capacity (from the third year of production to the end of mine life)	6 Mt/year
Processing plant capacity (first two years of production)	4.5 and 5.5 Mt/year
Processing plant capacity (from the third year of production to the end of mine life)	6 Mt/year
Minimum permissible average grade of plant	40%
Selling price	200 $/ton
Mining cost	21.22 $/ton
Processing cost	10.05 $/ton

6. Results and Discussion

All models were run on a PC with the following specifications: AMD EPYC-Rome Processor 2.00 GHz, 128 GB of installed RAM, 64-bit operating system with x64-based processor architecture, running Windows 10 Pro Version 22H2. To optimize resource extraction while considering environmental impact and technical constraints, both the scheduling model and PCSLC have been run in different mining directions at each level: left to right, middle to the sides, and right to left.

Figure 7 to Figure 12 show plots that include a cross-section view of the production schedule for the proposed model and PCSLC for all three mining directions. Inside each MU, the top number is the MU ID, the bottom number is the extraction period, and the middle number is the extraction percentage of the MU in the scheduled period (bottom number). In all the plots, the mining progress starts from the topmost level with the highest Z value to the lowest level with the lowest Z value. The first candidate mining unit at each level is determined based on the mining direction specified in each approach. The differences in mining unit sequencing between the scheduling model and PCSLC are related to the constraints and algorithms defined in the backend of both methods.

Figure 13 to Figure 18 represent the offset plan view of scheduling with both the scheduling model (top of the page) and PCSLC (bottom of the page) across all 11 levels of the SLC mine. According to the chosen colour scheme, as the colour shifts to yellow, the mining operation approaches the end of its life. Colour transition in both methods verifies that both sets of plots adhere to the specified mining directions.

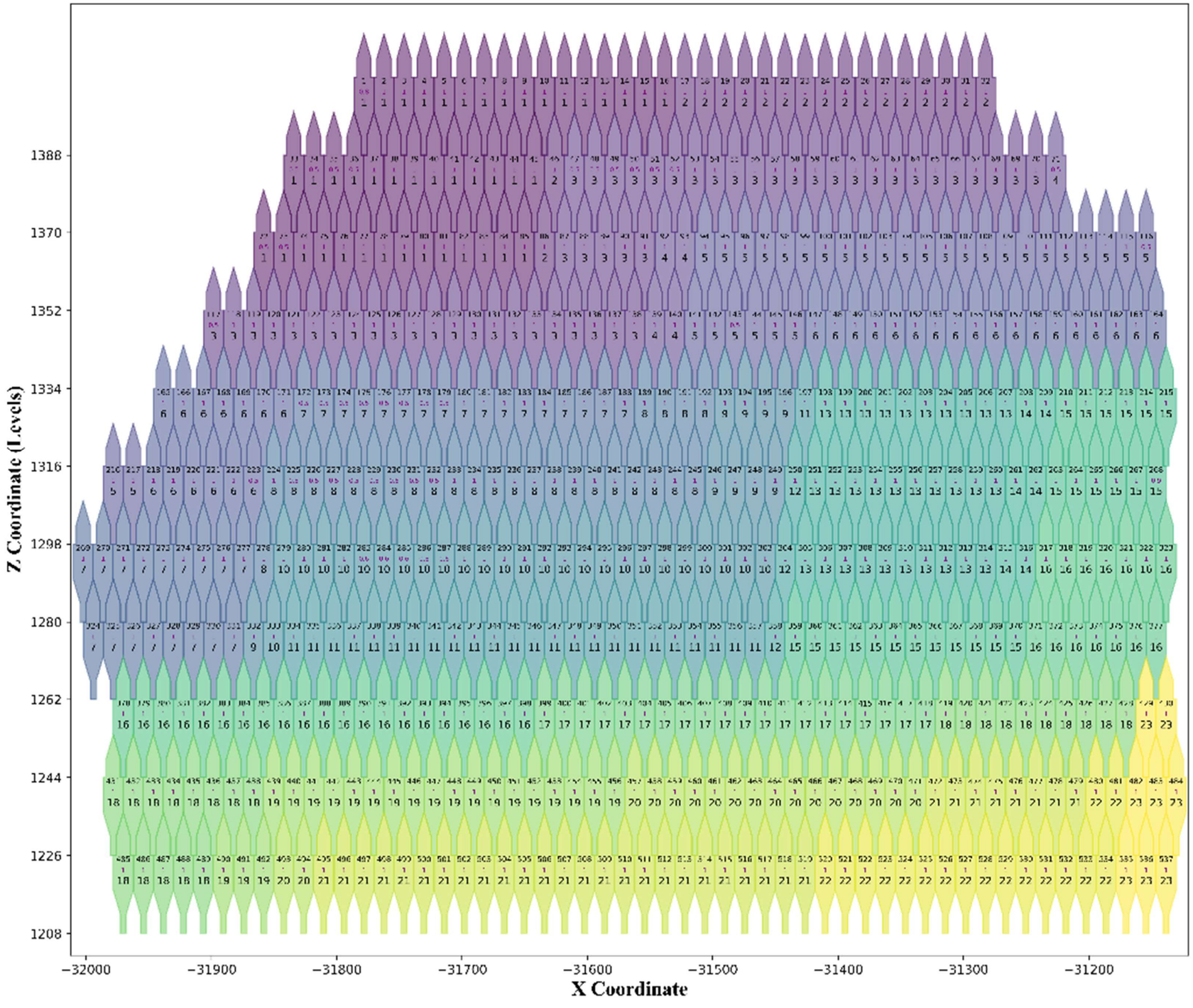

Figure 7. Cross-section view of starting time, and extraction percentage of mining units over the life of mine in scheduling model - Mining direction (Left-to-Right).

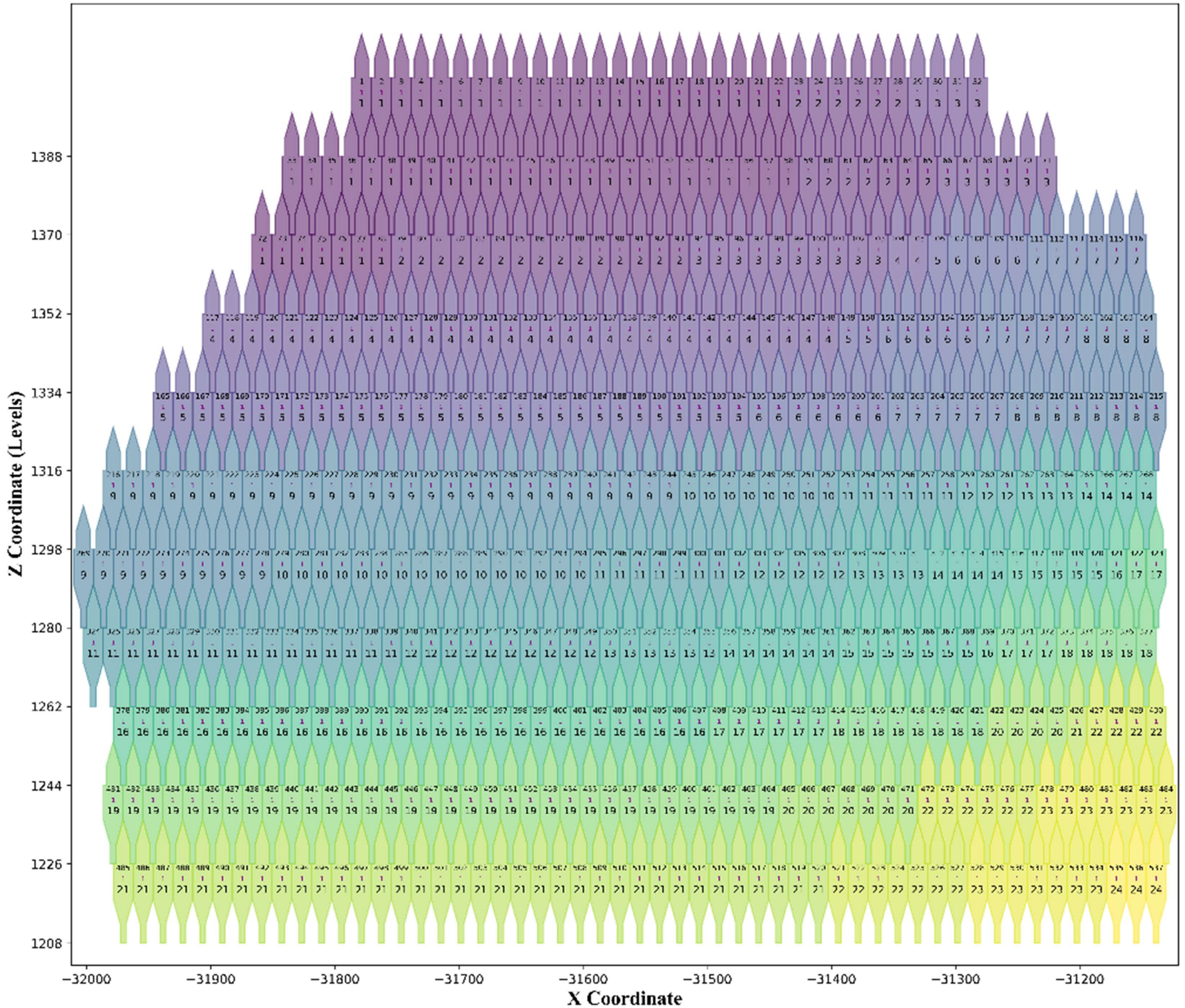

Figure 8. Cross-section view of starting time, and extraction percentage of mining units over the life of mine in PCSLC- Mining direction (Left-to-Right).

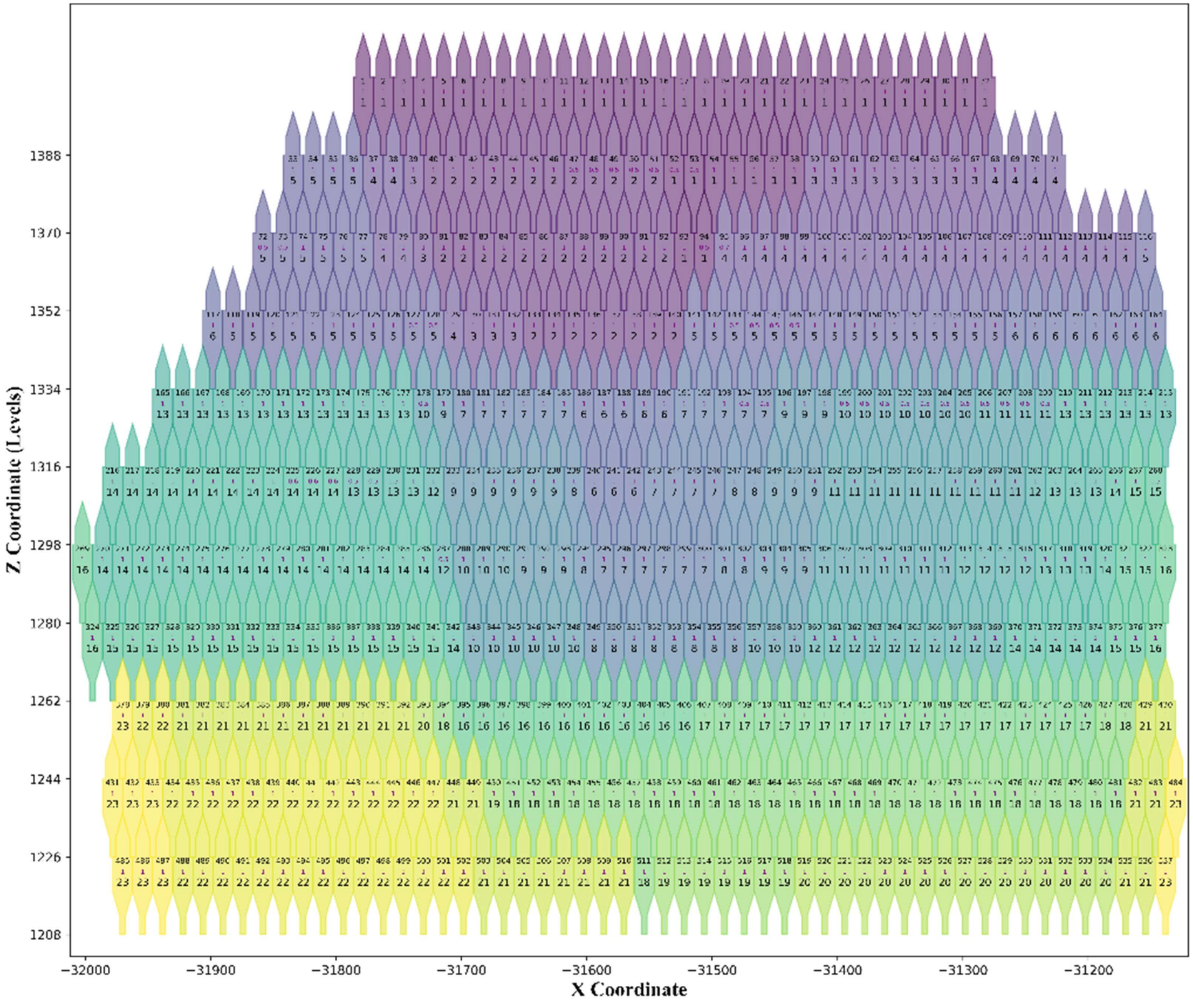

Figure 9. Cross-section view of starting time, and extraction percentage of mining units over the life of mine in scheduling model - Mining direction (Middle).

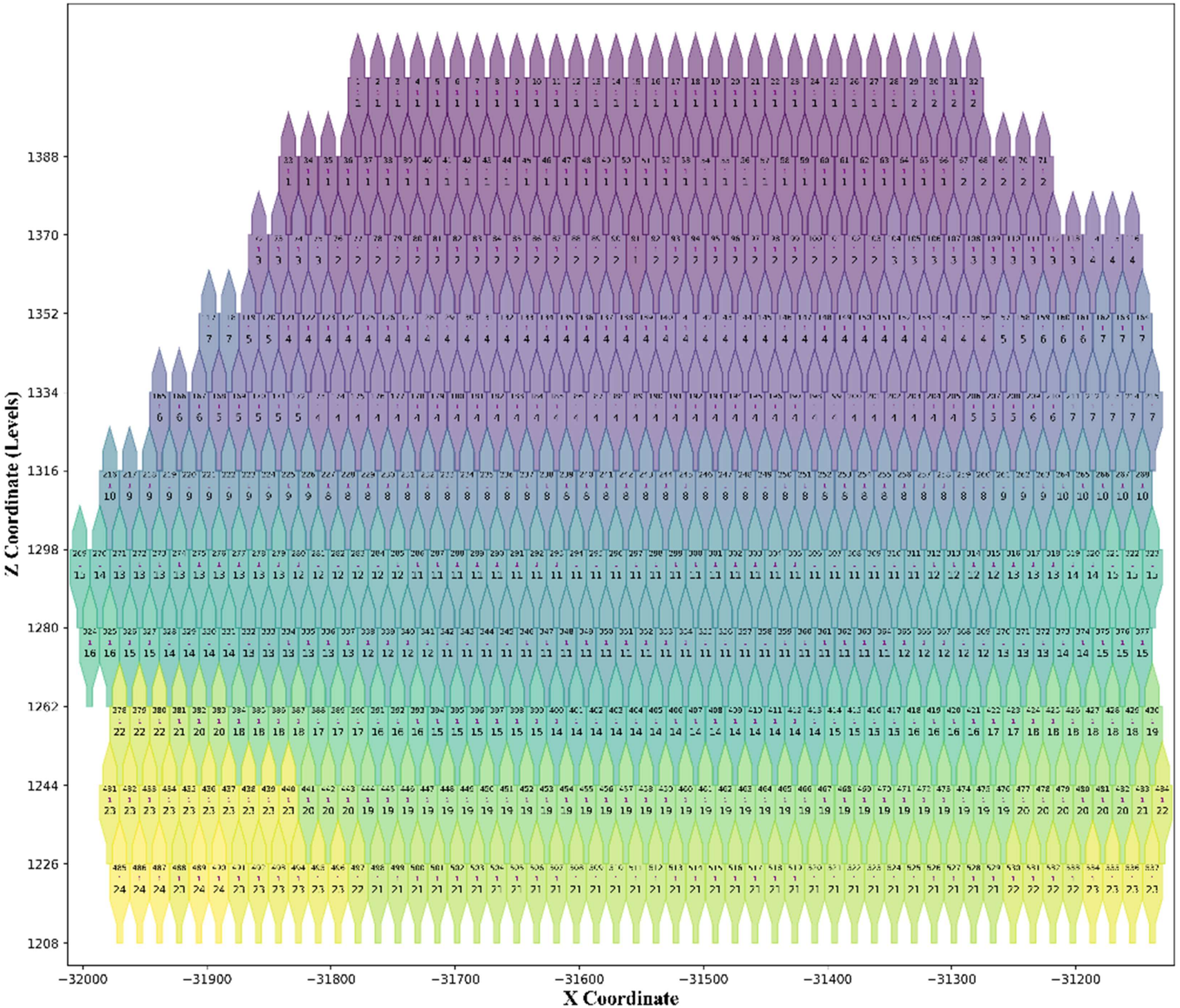

Figure 10. Cross-section view of starting time, and extraction percentage of mining units over the life of mine in PCSLC- Mining direction (Middle).

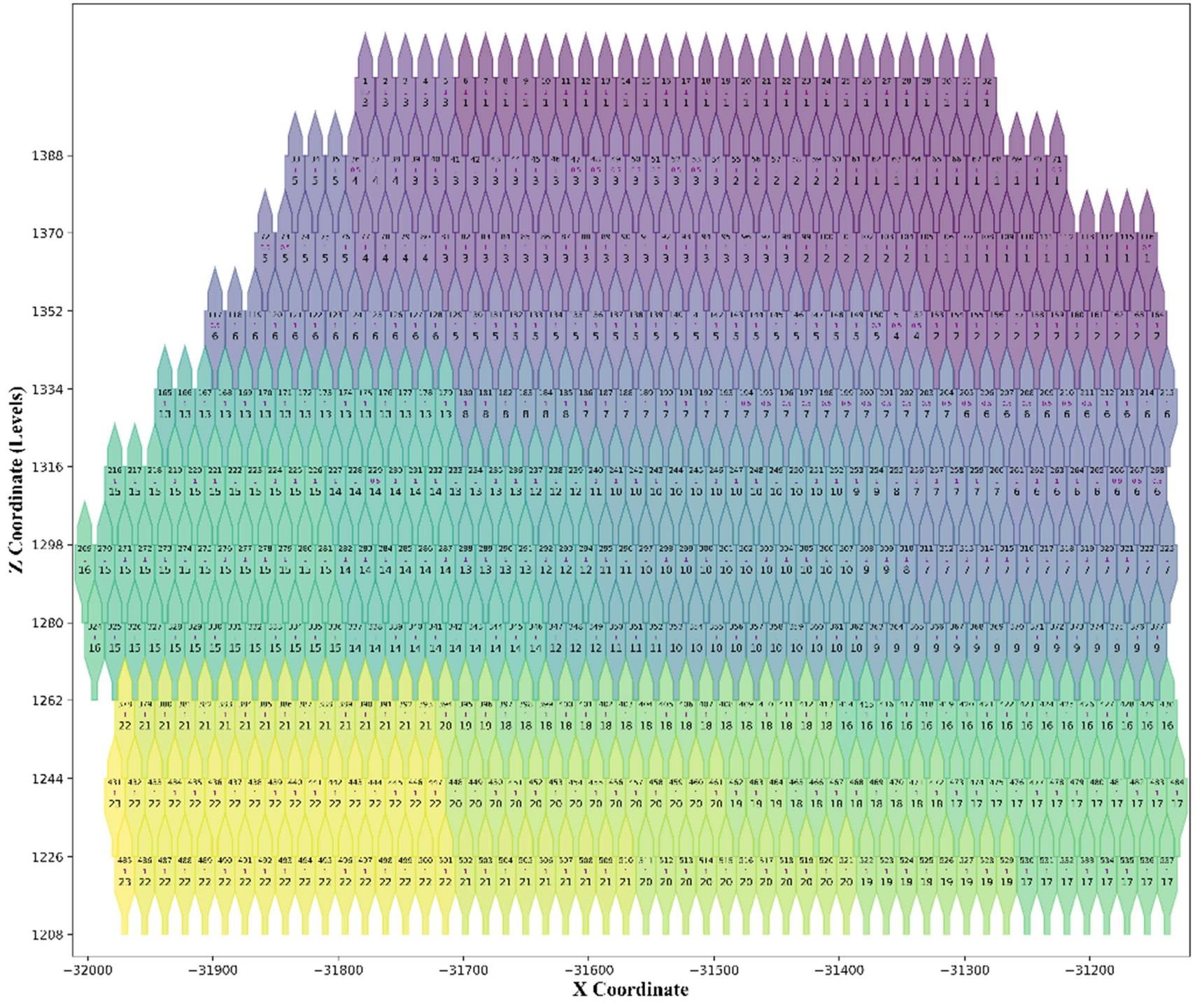

Figure 11. Cross-section view of starting time, and extraction percentage of mining units over the life of mine in scheduling model- Mining direction (Right-to-Left).

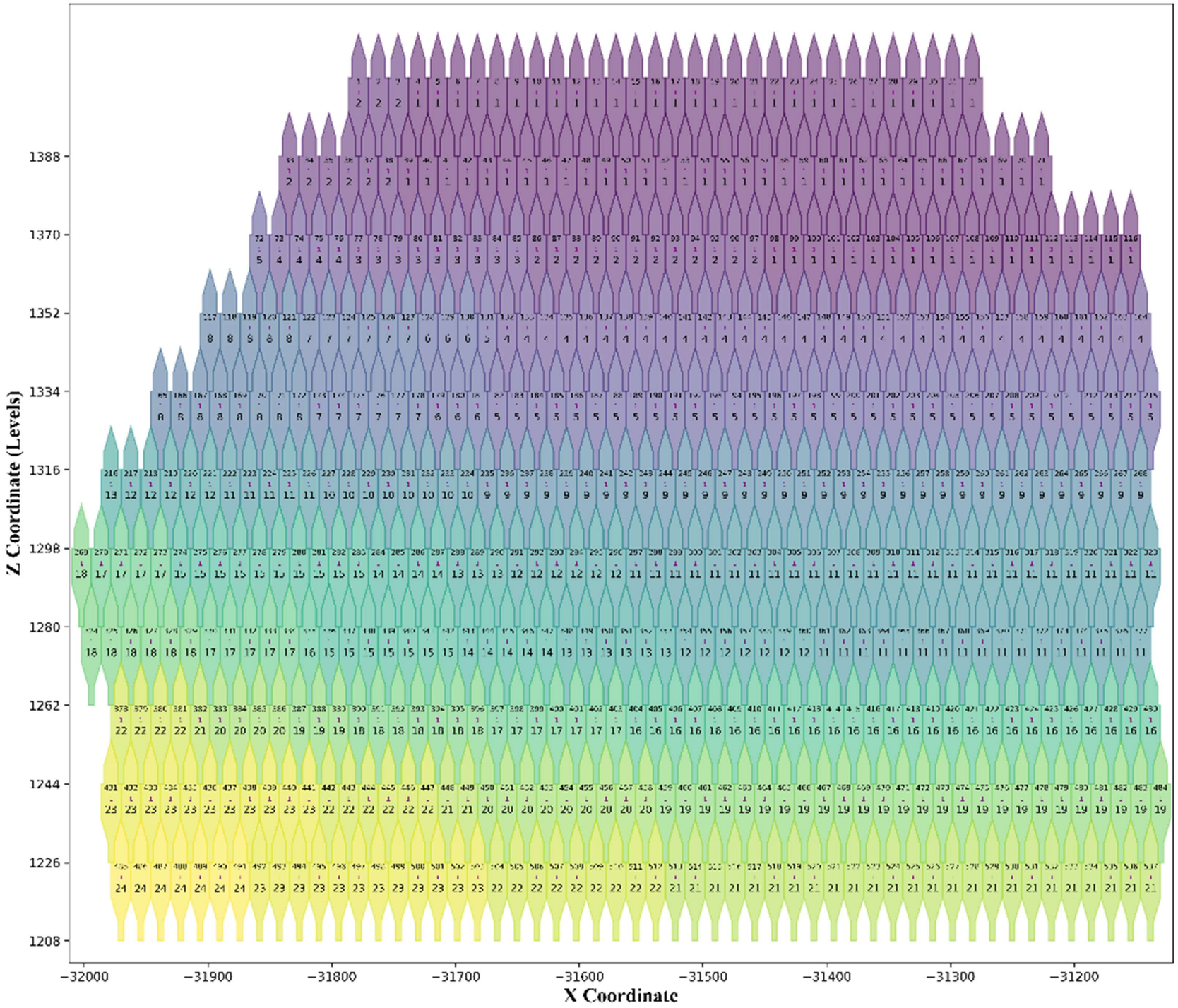

Figure 12. Cross-section view of starting time, and extraction percentage of mining units over the life of mine in PCSLC- Mining direction (Right-to-Left).

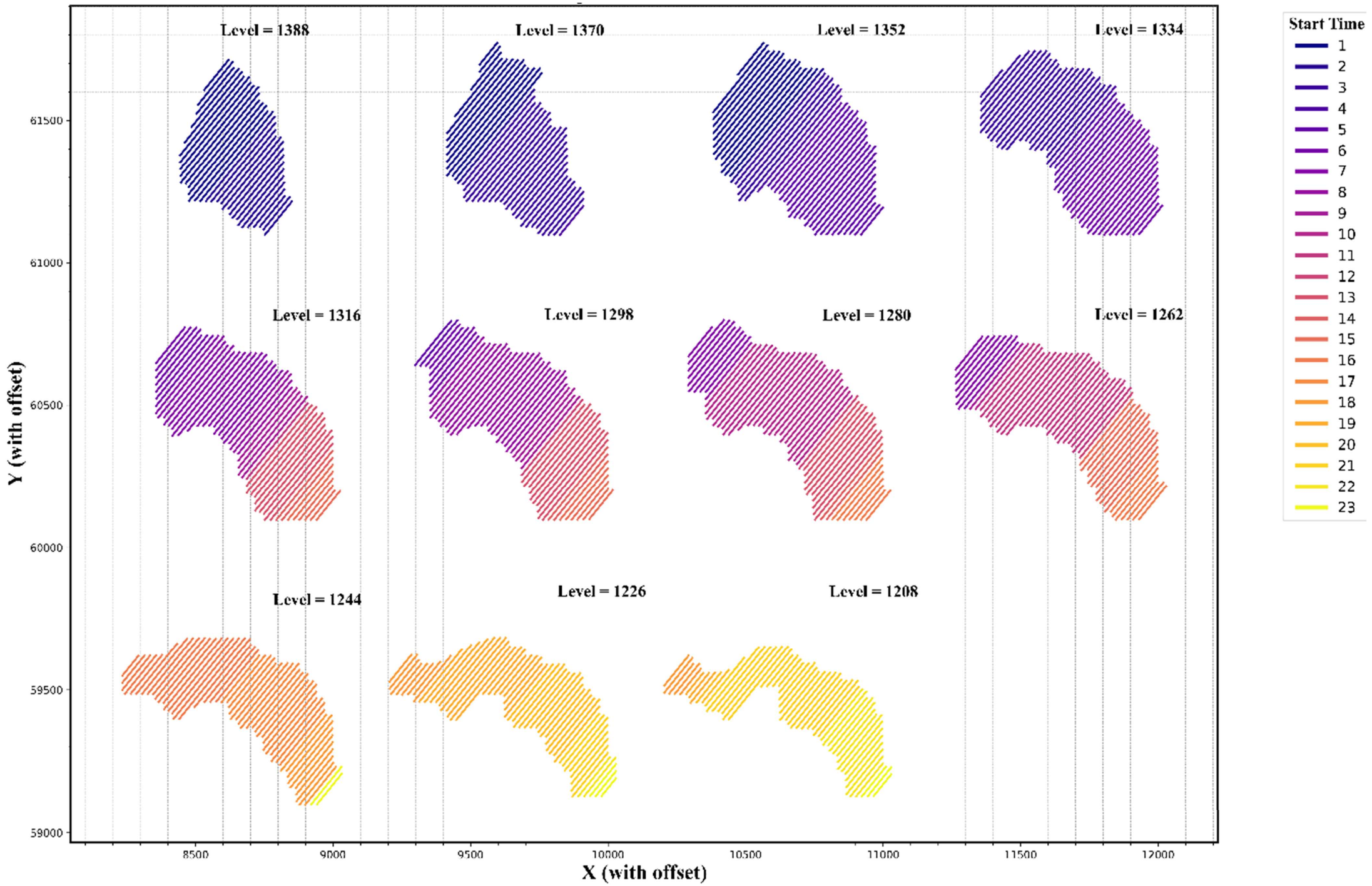

Figure 13. Offset plan view of mining units scheduling in all 11 levels in the scheduling model- Mining direction (Left-to-Right).

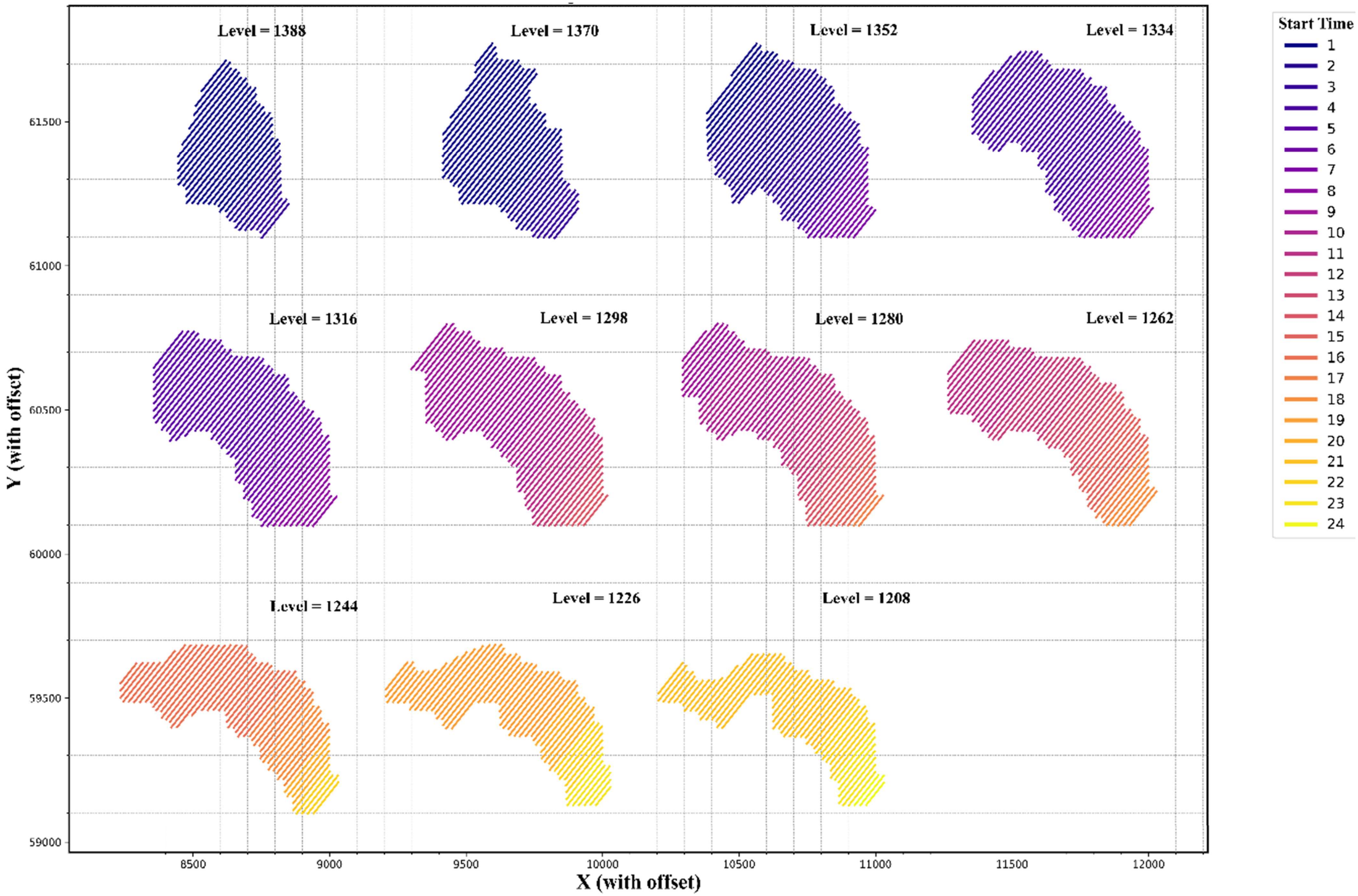

Figure 14. Offset plan view of mining units scheduling in all 11 levels in PCSLC- Mining direction (Left-to-Right).

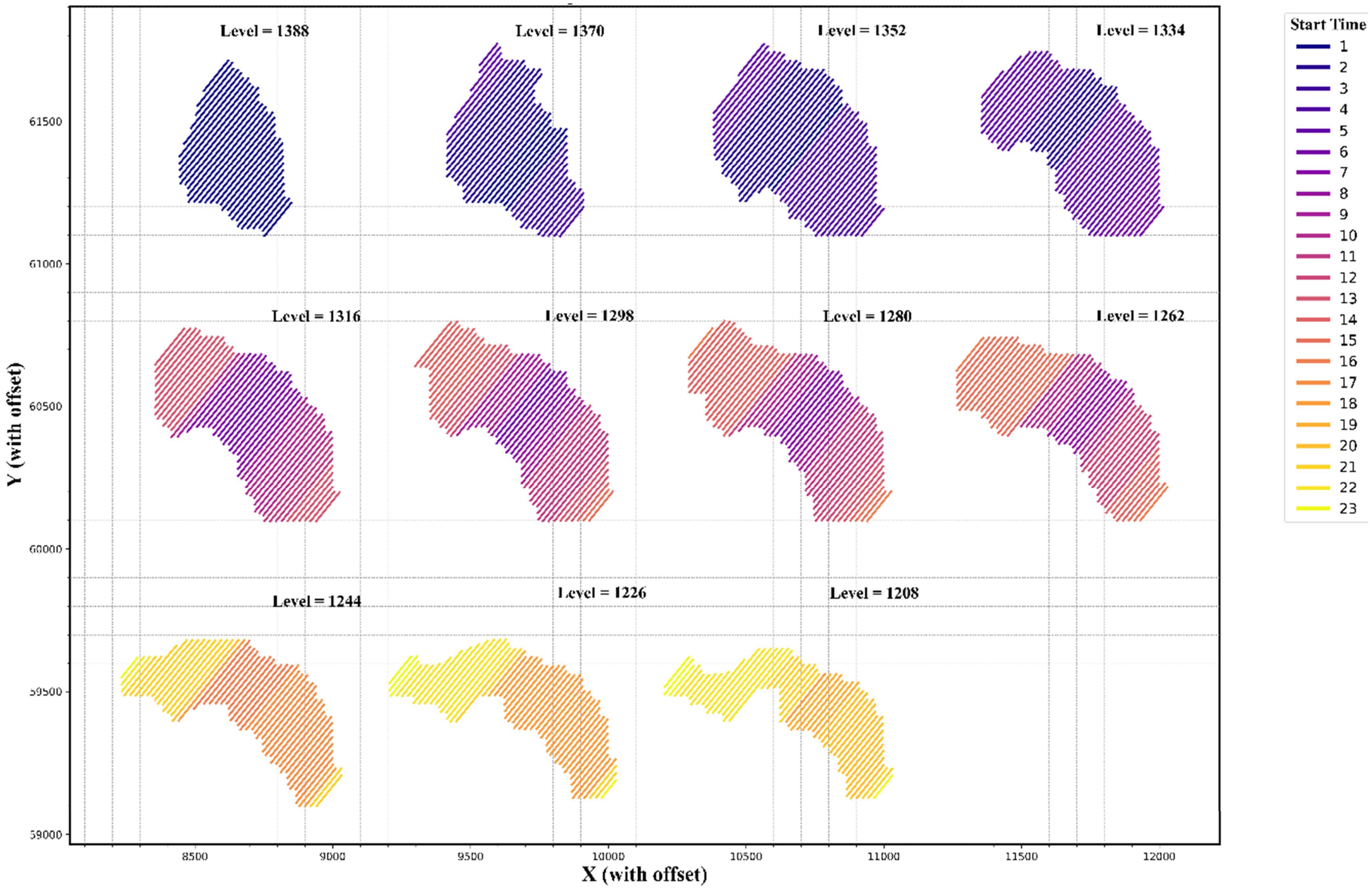

Figure 15. Offset plan view of mining units scheduling in all 11 levels in the scheduling model- Mining direction (Middle).

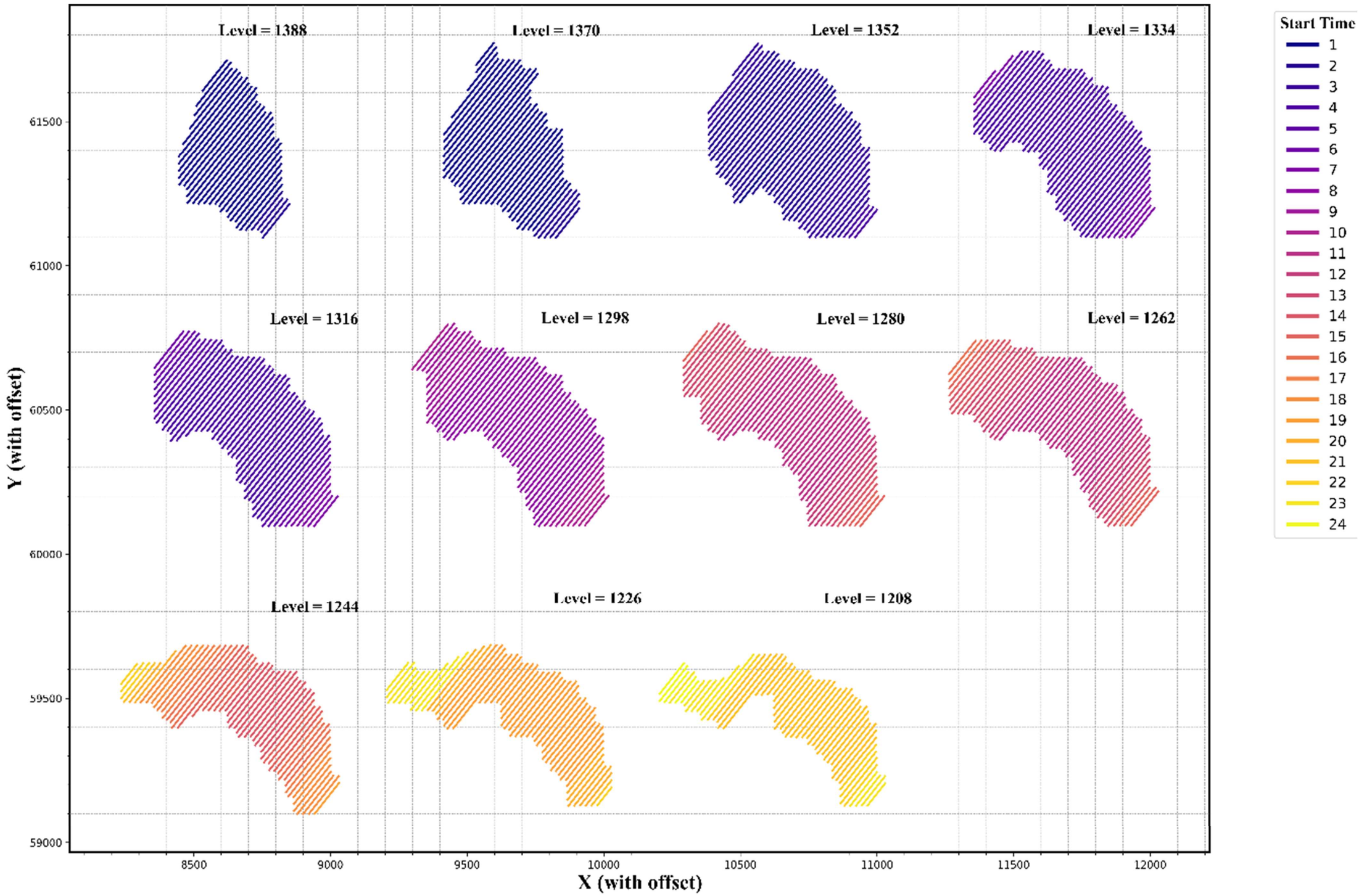

Figure 16. Offset plan view of mining units scheduling in all 11 levels in PCSLC- Mining direction (Middle).

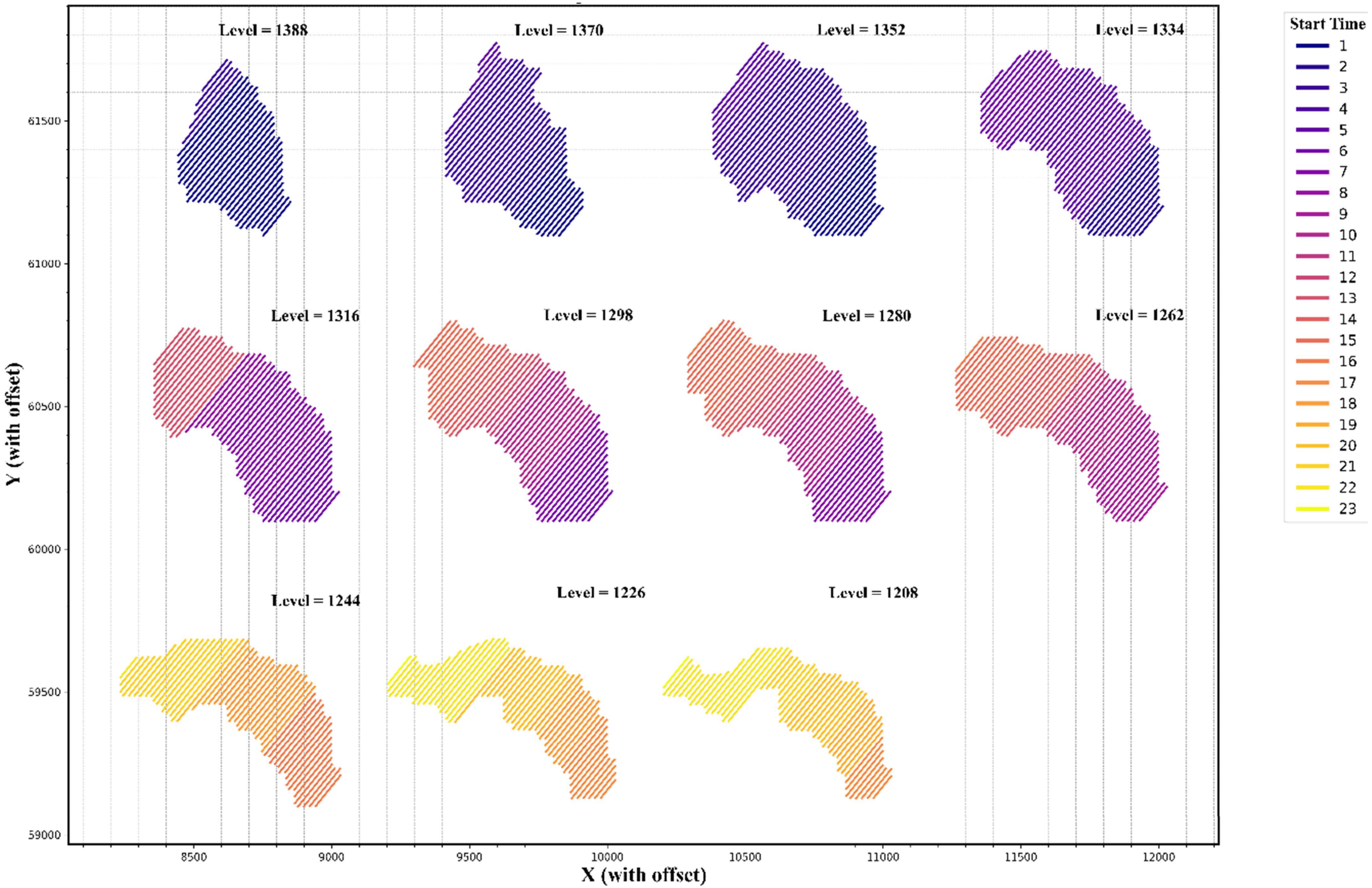

Figure 17. Offset plan view of mining units scheduling in all 11 levels in the scheduling model- Mining direction (Right-to-Left).

Figure 18. Offset plan view of mining units scheduling in all 11 levels in PCSLC- Mining direction (Right-to-Left).

In Figure 19 and Figure 20, a comparison of the tonnage and average grade for two different scheduling methods, including the scheduling model and PCSLC, is presented. In both plots, tonnage is divided into three categories: Left-to-Right (LtoR), Middle, and Right-to-Left (RtoL), represented by different colours. The average grade for these categories is also depicted with corresponding line graphs. The scheduling model with an 8% gap tolerance completes its operation in 23 years, while the PCSLC schedule finishes within 24 years. For the scheduling model, the tonnage remains relatively stable, with some fluctuations, especially in the final year. The average grade in this model shows more variability, indicating fluctuations in ore quality over the years. In contrast, the PCSLC demonstrates a more consistent tonnage distribution with a slight decline towards the end. The average grade in the PCSLC also shows fluctuations but appears to be more stable than the scheduling model.

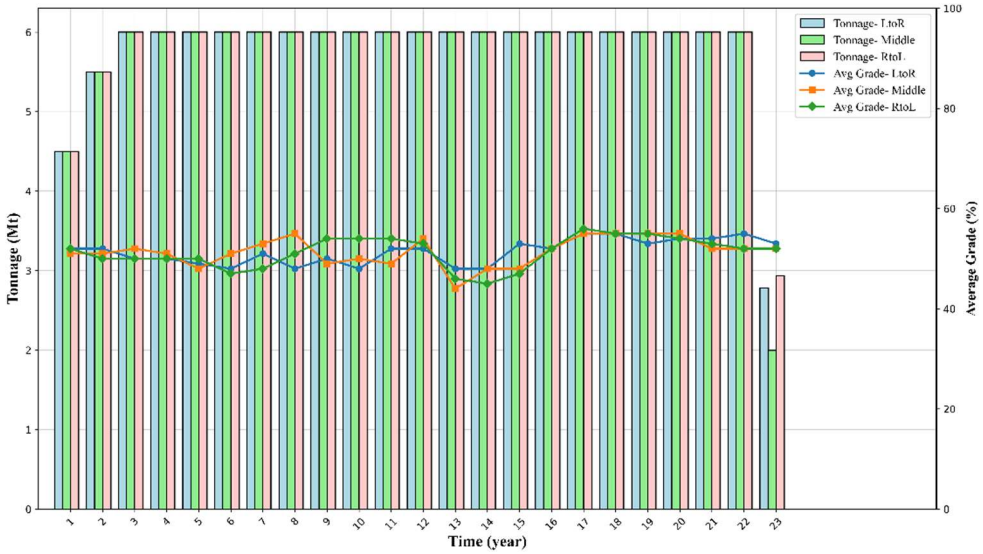

Figure 19. Tonnage-Average Grade plot in all mining directions (LtoR, Middle, RtoL)- Model.

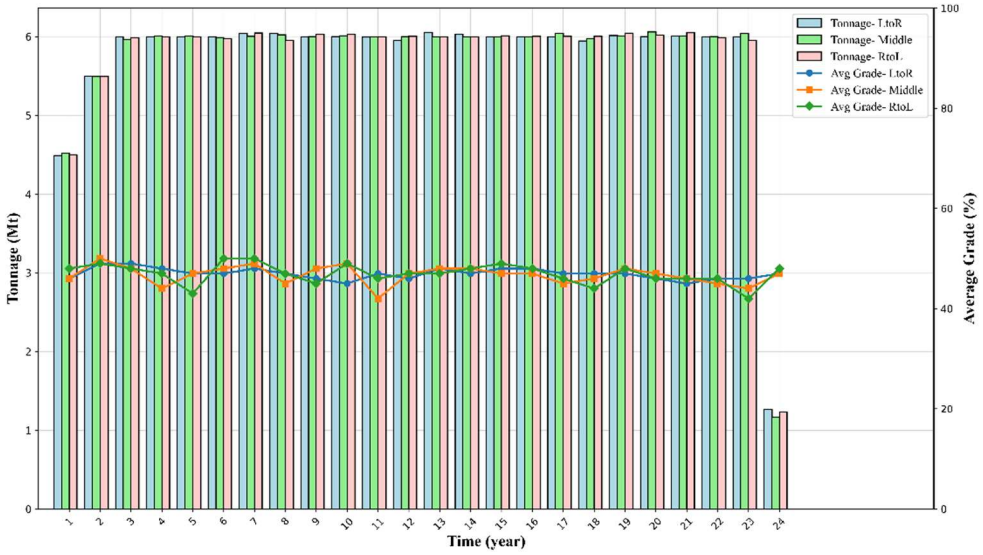

Figure 20. Tonnage-Average Grade plot in all mining directions (LtoR, Middle, RtoL)- PCSLC.

Figure 21 compares the NPV values for the scheduling model and PCSLC across three mining directions: LtoR, Middle, and RtoL. In both the LtoR and RtoL directions, the presented model achieves slightly higher NPV values than the PCSLC, with differences of 2.29% and 2.26%, respectively. However, the most significant difference is observed in the Middle approach, where the model outperforms PCSLC by 3.20%, indicating its maximum NPV advantage. Overall, the scheduling model demonstrates better performance compared to the PCSLC schedule, which indicates that the scheduling model generally provides higher economic values in all mining directions.

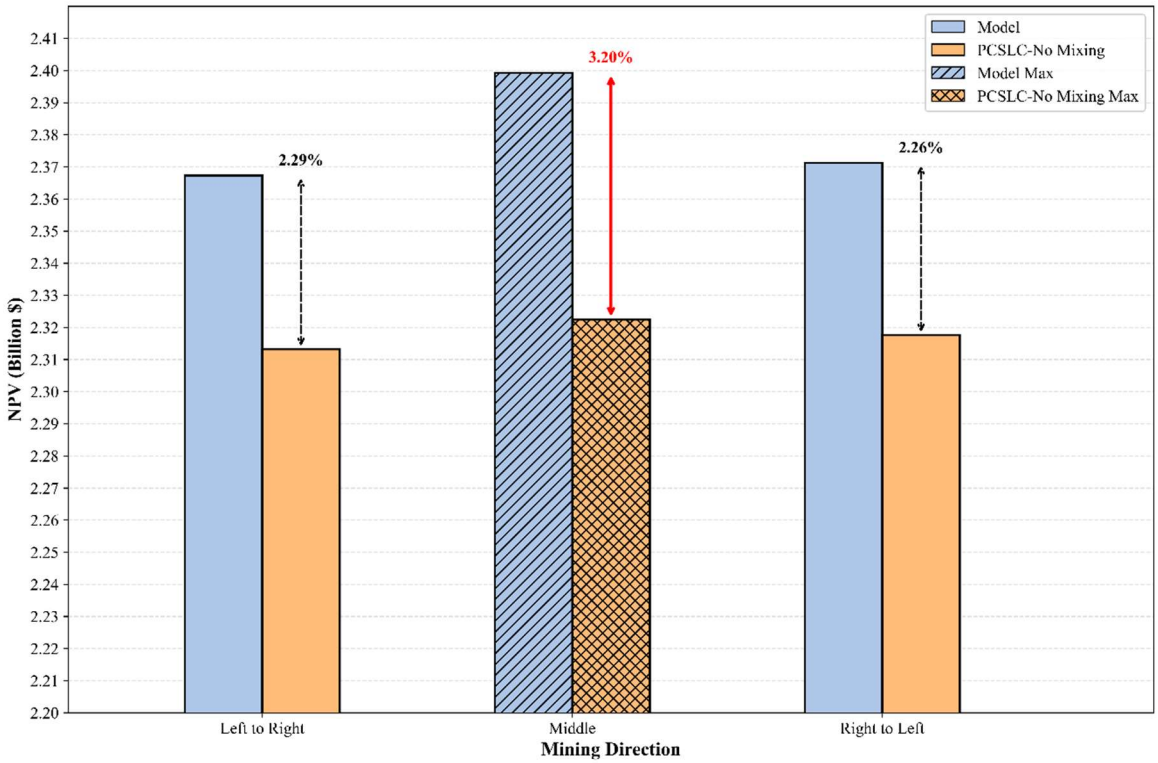

Figure 21. NPV values of the model (run on the gap tolerance of 8%) and PCSLC for different mining directions (LtoR, Middle, RtoL).

7. Conclusion

This study was a comparative analysis to validate the scheduling model developed for SLC long-term scheduling using PCSLC as a benchmark. The model constraints were designed to align closely with PCSLC scheduling setups while incorporating model-specific constraints. The performance of PCSLC, as the only commercial software for SLC scheduling, is undeniable in generating model input efficiently.

The comparative analysis reveals that the presented model and PCSLC exhibit distinct performance characteristics. The scheduling model with an 8% gap tolerance completes operations in 23 years, whereas the PCSLC finishes in 24 years. The PCSLC demonstrates more consistent and stable tonnage and average grade distribution. However, the presented model generally outperforms

PCSLC in terms of economic value in the LtoR, Middle, and RtoL mining directions, with NPV differences of 2.29%, 3.20%, and 2.26%, respectively.

Overall, while PCSLC offers some advantages in specific scenarios, the presented model provides better overall economic value. Additionally, the main advantage of using PCSLC is its significantly faster processing time compared to the scheduling model, making it a highly efficient tool for SLC scheduling. These findings can inform future decisions and methodologies when selecting the most appropriate scheduling approach to reduce solution time for real-world mines with large datasets.

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Stochastic Optimization and Deterministic Models in Strategic Mine Planning Problems: An Overview of Solution Methods and Comparisons

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ABSTRACT

Strategic mine planning is a critical aspect of mining, focusing on addressing long-term mining challenges to maximize economic or non-economic value while accounting for operational and financial constraints. There are two primary methods for modeling mining problems: deterministic and stochastic optimization. Deterministic models, or traditional models, are used for problems with fixed input parameters. However, these models often fail to consider the inherent uncertainties in geological, economic, and operational parameters. In real-world situations, it is essential to account for data uncertainty, making the application of stochastic parameters important in mining problems. Stochastic optimization is an ideal method for modeling all constraints and objectives of a mining problem while considering potential data uncertainties. In stochastic optimization, uncertainties are addressed by considering multiple scenarios or probabilistic distributions for the parameters. This study provides an overview of the methods, applications and comparisons of stochastic optimization and deterministic modeling in strategic mine planning. Evaluating the advantages and limitations of these two approaches reveals that stochastic optimization improves problem solutions and enhances the sustainability of mining operations under uncertainty, but it involves more computational complexity.

1. Introduction

Strategic mine planning is a comprehensive problem in the mining industry, involving the design, scheduling, and optimization of mining operations to ensure efficient and cost-effective extraction of minerals and their processing. This process encompasses various steps, from ore body modeling to the final production output. Despite advancements in ore body modeling, a significant gap remains in the integration of these models with downstream mining processes. Current approaches often lack realistic models of these processes, which are crucial for accurate planning and optimization. This gap highlights the need for improved methodologies that can seamlessly incorporate the sequence of inputs and outputs from staged processes, ensuring a more realistic and effective mine planning strategy to maximize financial, environmental and sustainability values [1].

In strategic mine planning there are different methods to model the mining problems, in which the ability to effectively manage and mitigate risk and uncertainty is significant. Initial studies on applying traditional approaches to production planning and scheduling involved methods based on Lagrangian relaxation and the branch-and-cut algorithm. These early methods faced significant limitations, primarily their inability to handle large-scale deposits containing millions of blocks. To address this issue, extensive research has been conducted to reduce the problem size, leading to the

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development of various methodologies and techniques [2]. The main advancements and techniques to solve the mine production planning problems include the fundamental trees methodology, heuristic approaches, dynamic programming and heuristics, and meta-heuristic techniques. However, despite these innovations, a common drawback of these methods is their tendency to produce unrealistic designs by not considering the inherent uncertainties in mining operations. In the next section, each method to solve the traditional model in strategic mine planning is explained in more detail.

After studying traditional models in strategic mine planning studies, researchers recognized the need to address the inherent uncertainties and variability in mining data. To mitigate these uncertainties and enhance the robustness of planning decisions, stochastic optimization techniques were introduced. Stochastic mine planning represents a critical advancement in optimizing mineral resource extraction by incorporating the inherent uncertainties of geological data, market prices, and operational conditions.

Recent advancements in stochastic mine planning have been driven by improvements in computational power and the development of sophisticated algorithms. These innovations enable the processing of large datasets and the simulation of complex models, leading to more accurate predictions. For instance, techniques such as Monte Carlo simulation, geo-statistical simulation, robust optimization and machine learning algorithms are increasingly being employed to enhance the precision and reliability of stochastic models. The mentioned approaches to address stochastic conditions of mine planning problems are investigated in the following sections. Recent studies emphasize the growing importance of stochastic models in improving decision-making and enhancing the economic viability of mining projects [3].

The most stochastic models which are used in mine planning problems consider three primary sources of uncertainty including geological, technical, and economic conditions. The uncertainties in mining impact the reliability and effectiveness of the mine planning model. To achieve more realistic and robust solutions, it is essential to incorporate these uncertainties into the planning process [4]. By addressing the uncertainties associated with geological, technical, and economic factors, the mining industry can develop more effective and sustainable long-term production plans.

2. Review of Literature

In this section, we investigate both stochastic and Traditional (Deterministic) models, exploring the primary approaches used to solve them across various scenarios in mining as well as other general applications. We begin by examining the fundamental principles and methodologies behind these models, highlighting their respective strengths and limitations. Following this, we present some of the most effective and widely used examples, providing detailed case studies to illustrate their practical applications. Finally, we compare these models in terms of their effectiveness, evaluating their performance and suitability for different types of problems. This comprehensive analysis aims to offer valuable insights into the advantages and challenges of each approach, guiding the selection of the most appropriate model for specific situations.

2.1. Traditional (Deterministic) Modeling

Key methods in addressing mine production and schedule planning problems in deterministic conditions encompass the fundamental trees methodology, heuristic approaches, dynamic programming combined with heuristics, and meta-heuristic techniques. These innovations represent significant progress in the field, offering various strategies to enhance the efficiency of mine planning. However, a limitation across these methods is their unrealistic designs in which all data is deterministic and constant. This shortfall arises from their failure to adequately account for the inherent uncertainties present in mining operations, such as variable geological conditions,

fluctuating market prices, and unpredictable operational challenges. Addressing these uncertainties is crucial for developing more accurate and feasible mine production plans.

2.1.1. Fundamental Trees Methodology

The Fundamental Trees methodology is a systematic approach used to understand, analyze, and visualize the essential components and relationships within a problem. This method breaks down the problem into its fundamental elements, often represented as nodes in a tree structure, and connects these elements through branches to illustrate their relationships. The key components of Fundamental trees methodology are nodes (root node, leaf node) and branches (connections).

Mixed integer programming (MIP) and linear programming (LP) mathematical optimization models offer the flexibility to incorporate multiple ore processing methods, such as milling and leaching, and various elements during optimization. This adaptability can lead to production schedules with significantly higher net present values (NPV) compared to traditional non-mathematical programming methods. However, MIP formulations for production scheduling often require many binary variables, making them challenging or even impossible to solve for real-world open pit mining operations.

Ramazan [5] introduced the Fundamental Tree Algorithm (FTA) for open pit mine production scheduling, using an LP model to consolidate blocks and reduce binary variables, making MIP models feasible. Also, Ahmad et al.[6] developed random tree and C4.5 decision tree models to predict pillar stability in underground mines, showing high accuracy and reliability. In the general area, Zhao [7] analyzed the Apriori algorithm for association rule mining, emphasizing its efficiency and noise control. Kundu [8] presented a random forest regression methodology for predicting the remaining useful life of spur gears, using a correlation coefficient from residual vibration signals, validated by five experimental datasets and improved by fusing data from multiple accelerometers. Also, deterministic problems can be modeled and solved by a goal programming framework and discrete event simulation for optimizing oil sands mining operations, focusing on production schedules, dyke construction, and tailings management [9].

2.1.2. Heuristic Approaches

Heuristic approaches are problem-solving strategies using practical and efficient methods to generate solutions that may not be perfect but are good enough given the constraints and time available. These methods rely on experience, and intuition rather than precise algorithms. Heuristic approaches are particularly valuable in situations where an exact solution is difficult or impossible to find within a reasonable timeframe. The common Heuristic techniques are Greedy Algorithms, Simulated Annealing, Genetic Algorithms, and Tabu Search.

The mixed integer linear goal programming model is useful to optimize extraction schedules, maximize net present value and minimize dyke construction costs, which can be solved by an agglomerative hierarchical clustering and branch and cut algorithm [12-16].An extraction sequences can be applied for an underground lead and zinc mine, reducing model size with exact and heuristic methods to solve complex problems quickly, tested on Lisheen mine data [10, 13, 17]. An open-pit mining scheduling is able to maximize net present value by hybrid heuristic algorithm[11], improving efficiency and solution quality, and solving previously unsolved instances from the MineLib library. For incorporating a stockpile and a greedy heuristic to enhance computational efficiency, a Simulated Annealing approach in the problem of open-pit mine production scheduling works efficiently [18]. To reduce solution time and memory usage in the sublevel stope layout problems a dynamic programming method including memorization and a greedy heuristic is important[19]. Long-term production scheduling models under grade uncertainty which apply a hybrid model using augmented Lagrangian relaxation and the human mental search algorithm are capable to improve and achieve higher net present value [20]. The mixed-integer programming

models can be solved by tabu search algorithm for optimizing autonomous truck trips and speeds to minimize energy consumption, verified in a real-time scheduling system in a coal mine [21].

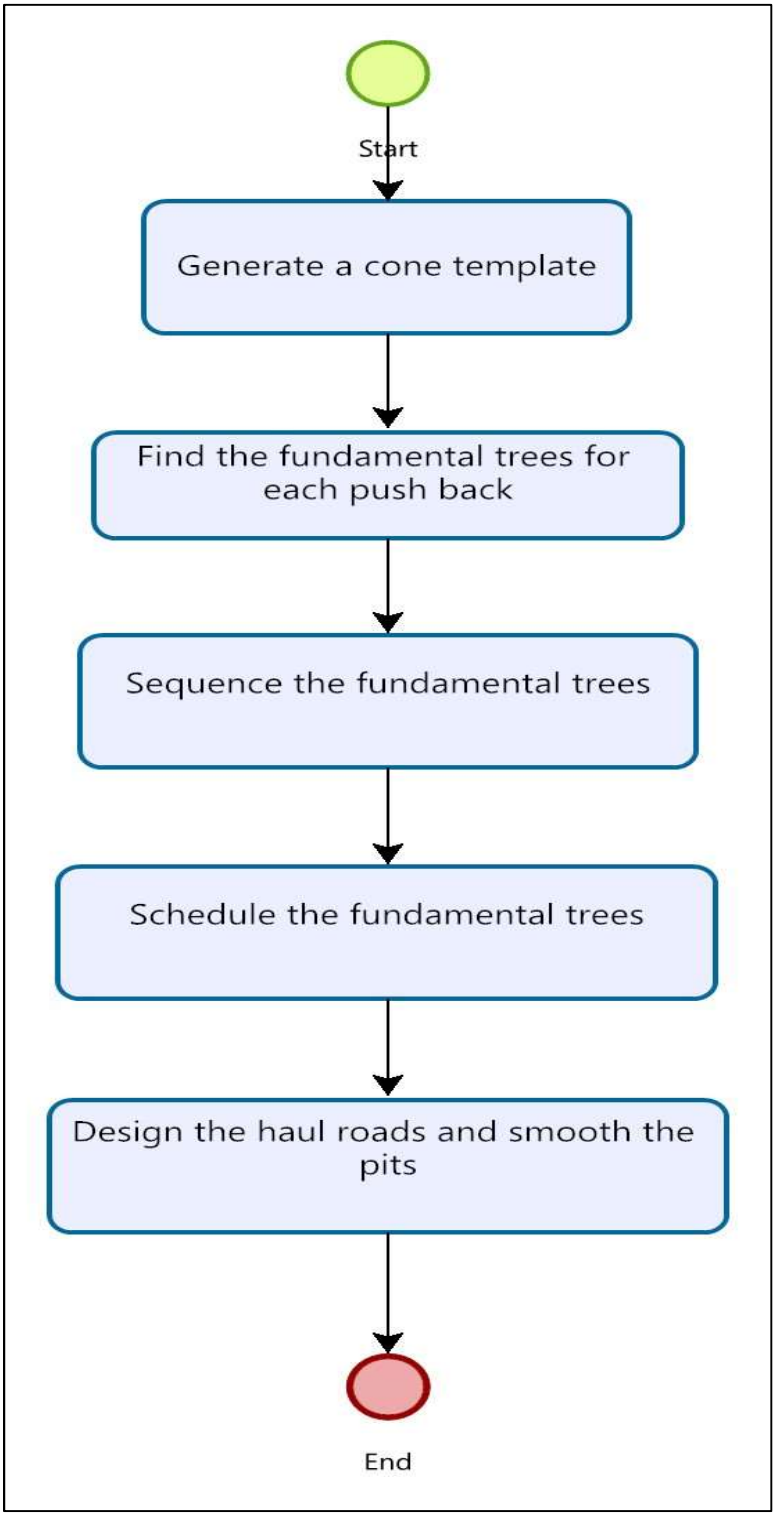

Figure 1, Mine planning based on the fundamental tree algorithm [5].

2.1.3. Dynamic Programming

Dynamic programming (DP) is a powerful algorithmic technique to solve complex problems by breaking them down into smaller sub-problems. The key idea behind dynamic programming is to use previously computed results to efficiently solve new sub-problems to avoid redundant work.

A dynamic stochastic programming approach was studied by Rimele [22] for open pit mine planning with geological and commodity price uncertainty. Their optimization method addressed both geological and market uncertainties, providing a life-of-mine production schedule that is scenario-independent regarding geological uncertainty but scenario-dependent concerning commodity price non-anticipatively. This allows the model to adapt to commodity price changes within reasonable limits for metal production targets and feasible mine designs. The method integrates a two-stage stochastic integer program with a stochastic dynamic programming algorithm. They used a case study to illustrate how the proposed method identifies policies that correlate price variations with metal production targets and consider both geological and commodity price uncertainties.

2.1.4. Meta-heuristic techniques

Meta-heuristic algorithms are high-level problem-solving strategies that guide underlying heuristics to find, generate, or select a heuristic that may provide a sufficiently good solution to an optimization problem. These algorithms are particularly useful for solving complex and large-scale problems where traditional methods are impractical due to the size and complexity of the search space. The most commonly used meta-heuristic algorithms in mining area in the recent years are Genetic Algorithms [23, 24], Simulated Annealing [25, 26], Particle Swarm Optimization [27-29], Ant Colony Optimization, Tabu Search [30, 31], and Differential Evolution [32]. These meta-heuristic algorithms are used in different mining fields and other areas to solve problems that are difficult to tackle using traditional optimization methods.

Optimization and decision-making in engineering are crucial today, with data processing demands escalating due to massive data volumes. Addressing these demands, heuristic and meta-heuristic algorithms play a significant role, especially when combined into hyper-heuristic solutions that optimize time and space complexities. The study by Chandra [33] explores nature-inspired computing, meta-heuristic models, hybrid models, and hyper-heuristics, proposing a hyper-heuristic approach derived from meta-heuristic algorithms for general problem domains. They categorize heuristic algorithms into population-based, evolutionary-based, swarm-based, agent-based, search-based, and hybrid-based, with agent-based multi-objective approaches proving efficient for global optimal solutions. It reviews various optimization algorithms, emphasizing the transition from meta-heuristics to hyper-heuristics and demonstrating performance improvements with fine-tuned algorithms. The paper highlights the evolution and application of these algorithms, advocating for multi-level heuristics to tackle real-world challenges effectively.

2.2. Stochastic Optimization

To consider uncertainty of data in mine planning models, and designing stochastic models, we can apply several methodologies, where the main methods are stochastic integer programming [34] and conditional stochastic [35]. After applying uncertainty in the mathematical models, the complexity level of the model is increased. Therefore, recent studies in stochastic mine planning have solved their proposed models by advanced methodologies reducing complexity and improving solutions. These methods are explained in the following.

2.2.1. Monte Carlo Simulation

Since presenting one method for each problem can exclude valid solutions and results, there is not any single and definitive Monte Carlo method. However, many simulations generally follow this pattern.

1. Model the system using one or more probability density functions (PDFs).

2. Repeatedly make samples from these PDFs.

3. Compute and analyze the statistics of interest.

Harrison [36] indicated the main considerations required to be defined in modeling Monte Carlo simulation including desired output, purpose of outputs, accuracy/precision, modeling specificity, input definition, and process modeling.

Figure 2 illustrates a brief introduction to Monte Carlo Simulation. The real-world problem represents the initial problem that needs to be solved. It is the starting point of the simulation process. By analyzing the data related to the real-world problem and developing a conceptual model, the conceptual model can be presented to capture the essential features of the problem. The conceptual model is a theoretical framework to outline the system's behavior. Then, with applying computer programming and implementing, the conceptual model is translated into a computer model through programming. It includes coding the model, implementing algorithms, and setting up simulations. Also, in the phase of simulation, the computer model is executed to perform simulations. This involves running multiple iterations to explore different outcomes based on varying inputs and random variables.

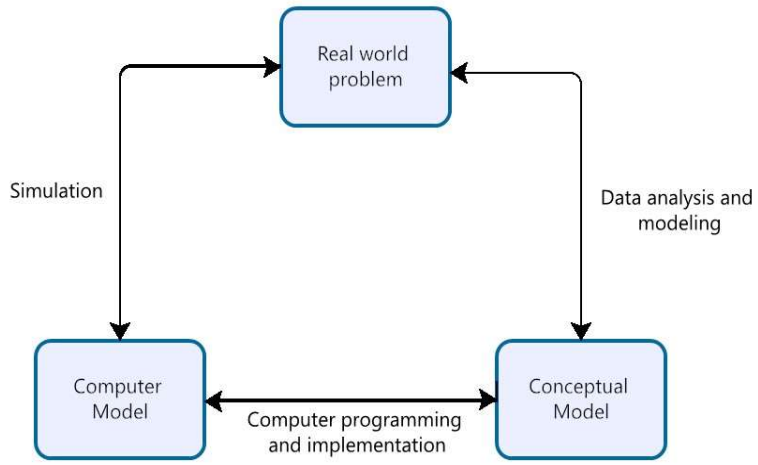

Figure 2. Framework of computer simulation for Monte Carlo simulation [37].

2.2.2. Geostatistical Simulation

Geostatistical simulation methods are valuable tools for generating multiple equally probable realizations of a spatial phenomenon, allowing for the quantification of uncertainty in the generated patterns. Before selecting a geostatistical simulation method for a specific problem, it is crucial to determine the nature of the variables involved. According to Emery [38] and Silva [31], variables can be categorized into three main types. Continuous variables typically represent physical properties such as percentage of tree cover. Categorical variables which are defined by a fixed number of states or categories, such as soil type. Also, objects have varying shapes, locations, and orientations, such as buildings, trees, or water bodies.

Geostatistical methods have become increasingly practical to predict spatial attributes and model the uncertainty of predictions, which are crucial for mineral resource estimation and ore reserve evaluation [39]. One of the key geostatistical interpolation methods is the linear robust estimator of Kriging [40] which has the drawbacks of smoothing effect with highly skewed data. In contrast, Gaussian simulation [41] provides more precise results for many continuous variables by transforming them to a Gaussian distribution.

2.2.3. Robust Optimization

Robust optimization (RO) does not rely on known probability distributions for uncertain data. Instead, it assumes that uncertain data exists within a specified uncertainty set. Basic RO models enforce strict constraints, meaning that no constraint violations are allowed for any possible realization of the data within the uncertainty set. RO is widely used because it is computationally efficient for many types of uncertainty sets and problems [42-44].

Robust optimization is a widely used method for handling optimization under uncertainty. The main idea is to indicate an uncertainty set containing possible values of the uncertain parameters and then optimize for the worst-case scenario within this set. When the uncertainty sets are well-chosen, robust models typically result in manageable optimization problems that perform better than other methods. However, if the sets are poorly chosen, robust models can become too conservative or difficult to solve. Therefore, selecting an appropriate uncertainty set is essential. In the recent studies, several theoretically and experimentally validated methods for constructing uncertainty sets are presented [43].

As illustrated in Figure 3, the optimizer generates solutions for the problem, which operates within a specific environment. The problem uses these solutions, and its performance is assessed using evaluation methods. This performance evaluation is shown back for the optimizer to inform the quality of the solutions. During operation, the system encounters uncertainties from both internal and external sources [44].

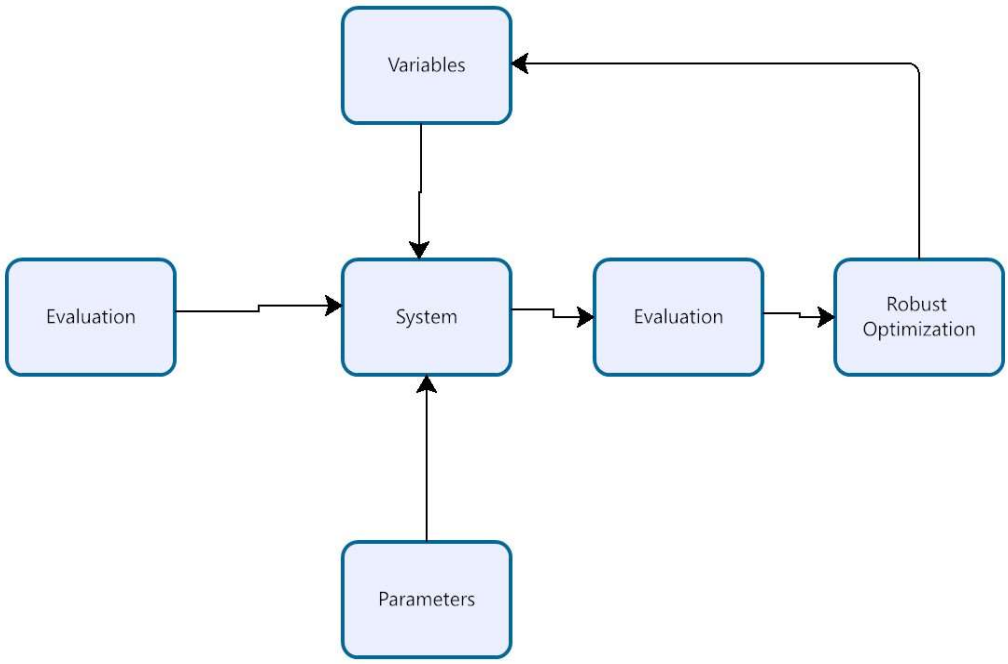

Figure 3. Sources of dynamics and uncertainties [44].

2.2.4. Machine Learning Algorithm

In the era of the Fourth Industrial Revolution (Industry 4.0), vast amounts of data are generated from IoT, cybersecurity, mobile devices, business transactions, social media, and healthcare. Effective analysis of this data for developing intelligent, automated applications requires knowledge of artificial intelligence (AI) and machine learning (ML). Sarker [45] provided an extensive overview of machine learning algorithms including supervised, unsupervised, semi-supervised, reinforcement learning, and deep learning, and their applications in domains such as cybersecurity, smart cities, healthcare, e-commerce, and agriculture. Their study defines the scope by considering the nature of real-world data and the capabilities of various learning techniques, enhancing the intelligence of data-driven applications. It discusses the applicability of ML-based solutions, potential research directions, and challenges for intelligent data analysis. The study emphasizes the importance of quality data and algorithm performance for successful ML models and highlights how ML methods can address real-world issues. By addressing these challenges, the paper opens new avenues for research and application development, serving as a valuable reference for academia, industry professionals, and decision-makers. Haul trucks in open-pit mines consume significant amounts of diesel fuel, resulting in high operating costs and substantial greenhouse gas emissions. Improving fuel efficiency is vital for cost reduction and environmental sustainability. Alamdari [46] modeled diesel fuel consumption in an iron ore mine using machine learning techniques. Payload was identified as the most significant factor, impacting fuel consumption by 47.9%. The study emphasizes the need for accurate, data-driven models to reduce costs and emissions in mining operations.

Hazrathosseini [47]explored intelligent Fleet Management Systems (FMSs) in surface mining, using SWOT analysis to identify strengths, weaknesses, opportunities, and threats, concluding that benefits outweigh drawbacks. Bnouachir proposed a distributed FMS architecture for real-time vehicle control using AI and IoT, enhancing agility and interoperability. Zhang [48] developed a reinforcement learning approach for vehicle dispatching, improving productivity and learning efficiency in dynamic environments. Huo used Q-learning to enhance fleet productivity and reduce GHG emissions, showing significant improvements in haulage efficiency. Carvalho[49] presented an adaptive truck dispatching policy using deep Q-learning, improving adherence to operational plans in mining complexes. Mastui introduced a deep reinforcement learning algorithm for real-time dispatching of autonomous haulage trucks, increasing efficiency and reducing fuel consumption. Noriega[50] developed a DRL-based dispatching system for open-pit mining, achieving robust policy learning and maintaining ore feed quality in a case study.

2.2.5. Sources of Uncertainty in Stochastic Optimization

Most stochastic models used in mine planning problems account for three primary sources of uncertainty: geological conditions, which involve the variability in mineral deposits and rock formations; technical conditions, which pertain to the efficiency and reliability of mining equipment and processes; and economic conditions, which encompass fluctuations in market demand, commodity prices, and operational costs.

1. Geological Uncertainty: Geological uncertainty refers to the variability in the spatial distribution of mineral resources within the earth. This uncertainty arises due to limited data from exploration drill holes, variability in orebody geometry, mineral grade distribution, and unknown geological features.

Brika [51] presented an innovative method for optimizing long-term production scheduling in open pit mines, incorporating multiple processing streams and investment decisions under geological uncertainty. Their approach begins with solving the linear relaxation using an extended Bienstock-Zuckerberg algorithm tailored for stochastic optimization. This is followed by a topological sorting-based rounding heuristic and a parallel multi-neighborhood Tabu search. The model, applied to a

multi-product open pit mine, allows investments in shovels, trucks, or crushers to enhance capacity. By incorporating capital expenditure options and geological scenarios, the aim is to maximize NPV of the mining complex from various customers and the spot market. The research enhances previous models by integrating investment options and using a stochastic Bienstock-Zuckerberg decomposition method with heuristics. A case study on an iron open pit mine demonstrated the model's effectiveness, achieving an optimality gap of 1.5% within 12–22 minutes and showing significant NPV improvement through early investment in additional crushing capacity.

Jelvez [11] introduced a multi-stage methodology for long-term production planning in open-pit mines, addressing ore grade uncertainty. The approach integrates geological uncertainty into defining the final pit, optimizing pushbacks, and scheduling production, using new mathematical optimization models and conditional simulation. The main contributions of their research include a model optimizing final pit value while minimizing conditional value at risk (CVaR), a pushback optimization model selecting nested pits with similar total tonnages, and a mixed-integer program for scheduling bench phases to minimize production target deviations. They revealed that the final pit limit stage contributes 31.4%, pushback optimization 12.6%, and production scheduling 56% to the overall value. This multi-stage approach helps determine the relative impact of each planning stage, guiding efforts to maximize value and minimize uncertainty costs. Results show that incorporating uncertainty reduces the risk of failing to meet production goals compared to a deterministic approach.

A comparative study on a gold mining complex proposed by Morales [52], evaluating two stochastic mine plans: one using conventional wireframes for geological domains and the other using high-order simulations. The study found that simulated geological domains produced a 20% higher expected net present value (NPV) and a 40% wider risk profile due to reduced waste handling costs and a lower environmental footprint. Key contributions include a methodology for simulating geological domains using high-order spatial statistics, validated up to the fourth-order statistics, and the integration of these simulations into a stochastic optimization framework to produce mine schedules. The study highlights the importance of incorporating geological uncertainty in mine planning, leading to different extraction sequences, ultimate pit limits, and practical adjustments in mine design, such as ramps and waste dump layouts. The 20% increase in expected NPV results from reduced waste handling rather than increased metal recovery, emphasizing significant financial and environmental benefits.

Quantitative modeling of geological heterogeneity is crucial for effective resource management in mining, particularly when data is limited to exploration drill holes, introducing uncertainty in the empirical cumulative distribution function (CDF). Erten [53] addressed this challenge by employing a multivariate spatial bootstrap procedure to quantify parameter uncertainty and incorporating it into geo-statistical simulations. Using data from the Lisheen lead and zinc mine, they compared three scenarios: (1) using all available data, (2) a representative subset without parameter uncertainty, and (3) the same subset with parameter uncertainty. The results showed that including parameter uncertainty provides a more realistic assessment of resource risk.

In the area of underground mine design, Noriega [54] introduced a novel approach using deep reinforcement learning (DRL) to address geological and mineral grade uncertainties, which are often overlooked by traditional methods, resulting in suboptimal decisions. The proposed framework employs the proximal policy optimization (PPO) algorithm and integrates multiple numerical realizations of a mineral resource to enhance financial performance. In the gold mine case study, the DRL approach achieved an 8.3% higher expected profit and extracted 3.4% more gold compared to standard industry methods. The primary benefit of this approach lies in its ability to incorporate geological uncertainty into mine planning, leading to improved decision-making.

2. Technical Uncertainty: Technical uncertainty encompasses the variability associated with the mining process, equipment performance, and operational conditions. Factors contributing to technical uncertainty include equipment reliability, mining method efficiency, processing plant performance, and variations in ore recovery rates.

Based on [55] study, uranium in situ recovery faces challenges in predicting fluid flow and geochemical reactions due to geological uncertainties. Traditional simulations are computationally intensive, making uncertainty propagation impractical. Therefore, they proposed a Scenario Reduction Method for 100 realizations of a production block to select a subset of geo-statistical simulations and approximate a larger set. This method, validated against full simulations, maintains accuracy in predicting median uranium production and confidence bounds while significantly reducing computational time. The results offer an effective way to quantify production uncertainty in uranium in situ recovery mining and reduce computational time.

Upadhyay [56; 57] developed a simulation optimization framework for mining operations, combining discrete event simulation with goal programming to account for uncertainties and enhance short-term production planning. This tool allows proactive decision-making through scenario analysis and was verified using an iron ore mine case study. Tabesh [58] presented four agglomerative hierarchical clustering algorithms incorporating geostatistical realizations to handle geological uncertainties, resulting in more robust and minable aggregates. In a separate study, Tabesh [59] used discrete event simulation to model iron ore processing plants, focusing on output quality and the impact of input uncertainties. Moradi-Afrapoli [60] created an integrated simulation and optimization framework for truck dispatching in surface mines, improving production by 11% compared to current models. Moradi-Pirbalouti [61] examined different mathematical models for mine planning under deterministic and uncertain conditions, comparing approaches to manage data uncertainty. Jelvez [62] proposed new optimization models and conditional simulation to address geological uncertainty, improving solution quality in a real case study and helping decision-makers identify risks.

3. Economic Conditions: Economic uncertainty results in fluctuations and in market conditions, commodity prices, and economic factors that affect the financial aspects of mining operations. Economic uncertainty arises from market demand, changes in commodity prices, exchange/inflation rate fluctuations, and broader economic trends.

Kizilkale [63] introduced a dynamic programming framework to optimize production rates across multiple metal mines under financial uncertainty. Each mine's production rate is treated as a stochastic optimization problem, with solutions provided via dynamic programming and Markovian feedback control based on current price data. The hierarchical approach separates individual mine scheduling from global extraction rate targets, addressing metal content uncertainty locally and financial uncertainty globally. Using a distributed policy iteration method, each mine's extraction rate is optimized in parallel until a unique equilibrium is achieved. Numerical results indicate that this global optimization method outperforms individual mine optimizations, enhancing financial performance and robustly managing mining rates under uncertainty.

3. Discussion and Results

In the following there is some analysis about the studies on stochastic optimization and traditional modeling in mine planning problems.

Table 1. The summary of publications on Stochastic Optimization in mine planning.

Author	Year	Method	Outcome
Gilani [2]	2020	Particle Swarm Optimization (Geological Uncertainty)	High performance on a large-scale open pit mine; higher NPV with reduced solution time.
Rimele [64]	2018	Stochastic Integer Optimization Programming	Integrated disposal of mining waste and tailings directly inside the pit into life-of-mine planning, saving costs and environmental impact.
Fattahi [65]	2021	Multi-Stage Stochastic Optimization	Designed a sustainable mining supply chain with renewable energy, showed the impact of improving environmental and social objectives on total cost.
Dimitrakopoulos [66]	2022	Simultaneous Stochastic Optimization	Highlighted managing uncertainty and technical risks; increased metal production, operational capability, and net present value.
Morales [52]	2024	High-Order Simulation Of Geological Domains	Presented a 20% higher NPV and up to 40% wider risk profiles.
Nelis [67]	2022	Optimization Model For Scheduling And Mining Cuts	Captured profit and met mining, processing, and operational constraints.
Joshi [68]	2022	Integrated Parametric Graph Closure and Branch-and-Cut Algorithm	Reduction in computational time with reasonable optimality gap.
Guo [69]	2021	Artificial Neural Network Approach	Estimating mining capital cost with ANN model; demonstrated superior performance
Levimson [70]	2023	Reinforcement Learning with Mathematical Programming	Increase in annual cash flow
Whittle [71]	2018	Global Optimization Principles	Discussed global optimization principles and their application in various industries
Kumral [72]	2010	Robust Stochastic Optimization	Improved resilience and efficiency in a case study of production scheduling.
Carpentier [73]	2016	Stochastic Integer Programming	Designed a SIP model for underground mine production scheduling; showed higher project value and better production risk control.
Dimitrakopoulos [74]	2011	Stochastic Simulation And Optimization	A risk-based framework for strategic mine planning; increased production schedule value by 25%.
Montiel [75]	2015	Simulated Annealing	Optimized mining complexes achieved a 5% increase in NPV and reduced risk.
Montiel [76]	2017	Heuristic Approach	Significant improvement in expected NPV and capacity management.
Lin [44]	2024	Mixed Integer Programming (MIP)	Sustainable production scheduling with reduced GHG emissions by 47%; superior performance in NPV maximization.
Carvalho [77]	2023	Actor-Critic Reinforcement Learning	Production planning and fleet management with 47% increase in cash flow.
Faria, et al. [78]	2022	Integrated Stochastic Optimization	Stope design and long-term scheduling with 11% higher NPV and shorter mine life.
Yaakoubi [79]	2022	Learn-to-Perturb (L2P) Hyper-Heuristic	Reduced iterations and computational time with enhanced efficiency in mining complexes.

Minniakhmetov [80]	2021	Data-Driven High-Order Simulation	Practical utility demonstrated in copper deposits.
Rendu [81]	2014	Cut-off Grade Estimation	Enhanced understanding of cut-off grade estimation; crucial for profitability and socio-economic impacts.
Saliba [82]	2019	Stochastic Optimization	Improved operational flexibility and profitability for gold mining operation.
Sepúlveda [83]	2020	Metaheuristic and Simulation Tools	Incorporated uncertainties in mine planning; recommended inclusion of environmental and social variables.

Table 1 shows that most of the research has been conducted in recent years (2018-2024), indicating an increasing focus on optimization methods in mining. Particularly, there is a notable increase in publications from 2020 onwards. Earlier studies (e.g., from 2010 and 2011) laid the foundation for robust and stochastic optimization, which evolved into more sophisticated and integrated approaches seen in recent years.

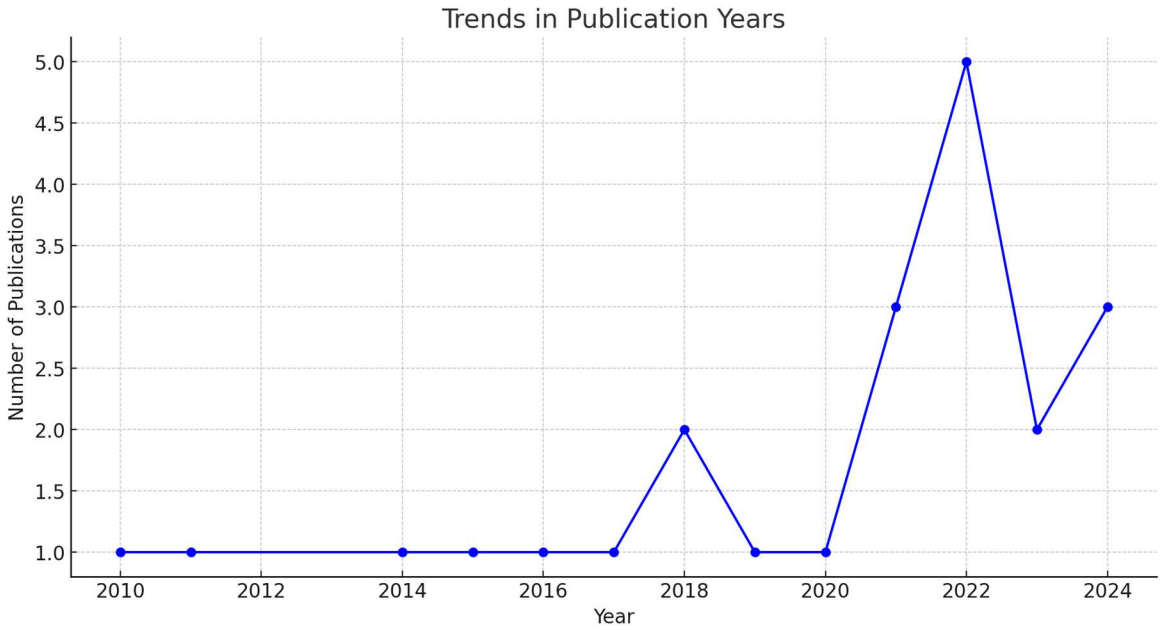

Figure 4. Trends in publications on stochastic optimization in mine planning problems.

Here we analyze the summary of stochastic optimization studies based on year, method, and findings.

- Stochastic Optimization: Most papers reflect the importance of handling geological and operational uncertainties in mining.
- Many studies focus on maximizing the Net Present Value (NPV) of mining operations, showing that this is a critical measure of success. Studies such as those by Gilani et al., Morales et al., Joshi et al., Levimson et al., and Lin et al. report significant improvements in NPV.
- A significant portion of the findings emphasize managing risk and uncertainty. For instance, the work by Dimitrakopoulos [66] and Faria [78] show that integrating uncertainty into planning leads to better risk control and higher project values.
- Several studies, such as those by Rimélé [64] and Lin [44] , highlight cost savings and reduced environmental impacts as key outcomes, demonstrating the dual focus on economic and environmental sustainability.

- The integration of advanced technologies such as AI and reinforcement learning ([69; 77] is a notable trend, indicating a shift towards leveraging modern computational tools for optimization.
- The increasing number of publications in recent years reflects growing interest and advancements in mining optimization techniques.

Top and commonly used methods in 2010-2024 on the studies on stochastic optimization in mine planning are as follows respectively. While Meta-heuristics, Simulation, and Mixed-integer programming remains dominant, there is significant exploration of other innovative methods such as data-driven simulation and heuristic algorithms.

1. Meta-heuristic algorithms
2. Stochastic simulation and optimization
3. Mixed integer programming (MIP)
4. Data-driven high-order simulation method
5. Heuristic approach

Table 2. Summary of publications on Traditional Modeling in mine planning.

Author	Year	Method	Finding
Ramazan [5]	2005	Fundamental Tree Algorithm (FTA) Based on LP Model	Consolidates blocks reducing binary variables for production scheduling in large open pit mines, making MIP models feasible.
Sullivan [10]	2015	Integer Programming	Improving computational efficiency, and practical applicability for mine scheduling.
Jelvez [11]	2020	Hybrid Heuristic Algorithm	Providing feasible and near-optimal solutions for scheduling problems, improving efficiency and solution quality.
Desale [84]	2015	Heuristic and Meta-Heuristic Algorithms	Provide robust near-optimal solutions efficiently, invaluable for NP-complete challenges.
Denardo [85]	2012	Dynamic Programming	Shares features among sequential decision processes, identifying it as a branch of applied mathematics.
Souza [86]	2022	Dynamic Programming Review	DP may not be extensively explored for scheduling, but advances come from DP's theoretical findings.
Chandra [33]	2022	Hyper-Heuristic Approach Derived From Meta-Heuristic Algorithms	Explores nature-inspired computing models and hyper-heuristics, advocating for multi-level heuristics for real-world challenges.
Tolouei [87]	2021	Hybrid of Lagrangian Relaxation (LR) with Meta-Heuristic Methods	Hybrid LR-meta-heuristic approach outperforms others in NPV, and computational time, suggesting potential of LR-BA method.

It appears that research methodologies in the summary of deterministic modeling studies are different. This might indicate a diverse range of methods used across the papers. The most used methodologies are as follows.

1. Integer programming
2. Heuristic and meta-heuristic algorithms
3. Hybrid heuristic algorithm
4. Fundamental Tree Algorithm (FTA) based on LP model
5. Dynamic programming

We observe that the most common method in traditional modeling is integer programming. This method is favored for its efficiency and straightforward modeling process. Additionally, heuristic

and meta-heuristic methods are widely used in many studies. These methods are particularly useful for tackling large-scale problems due to their ability to provide robust and near-optimal solutions.

4. Conclusion

This study highlights the critical role of stochastic optimization in strategic mine planning, especially in addressing the inherent uncertainties of geological, economic, and operational parameters. Traditional deterministic models, while useful in scenarios with fixed input parameters, often fall short in capturing the dynamic nature of real-world mining conditions. The integration of stochastic methods, such as Monte Carlo simulation, geostatistical simulation, and robust optimization, offers a significant improvement in the reliability and effectiveness of mine planning by considering multiple scenarios and probabilistic distributions. While stochastic optimization presents a more complex computational challenge, its ability to produce more realistic and robust solutions makes it an invaluable tool in strategic mine planning.

Recent advancements in computational power and algorithm development have enabled more precise and reliable stochastic models, enhancing the decision-making process and the economic viability of mining projects. Techniques such as machine learning and reinforcement learning are becoming increasingly prevalent, further refining the accuracy of predictions and operational strategies.

Furthermore, the emphasis on sustainability and environmental considerations within stochastic mine planning is a significant development. By incorporating environmental impact assessments and sustainability metrics, these models ensure that resource extraction is conducted responsibly, aligning with regulatory requirements and the growing demand for sustainable mining practices.

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An Optimization Approach for Ultimate Pit and Push-Back Design in an Open-Pit Mine Planning

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ABSTRACT

Designing an open pit mine plan is a specialized problem focused on optimizing the economic value of a mining project before implementation. Two primary operations in an open-pit mine planning are ultimate pit and push-back design. This paper develops an ultimate pit and push-back optimization by incorporating maximum flow network problem while considering the precedence relationships between all blocks in the block model. Using GEOVIA SURPAC, a block model comprising 26,162 blocks was developed, each characterized by volume, gold grade percentage, rock code, rock type, and density. Then, the block data was prepared for use in Python to solve a Mixed-Integer Model for ultimate pit and push-back optimization. For push-back design, a mixed-integer model was used to constrain the capacity of each push-back. In this way, each block is assigned to a specific push-back and evaluated to determine its inclusion within the ultimate pit. The designed block model was applied to generate pushbacks and implement a production schedule using Whittle software, in which the Milawa Balanced algorithm obtained a more robust production schedule. Comparative analysis indicated that solving the push-back optimization problem using Mixed-Integer Programming yielded a higher Net Present Value compared to implementing in Whittle.

1. Introduction and Literature Review

Open-pit mines are surface excavations designed to extract ore located near the surface by creating a series of benches, or horizontal layers, that are mined sequentially from top to bottom. The process begins by exposing a sufficient area and then progressing to deeper levels until the pit limit is reached. Significant amounts of waste material are removed in this process, known as stripping, and the extracted ore is sent to processing plants while waste is disposed of in designated areas [1].

The mining region is represented as a 3D grid of blocks, each containing geological and economic information. Effective mine production requires practical pushback designs, which connect regions with sufficient width and access via haulage ramps. These pushbacks maximize the financial return of the mine and form the ultimate pit. However, models used to define pushbacks often lack operational constraints, leading to manual adjustments by engineers. Previous attempts to model operational conditions include heuristic methodologies and optimization techniques, aiming to create optimal semi-practical pushback designs that ensure connectivity and minimum mining width [2].

A hybrid methodology for long-term open-pit production planning was proposed by Tabesh [3], focusing on three key components: optimal phase design, selective mining-unit characterization, and long-term scheduling optimization. The approach integrates integer programming with a local search heuristic for phase design and employs hierarchical clustering to aggregate blocks into minable

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polygons within pushback boundaries. A mixed-integer linear programming model then generates near-optimal life-of-mine schedules, allowing planners to optimize large-scale multi-pit and multi-process scenarios, including cut-off grade optimization. Two case studies, involving small and large iron ore deposits, demonstrate the methodology's effectiveness. The first case study uses a small pushback from a block model for exact design, while the second employs heuristic procedures for larger pushbacks. The results show that the pushback designs are practical and uniform in tonnage, improving over traditional parameterized revenue methods. The MILP model ensures optimal production schedules and dynamic cut-off grade management, proving the robustness and efficiency of the proposed multi-step approach.

In open pit mining, achieving stable pit slopes is crucial for both safety and economic efficiency. However, many mines are designed with insufficient geotechnical investigations, leading to inaccurate slope angle estimations. Conservative slopes increase operating costs due to higher stripping ratios, while overly steep slopes risk failures and potential mine closure. This study highlights the importance of geotechnical assessments for optimizing pit slopes. Using Pickstone Peerless mine as a case study, geotechnical data was collected through core logging and face mapping, then analyzed using empirical, kinematic, limit equilibrium, and numerical modeling methods with Rocscience software. The study of Nyamande [4] used the current 52° slope angle as steepened by 1° without compromising stability, potentially saving over $12 million in stripping costs. However, further evaluations are necessary for pit extensions to ensure stability. The analysis also indicated that the pit could be deepened by 5 meters without requiring a pushback.

The problem of open-pit mining aims to maximize the net present value (NPV) by defining an optimal extraction sequence under various constraints and uncertainties. Jelvez [5; 6] presented a multi-stage methodology that integrates mathematical optimization and conditional simulation to address geological uncertainty at all stages of planning: computing the ultimate pit, optimizing pushbacks, and scheduling production. Unlike previous models that treat each stage independently, this approach evaluates the impact of uncertainty across the entire process. Using a real case study, the methodology demonstrates that incorporating uncertainty can improve solution quality and reduce the risk of failing to meet production goals, though its effects vary across different planning stages. Their study emphasizes the need for robust models and further experiments to refine understanding and management of geological uncertainty in mine planning.

Mining companies need advanced mathematical tools and techniques for effective decision-making, leading to better returns on investment and benefits for local communities. Despite a trend towards mining larger, lower-grade deposits and an increasing preference for underground mining methods like block caving, surface mining remains popular due to its lower costs. Operations research plays a vital role in mine planning, providing mathematical models to address complex engineering challenges. Deutsch [7] studied these tools to address under-represented operational constraints and improve long-range open pit mine planning. Accurate models are essential, but increased accuracy often leads to greater complexity and longer computational times. Thus, the focus is on developing computationally efficient techniques applicable to real mining datasets. The dissertation aims to create high-quality, flexible, and efficient models for long-range open pit mine planning, detailed through a structured review of literature, algorithmic improvements, and computational comparisons. In the other study [8], the floating cone optimization algorithm was presented, replacing complex programming loops with efficient SQL queries,

significantly speeding up calculations. A case study showed a 35% reduction in computation time compared to traditional methods. The approach demonstrated SQL's potential in mining applications, offering faster and more efficient data management.

In open pit mine design, pushbacks are subregions mined in distinct phases. Practical pushbacks must be connected, maintain a minimum width for equipment, and include a haulage ramp. Current models often overlook these conditions, requiring significant adjustments by engineers. Yarmuch [9] presented an integer programming model to generate high-value, practical pushbacks. It introduces a compactness factor, weighting blocks by their distance from the ramp, and a closeness factor to measure design similarity, optimizing the balance between value and mine-ability. The solutions showed that the model produces more practical and valuable pushbacks than traditional methods. To handle larger instances, re-blocking and sequential generation of pushbacks were used. The model achieved better mineability compared to traditional methods, improving the net present value. An integer linear programming model was proposed in a research work to optimize pushback designs [10]. The model ensures adequate space for large equipment and maximizes profit. The model generated practical solutions in minutes, improving design quality and computational efficiency compared to traditional methods. The optimized pushbacks achieve near-optimal profits with better geometric properties and faster computation times.

Developing a mine is a complex task requiring significant initial investment and efficient mine planning to ensure economic success. The planning process has evolved due to advancements in extraction and processing technologies, the decline in average ore grades, and the increasing complexity of permitting and environmental policies. High-quality mine development plans are essential for securing stakeholder support and financial backing. Push-back design using ultimate pit parameterization often encounters the gap problem, characterized by large jumps in push-back size. Mieth [11] proposed an alternative approach, iteratively solving an optimization model to create pushbacks of predefined sizes in terms of overall and ore tonnage. This method, which falls under precedence constrained knapsack problems, employs linear relaxation and two heuristics to overcome long runtimes. The developed program was tested on three deposits (copper, iron ore, and gold), showing it can mitigate the gap problem. However, it trades off between runtime and solution quality, with heuristics failing to always find the optimal solution.

Optimizing open pit mine design involves managing geological uncertainties, particularly ore grade. A minimum cut algorithm is able to determine ultimate pit limits and pushback designs, integrating economic values and geospatial constraints [12]. The push–relabel algorithm efficiently processes block values under multiple scenarios. Applied to an Indian iron ore mine, the new method increased net present value compared to traditional models, despite greater complexity and computation time. The proposed approach enhances mine planning by incorporating uncertainties, yielding higher cumulative metal production and more reliable production schedules, ultimately maximizing profitability and reducing risks. Designing pushbacks in open-pit mines is essential for optimizing economic value and operational feasibility. An advanced Geometrically Constrained Production Scheduling Problem using a parallel genetic algorithm (PGA) is able to generate efficient pushbacks while considering geometric constraints [13]. The PGA, implemented on a network of computers, evaluates potential solutions, ensuring operational space and optimal resource utilization. Applied to test cases, the algorithm showed consistent ore grades and realistic

mine geometries. The study highlights the PGA's robustness and effectiveness in handling real-world constraints, offering a significant improvement over traditional methods in terms of profitability and computational efficiency.

Determining the ultimate pit limit is vital in open-pit mining and is usually calculated using profit-maximizing algorithms like Lerchs-Grossman. Saleki [14] proposed a mathematical model that integrates ultimate pit limit determination with long-term production planning to maximize profit. To manage the model's nonlinearity, it is broken down into two linear sub-problems, thereby simplifying the solution process and reducing the number of decision variables, even though it remains NP-Hard. The Dynamic Pit Tracker heuristic algorithm, developed for this purpose, uses economic block models to guide the optimization. By comparing economic values and positional weights of blocks, the algorithm identifies the optimal blocks at each step. A comparative analysis with a two-dimensional block model demonstrates that the ultimate pit limits generated by the new model, LG, and Latorre-Golosinski algorithms are consistent. When applied to a 3D block model, the Dynamic Pit Tracker achieved a final pit profit that was 97.95% of the LG ultimate pit limit profit.

In the other study on the ultimate pit design [15], a large-scale open-pit mine production planning model was designed which is NP-hard, requiring efficient solutions. The research compares the genetic algorithm (GA) with Linear Programming (LP) and the Floating Cone (FC) algorithm for designing the ultimate pit limit. Using the Marvin mine block model, the study found that LP provides the highest UPL value, but GA offers a near-optimal solution much faster, crucial for large-scale planning. Sensitivity analysis improved GA's UPL value to just 8% less than LP's. When optimizing an ultimate pit limit, ecological costs into open pit mine planning can also be modeled [16]. By calculating carbon emissions, ecological service value loss, and reclamation costs, an iterative optimization algorithm adjusts the ultimate pit design. A case study shows that incorporating ecological costs reduces land damage, carbon emissions, and overall ecological costs, while economic profits decrease. Despite lower profits, the comprehensive benefit of the ecological pit is higher than the traditional pit, achieving a better balance between environmental and economic outcomes.

Open-pit mining, while profitable, significantly harms the environment. Traditional mine design focuses on economic benefits, often neglecting ecological costs. The study of Xu [17] aims to integrate ecological costs into the mine design process for more sustainable development. Ecological costs, including ecological service value loss, reclamation costs, and carbon emissions, are calculated using specific equations. An iterative optimization algorithm for pit design, considering these costs, was applied to a coal deposit in Northwest China. The case study revealed that incorporating ecological costs reduced the mine's environmental impact: the ecological optimum pit had 31.08% less damaged area, 36.17% lower carbon emissions, and 34.63% reduced overall ecological costs compared to the economic optimum pit. Despite a 19.01% decrease in economic profit, the ecological optimum pit provided a 2% greater comprehensive benefit. This approach demonstrates the potential for balancing economic and ecological benefits in open-pit mining.

For defining final pit boundaries in open-pit mining, using the maximum flow Pseudo flow method is useful which can be solved by programming software such as Python and SGeMS [18]. The analysis of 480,000 blocks (10x10x10 meters) generated 20 pits with varying revenue factors. Pit 20 emerged as optimal, with an estimated NPV of 17,855 MUSD, extracting 212 million tons of ore and 58 million tons of waste, resulting in a favorable

stripping ratio and high economic feasibility. The ultimate pit problem in open pit mine planning is crucial but computationally intensive. An open-source C++ library was designed to solve this problem efficiently using the pseudo flow algorithm which is Mine-Flow [19]. This method processes large block models significantly faster than commercial alternatives by employing implicit precedence schemes. In a test, it handled 16 million blocks in nine seconds, compared to over two minutes for the fastest commercial solver. Mine-Flow, available under the MIT license, supports extensive models with millions of blocks and constraints. The tool is designed for academic and commercial use, facilitating quicker and more efficient mine planning and optimization.

Despite significant advances in ultimate pit design and pushback optimization through the application of mixed-integer programming (MIP) models, the following critical gaps remain unaddressed in the current literature:1) The integration of maximum flow network and minimum cut problems into the ultimate pit design, considering precedence relationships among blocks, presents a complex challenge that has yet to be fully explored; 2)Existing models, such as those implemented in Whittle software, typically simplify these relationships, potentially leading to suboptimal solutions. While the use of MIP has demonstrated a higher net present value (NPV) compared to traditional methods, there is a need for more sophisticated models that can accurately represent the spatial and economic attributes of the block model, including coordinates, block size, volume, gold grade, rock type, and density; and 3) Current methodologies often lack robust techniques for dynamically adjusting pushback designs based on real-time data and evolving geological conditions. Further research is required to develop integrated frameworks that can seamlessly transition from data preparation in mining software such as Surpac to advanced optimization in Python, ensuring that each block is optimally assigned to pushbacks while maximizing overall NPV. Addressing these gaps will enhance the accuracy, efficiency, and economic outcomes of open pit mine planning.

In the rest of this paper, we present the model for ultimate pit limit and push back optimization, then the methodology which is applied for the problem. Then, the results and outcome are discussed, and the potential developments for the future are proposed.

2. Methodology

This section explores the complexities of mine planning, focusing on ultimate pit limit and pushback design in open-pit mining. The primary objective is to address irregular increments in nested pits result in inefficient pushbacks. We use an alternative method using operations research and linear programming to create pushbacks of specific overall and ore tonnage, developed by Mieth [20]. This method iteratively solves an optimization model, incorporating techniques such as linear relaxation and heuristics to manage the complexity and computational demands. The developed approach was implemented in a computer program and tested on a gold deposit. The expected results should show that the program effectively creates practical pushbacks and improves conventional parameterization methods. The developed method is driven by advancements in extraction and processing technology, depletion of high-grade deposits, stricter environmental policies, and rising commodity prices. Efficient mine planning is crucial for the economic success of mining projects, and pushback design plays a central role in long-term production scheduling.

The methodology is divided into two main steps of ultimate pit limit and pushback optimization.

1. **Ultimate Pit Calculation:** The ultimate pit is calculated using the maximum flow algorithm, where blocks outside the ultimate pit are discarded as they are not included within the economic extraction boundaries of the pit. Simultaneously, this will reduce the problem size.

The general maximum flow network model is as follows.

$$\text{Min} \sum_i \sum_j c_{ij} x_{ij} \tag{1}$$

$$\sum_j x_{ij} - \sum_k x_{ki} = b_i \quad \text{for } i = 1, \ldots, n \tag{2}$$

$$l_{ij} \leq x_{ij} \leq u_{ij} \tag{3}$$

$$x_{ij} \geq 0 \tag{4}$$

Where the parameters and variables are as below.

c_{ij} The cost of each arc.

b_i The supply for each node.

x_{ij} The flow from node i to node j.

l_{ij} The lower bound on the flow amount from node i to node j.

u_{ij} The upper bound on the flow amount from node i to node j.

Based on the block data obtained from mining software, precedence graph, Picard's graph and the max flow network model we can model ultimate pit limit programming model in a programming language (Python or Matlab) to get the optimized ultimate pit limit. This final pit limit is used in the next step, pushback optimization.

The Picard graph is a concept used in open-pit mining optimization, particularly in the context of maximum flow problems. Introduced by J. C. Picard [21], it involves creating a network flow model to solve the open-pit mine design problem. The model utilizes nodes and edges to represent blocks and their precedence relationships, respectively. The maximum flow algorithm is applied to determine the optimal sequence of mining blocks while satisfying spatial and temporal constraints. This approach helps identify the ultimate pit limit and subsequent pushback phases efficiently [22].

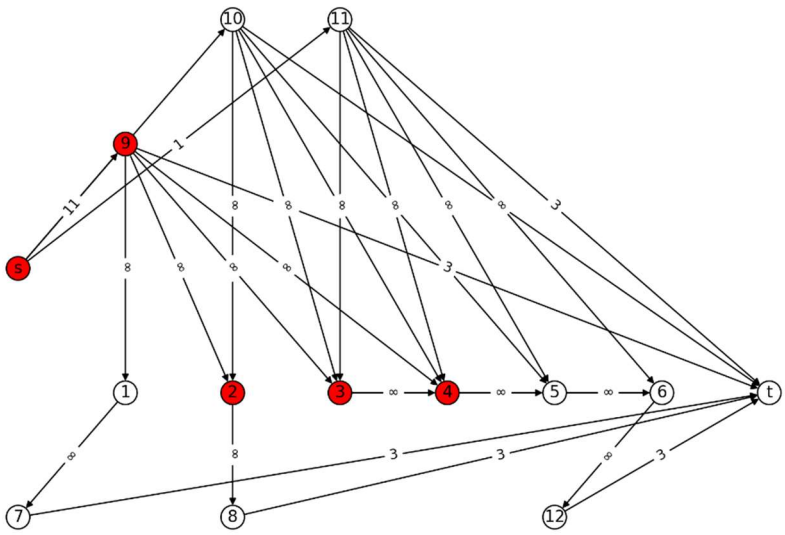

Figure 1. Visual indication of Picard's graph.

This Picard graph represents a maximum flow problem applied to an open pit mining scenario, including these components.

- The starting point for the flow of network, which is a source node.
- The endpoint for the flow of network, which is a sink node.
- Other nodes are blocks within the mining pit and included in precedence graph.
- A flow capacity between nodes on the arcs.
- A constraint-free flow, indicating no limit on the flow capacity for those connections.
- The specific limits on the flow capacity between nodes.

The graph helps in determining the maximal closure, which is a subset of nodes (blocks) where the sum of the values is maximal, and all predecessors of each node are included. The edges and their capacities represent the precedence constraints in mining, ensuring that certain blocks must be mined before others. By solving the maximum flow problem on this graph, we can determine the optimal sequence of blocks to mine to maximize economic returns while adhering to operational constraints.

1. **Push-Backs Optimization:** The following three steps are followed here:

- Mixed integer linear programming: Pushbacks are sequential sub-regions of an open pit mine designed to be mined in phases, guiding the spatial advancement of mining activities. Traditional methods for creating pushbacks involve parameterizing the ultimate pit limits, resulting in nested pits that often suffer from the irregular jumps in pushback sizes, leading to inefficiencies in production scheduling. In this way, we used Operations Research (OR) and Linear Programming (LP), where OR offers mathematical and computational tools to optimize complex decision-making processes, and LP, a subset of OR, is used to model and

solve optimization problems where relations are linear. The applied approach leverages OR techniques to address the pushback design problem, formulating it as a precedence constrained knapsack problem.

- Model constraints: The model includes constraints for mining and processing capacities and ensures slope stability through block precedence. Due to the NP-hard nature of the problem, exact solutions are computationally intensive. Therefore, the model employs linear relaxation and heuristics to approximate solutions efficiently.
- Implementation and Testing: Implement the model in a computer program, and test on the case study of a gold deposit. The expected output is the efficient and practical pushbacks with reduced deviations from capacities.

The following mathematical model optimizes the pushback decision.

$$\max \sum_{i \in \mathcal{N}} p_i x_i \tag{5}$$

$$x_i - x_j \leq 0 \quad \forall (i,j) \in E \tag{6}$$

$$\sum_{i \in \mathcal{N}} t_i x_i \leq mc \tag{7}$$

$$\sum_{i \in \mathcal{N}} o_i x_i \leq pc \tag{8}$$

$$x_i \in \{0,1\} \quad \forall i \in \mathcal{N} \tag{9}$$

Where the parameters, variables and indices are as the following.

$\mathcal{N}$	Set of all nodes in the precedence graph representing all blocks in the block model.
E	Set of all edges in the precedence graph.
p_i	Economic block value of block i.
t_i	Overall tonnage of block i.
o_i	Ore tonnage of block i.

mc	Push-back overall tonnage.
pc	Push-back ore tonnage.
$x_i \in \{0,1\}$	Binary integer variable representing block extraction. x_i is 1 if block i is extracted, otherwise 0.

3. Results and Discussion

The developed approach is implemented in Python and tested on a gold deposit. The problem is expected to manage pushback sizes, reducing deviations from mining and processing capacities, and achieving more uniform and practical pushbacks compared to traditional parameterization methods.

One sample result is expected to be same as the below which is from Clemens [11]. The chart demonstrates a well-managed pushback strategy that maximizes net value while adhering to tonnage and ore tonnage restrictions, but also highlights the natural decline in economic returns as mining progresses.

- The consistent alignment of the total tonnage and ore tonnage with their respective restrictions for the first 15 pushbacks indicates an efficient mining strategy that maximizes resource extraction while adhering to capacity limits.
- The decreasing trend in net value suggests that the economic returns from mining diminish over successive pushbacks. This could be due to the depletion of high-value ore blocks or increasing extraction costs.
- The significant drop in both tonnage and net value in the last pushback suggests the end of economically viable mining operations within the given constraints.

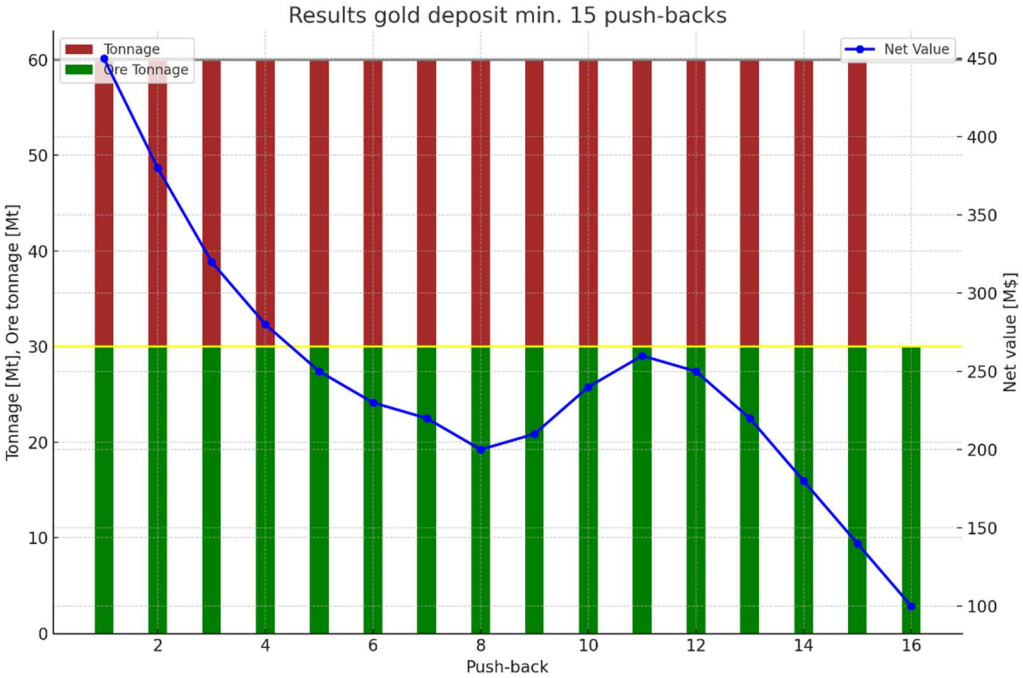

Figure 2. The sample result from solving ultimate pit limit and push back optimization problem.

In addition to Mixed-Integer Programming (MIP), the pushback optimization problem was also solved using the Whittle software. The designed block model was applied to generate pushbacks and implement a production schedule using Whittle software. Whittle uses the Milawa Balanced algorithm, known for its robustness in creating balanced production schedules over the mine life. The Milawa Balanced algorithm focuses on balancing the stripping ratio and ore grades, ensuring that each pushback phase contributes to a stable production output. This approach aims to optimize operational efficiency and economic returns within each mining phase.

Comparative analysis between the two methods revealed that the MIP approach obtained a higher Net Present Value compared to the implementation in Whittle, which indicates a more profitable mining operation. While Whittle's Milawa Balanced algorithm provided a robust and balanced production schedule, the flexibility and precision of MIP allowed for better optimization of the mining sequence. The MIP approach could also tailor the pushbacks more closely to the specific economic and operational constraints of the mine, leading to enhanced financial outcomes.

4. Conclusion and Future Directions

The integration of advanced optimization techniques, particularly Mixed-Integer Linear Programming, in mining operations has demonstrated significant advantages in terms of economic returns and operational efficiency. While traditional software such as Whittle provides a robust foundation for production scheduling through algorithms such as Milawa Balanced, incorporating MILP allows for more detailed and precise optimization, thereby unlocking higher profitability. The comparative analysis revealed that solving the pushback optimization problem using MILP yielded a higher NPV compared to the implementation in Whittle, highlighting the superior financial outcomes achievable with MILP.

The proposed MILP model and heuristic algorithms have provided a robust solution to the pushback design problem, effectively addressing the gap problem and improving mine planning efficiency. This research contributes to the field of mine planning by developing a MILP model for direct pushback creation without the need for nested pits and by utilizing maximum flow network, linear relaxation and heuristics to solve large-scale optimization problems efficiently. The implementation of this model in a computer program, tested on real-world deposit data, has demonstrated its practical applicability and effectiveness.

Future research directions should focus on incorporating additional constraints such as greenhouse gas emissions considerations to enhance the sustainability of the problem. Incorporating minimum mining width considerations into the model will further improve its practicality by ensuring the designed pushbacks adhere to operational constraints and safety standards. Further improvements in algorithmic efficiency can be achieved by applying advanced algorithms such as simulated annealing and Tabu search for the implementation of problem. This would enable the handling of even larger datasets and more complex mining scenarios.

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Short-term Planning Optimization of Open Pit Mines with Monte-Carlo Haulage Simulation in Presence of Semi-Mobile IPCC

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ABSTRACT

In-pit crushing and conveying (IPCC) is emerging as a viable alternative to traditional truck-shovel haulage in open-pit mines, driven by the rising cost of gas and concerns over greenhouse gas (GHG) emissions. Effective short-term planning in open-pit mines must account for operational and equipment uncertainties. However, optimizing short-term planning with IPCC integration is an underexplored research area. This study addresses this gap by developing a simulation-optimization framework for short-term mine planning and haulage. A mixed-integer linear programming (MILP) model, that minimizes haulage costs while meeting long-term production targets, generates schedules by optimal shovel allocation to mining cuts. These schedules are then input into the Monte Carlo haulage simulation model, which captures operational uncertainties related to trucks, shovels, and IPCC. Additionally, the simulation estimates the maximum tonnes per gross operating hour (TPGOH) and the proximity to optimal production under uncertain conditions for scenarios with and without IPCC. This model has been validated through a case study in an iron ore mine over a twelve-month planning horizon, yielding promising results that support the adoption of semi-mobile IPCC systems over traditional truck-shovel operations.

1. Introduction

This paper presents an innovative approach that combines simulation and optimization to create near-optimal short-term schedules while accounting for haulage uncertainties. A MILP model generates monthly production schedules by optimally assigning shovels to mining faces or cuts. These schedules are then input into the Monte Carlo haulage simulation model, which incorporates probability distributions for shovel loading time, truck travel time, dumping time, and failure probabilities for trucks, shovels, and the IPCC system. While the MILP model excels in producing near-optimal short-term schedules for both IPCC and pure truck-shovel haulage, the Monte Carlo simulation ensures that all haulage uncertainties are thoroughly captured. The biggest challenges of this study lie in accurately capturing and modeling the inherent uncertainties and variabilities in shovel loading times, truck travel times, dumping times, equipment failure rates, and other

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operational disruptions. Integration of the simulation model to get the required inputs from the MILP in a reasonable amount of time is also a substantial challenge associated with this research.

The primary goal of any mining project is to maximize net present value (NPV) while minimizing costs. Mine planning is divided into long-term and short-term planning based on the time horizon and specific objectives. Long-term planning is strategic, aiming to maximize NPV over the mine's lifespan. Short-term planning, on the other hand, focuses on optimizing operational activities such as shovel allocation, grade blending to meet plant head grade requirements, and truck deployment. These plans can be monthly, weekly, or even daily, and they are designed to support the long-term schedule.

Efficient use of mining equipment is crucial, as haulage costs can account for over 50% of total operating expenses in a truck-shovel operation [28, 38]. Optimal equipment utilization can only be achieved by efficiently using all assets to meet the production targets set by the long-term plan. Therefore, the strategic allocation of shovels and trucks in short-term production scheduling is essential to ensure cost control and the achievement of long-term goals. Mining fleet optimization, for the same reason, gets a lot of attention among researchers as demonstrated by [30, 31, 29, 13, 27, 44, 32]. These articles propose several methodologies and algorithms for mining fleet management.

Many contemporary short-term planning models rely on mixed-integer programming (MIP) and incorporate explicit precedence constraints. Eivazy and Askari-Nasab [9] presented a short-term planning model using mixed-integer programming (MIP) that incorporates various mining directions and precedence constraints to reduce overall mining expenses, such as processing, haulage, rehandling, and rehabilitation costs. However, by utilizing aggregated mining blocks, the model may fall short in optimality, as it neglects specific ore type selection and real-world hauling dynamics. Additionally, the model focuses solely on cost reduction, omitting profit considerations. L'Heureux et al. [21] developed a comprehensive mathematical optimization model for short-term planning, covering operational details for up to three months. The primary goal is to reduce the operational costs of truck and shovel activities, as well as drilling and blasting. This model was successfully applied to scenarios involving up to 5 shovels, 90 periods, and 132 faces.

Kozan et al. [19] created a model to manage drilling, blasting, and mining of blocks, along with equipment allocation to these tasks, aiming to minimize the make-span, which is the total time from the start to the end of the schedule. Later, Kozan and Liu [20] introduced another short-term planning model designed to maximize throughput and minimize equipment idle times during drilling, blasting, and excavation. This model considers equipment capacity, speed, read times, and activity precedence constraints. In their latest work, Liu and Kozan [23] proposed an innovative mine management system that integrates various mathematical models to determine the ultimate pit limit for long-term and medium-term block sequencing. This system also optimizes equipment planning using a job-shop scheduling model to enhance mining efficiency. The overall goal of this methodology is to improve mining operations by integrating diverse planning and scheduling models.

Blom et al. [7, 6] introduced a mixed-integer programming (MIP) model to generate multiple short-term production schedules. This model aims to optimize equipment and shovel utilization while considering constraints such as blending requirements, equipment availability, trucking hours, and task precedence relationships. It employs a rolling planning horizon technique and accounts for multiple processing paths.

Thomas et al. [56, 57] tackled the challenge of integrated planning and scheduling within a coal supply chain comprising of several independent mines that must share a limited transportation capacity. Their objectives included minimizing total earliness, tardiness, and operational costs while adhering to due dates and transportation constraints. They developed a solution approach based on Lagrangian relaxation, which outperformed traditional MILP models in terms of generating upper

and lower bounds and reducing CPU time. Mousavi et al. [34] developed a comprehensive mathematical model for short-term block sequencing, incorporating constraints like precedence relationships, machine capacity, grade requirements, and processing demands. The goal is to minimize total costs, including rehandling, holding, misclassification, and drop-cut costs. The authors proposed a hybrid solution combining branch and bound with simulated annealing, which can produce solutions with an optimality gap of less than 1% compared to the CPLEX solution when a large neighborhood search is utilized. A recent optimization model for short-term open pit planning has been proposed by Nelis and Morales [35]. Their approach maximizes profits while meeting operational constraints. Applied to a real copper mine, the model efficiently defines mining cuts and production plans simultaneously. Results demonstrate its effectiveness in generating mining cut configurations quickly, a task that traditionally requires days, completed in less than fifteen minutes.

Manriquez et al. [25] created a short-term planning approach for open-pit mining to optimize hierarchical objectives, such as minimizing deviations in ore tonnage, plant capacity, metal fines, and shovel movement costs. Using goal programming techniques (weighed sum and hierarchical method), they found both methods produced optimal plans in a copper mine case study, though the model is deterministic and excludes geological uncertainties. Similarly, Upadhyay et al. [61] developed a goal programming-based short-term planning model focusing on optimal shovel allocation, aiming to maximize production and minimize mill grade deviation and shovel movement. Silva-Júnior et al. (2023) addresses the complexities of short-term planning in open-pit mining operations via a mixed-integer linear goal programming model to optimize truck allocation, routes, and the amount of material transported, aiming to minimize deviations from production targets, chemical grades, and particle sizes, while also reducing the number of trucks required. The study utilizes real data from an iron ore mine to validate the approach, demonstrating its effectiveness in enhancing decision-making for truck fleet management and meeting production and quality goals under varying operational scenarios.

Simulation in conjunction with optimization is widely used in short-term mine planning because simulation can handle uncertainty involved in operations. Ben-Awuah et al. [4] developed a discrete event simulation model to align long-term and short-term mine planning by addressing uncertainties in mining and processing capacities, crusher availability, stockpiling, and blending. This model integrates deterministic long-term plans with dynamic short-term adjustments, enabling planners to evaluate the feasibility and robustness of long-term schedules.

Bodon et al. (2011) and Sandeman et al. (2011) developed simulation optimization models to maximize tonnes mined and shipped, minimize deviation from quality targets across mine and port stockpiles, and meet blending requirements under constraints of equipment capacity, port capacity, and precedence. Their linear program (LP) integrates optimization and simulation, offering a more accurate system representation, better solutions, albeit with longer runtime. It facilitates trade-off analysis for capital expenditure and alternative operating practices, including maintenance options. Shishvan and Benndorf [50, 51] introduced a stochastic simulation method for optimizing short-term production planning in complex continuous mining operations, considering geological uncertainty. Their approach, which combines penalties for production deviation and equipment utilization in a weighted objective function, helps foresee critical supply and system performance issues. The model utilizes geostatistical simulation (20 block model realizations) and discrete event simulation to manage geological and operational uncertainties. This methodology was later applied in industrial case studies by Shishvan and Benndorf [52].

Torkamani and Askari-Nasab [58] devised a stochastic discrete event simulation model to analyze truck-shovel material handling and haulage systems in open pit mining. Initially, they formulated an MIP model for optimal truck and shovel allocation across mining faces, integrating these solutions into their simulation framework. Upadhyay and Askari-Nasab [59, 60] applied goal-programming to develop a simulation optimization model for short-term planning in mining. Their approach

highlights the integration of proactive decision-making in a dynamic environment, synchronizing operational plans with long-term strategies to minimize opportunity costs while optimizing production and equipment utilization. A similar framework has been proposed by Manriquez [26] to generate an initial schedule and then replicate it to find key performance indexes like equipment utilization using a discrete event simulation software. Incorporating simulation addresses equipment uncertainty in this otherwise deterministic model, making it applicable across various mining contexts, including open pit mines. However, a limitation of the model is its sole focus on maximizing extraction value without considering operational costs in the optimization process.

IPCC can be a viable alternative to truck haulage in an era of constantly rising environmental concerns over mining. While IPCC is not a new concept, it is yet to be adopted widely in open pit mines across the world. Several life cycle assessment studies and environmental comparisons [36, 12, 10, 3] have found IPCC system to be more ecofriendly compared to pure truck-shovel haulage. Moreover, several economical comparative studies between IPCC and truck-shovel haulage systems found IPCC to be more cost effective [8, 37, 33]. Despite that, mine planning with IPCC has been underexplored. A comprehensive review of short-term mine planning and IPCC by Habib et al. [15] shows that mine planning, more specifically short-term mine planning considering IPCC is an almost unexplored area of research. Majority of the IPCC literature, for example, Konak et al. [18], Taheri et al. [55], Rahmanpour et al. [45], Roumpos et al. [46], Paricheh and Osanloo [39, 42, 43, 41] have been concerned with finding an optimum crusher location and time to install IPCC systems without considering the fact that the optimality of an IPCC system needs to be integrated to the mine plan.

Several methodologies have been developed for simultaneous optimization of IPCC locations and long-term schedules. Key contributors include Paricheh and Osanloo [40], Samavati et al. [47], Shamsi et al. [49], Liu and Pourrahimian [22], Kamrani et al. [17], Liam and Dimitrakapoulos [11] etc. The primary objective of these studies is to maximize the net present value of the mine while leveraging IPCC as the primary mode of material transport. Shamsi and Nehring [48] analyzed scenarios to find the optimal depth for switching from truck-shovel haulage to Semi-Mobile In-Pit Crushing and Conveying (SMIPCC). Using a hypothetical cone-shaped mine with four pushbacks, they found the switch is most economically advantageous at 335 meters during the second phase.

Bernardi et al. [5] used an ARENA simulation model to compare semi-mobile and fixed IPCC systems for open-pit mines, focusing on NPV and production target proximity. For a simplified cone-shaped mine, results showed semi-mobile IPCC generated 10% higher NPV and better met production targets. However, the simplified cost model and mine geometry may not reflect typical mining project complexity. Abbaspour and Drebenstedt [1] compared various transportation systems in open-pit mining, including truck-shovel, fixed IPCC, semi-mobile IPCC (SMIPCC) and fully mobile IPCC (FMIPCC) using a system dynamics modeling. The study introduces a technical index based on system availability, utilization, and power consumption to evaluate the performance over the life of mine. The research finds that while the truck-shovel system is generally the most preferred, certain periods favor the FMIPCC system.

Gong et al. [14] introduced a near-face stockpile (NFS) mining method that integrates in-pit crushing and conveying (IPCC) with an in-pit near-face stockpile to decouple mining and processing subsystems, enhancing operational flexibility and efficiency. The case study demonstrates that the NFS method leads to a 9.3% increase in net present value (NPV) and a 20% reduction in head grade deviation compared to traditional methods. This approach aligns with IPCC concepts by enhancing production stability and reducing operational costs through improved equipment utilization and lower haulage. In a subsequent study, Gong et al. [13] further developed the NFS method, employing discrete event simulation and MILP optimization to assess its performance. Their case study in an oil sand mine confirms NFS's advantages, demonstrating increased production and reduced transportation costs.

The above discussion highlights that short-term planning optimization using IPCC is a largely unexplored research area. Key decisions regarding IPCC, including optimal location, relocation timing, and conveyor design, are made during the strategic phase of mine planning. Short-term planning must adapt to the installation and movement of crushers and align with long-term strategies to achieve the desired NPV. Furthermore, the uncertainties associated with IPCC, truck and shovel operations add to the complexity of short-term planning optimization. To address this issue, the paper introduces and verifies a simulation-optimization framework designed to optimize short-term planning schedules for open-pit mines, accounting for equipment operational uncertainties. This general framework is applicable to mines utilizing pure truck-shovel haulage and/or IPCC systems. The framework builds upon and enhances the short-term planning methodology proposed by Habib et al. [16] by addressing operational uncertainties. Additionally, it can serve as a comparative tool to determine the optimal year for implementing an IPCC system to maximize haulage cost savings during strategic planning.

2. Problem Definition

This study seeks to create a robust short-term planning methodology to enhance production schedules amidst uncertainties involving trucks, shovels, and/or IPCC systems. The approach utilizes a Mixed-Integer Linear Programming (MILP) model to allocate shovels to mining faces, aiming to achieve production targets and maximize profits. The optimized schedule, along with probability distributions for trucks, shovels, and IPCC systems, is used as input for a Monte Carlo haulage simulation model, ensuring accurate representation of operational uncertainties. Although simulation optimization models have their limitations, such as, difficulty modeling, high computational expenses etc., it demonstrates how effectively a mining operation can meet its production targets while considering the variability and uncertainties in haulage operations.

The traditional comparison between IPCC and truck-shovel haulage systems often fails to account for the inherent uncertainties in equipment performance, leading to suboptimal decision-making. By integrating Monte Carlo simulation, we aim to provide a more robust and realistic assessment of these haulage systems under varying operational conditions. This approach will allow us to generate a range of potential outcomes and assess the impact of uncertainties on the overall performance of the mine.

The research questions this article poses are: How does IPCC impact short-term mine sequencing? Does IPCC provide better haulage performance than pure TS haulage in the presence of operational uncertainties?

The objectives of this research include: 1) Quantifying the impact of haulage uncertainties: By simulating different scenarios of equipment performance, we will measure how uncertainties affect haulage costs, production targets, and overall revenue, 2) Comparing haulage systems under uncertainty: We will compare the performance of IPCC and truck-shovel haulage systems by considering the variability in haulage conditions, providing a more comprehensive evaluation than deterministic models, and 3) Enhancing decision-making for mine planners: The insights gained from this simulation will help mine planners make more informed decisions regarding the implementation of IPCC systems, particularly in terms of annual cost savings and revenue generation.

2.1. Scope and Assumptions of the Proposed Model

As discussed before, the methodology presented here is an improvement of the short-term planning model proposed by Habib et al. [16] to capture haulage uncertainties. The assumptions associated with the MILP model and the simulation model are briefly summarized below.

2.1.1. MILP Assumptions

1. Semi-Mobile IPCC System: The IPCC system is semi-mobile and exclusively used for ore crushing and conveying. Due to the high capital investment and inefficiencies in handling waste material, the installation of a waste IPCC system is not included in the case study. Waste material does not generate revenue and crushing it would inefficiently utilize energy. Hence, we did not consider waste crusher in the current state of the art of the model.
2. Crusher Locations and Relocation: The optimal locations and relocation times for the crusher are predetermined based on strategic planning for the entire life of the mine.
3. Ore and Waste Face Identification: Ore and waste faces are identified from long-term plans. Consequently, ore material is directed to the mill or crusher, while waste material is directed to the waste dump.
4. Shovel Allocation: Ore shovels are dedicated to ore faces, and waste shovels are dedicated to waste faces.
5. No Stockpiling: The model assumes that there is no stockpiling of materials.
6. Mine Life Duration: The mine is expected to operate for more than 20 years.
7. Ore Blending: The current model does not incorporate ore blending.
8. Processing Destinations: The model does not consider multiple processing destinations for the ore.
9. Deterministic Model: The MILP operates under deterministic assumptions, without incorporating stochastic elements.

2.1.2. Monte Carlo Simulation Assumptions

1. Probability Distributions: Haulage speeds, loading/unloading time, bucket capacity and other uncertain variables follow specific probability distributions (e.g., normal, lognormal, exponential). These distributions are based on historical mining data and modified for confidentiality reasons.
2. Fixed Operational Parameters: Certain parameters, such as route lengths, payload capacities, and speed limits, are assumed to be constant.
3. Failures and Downtime: Equipment failures and downtime are incorporated into the simulation and modeled using statistical distributions.
4. Steady-State Conditions: The simulation assumes the system reaches steady-state conditions, where the effects of initial transient states are negligible.
5. Schedules: Production schedules and haulage demands are fixed across all simulated scenarios and extracted from the MILP model.
6. Mine Layout: The physical layout of the mine, including road networks and dumping locations, is predefined and does not change during the simulation.
7. Resource Allocations: The allocation of shovels to mining faces is determined by the MILP model. The ore and waste trucks are separate and locked to respective ore and waste shovels throughout the simulation.
8. Equipment interactions: Queuing at loading or dumping points is ignored due to the unavailability of historical data at waiting times.

3. Methodology

This paper presents a haulage simulation model combined with a MILP model for short-term planning. Figure 1 provides a simplified overview of the comprehensive simulation optimization framework. Initially, the block model data for the planning period is utilized to cluster blocks into mining cuts. Shovels are then allocated to these clusters, and a monthly production schedule is generated using a Mixed-Integer Linear Programming (MILP) model. The inputs for this model include face IDs, tonnages in each face, costs associated with haulage, mining, and processing, ore price, and the locations of the crusher, conveyor, and waste dumps.

The resulting schedule, alongside the detailed road network and statistical distributions of critical operational parameters, is then fed into a sophisticated haulage simulation. These parameters include loading time, travel time, spotting time, potential truck-shovel failures etc. The simulation aims to calculate and compare key performance indicators, such as tonnes per gross operating hour, truck cycle time, and actual production levels between scenarios with IPCC and pure truck-shovel haulage system.

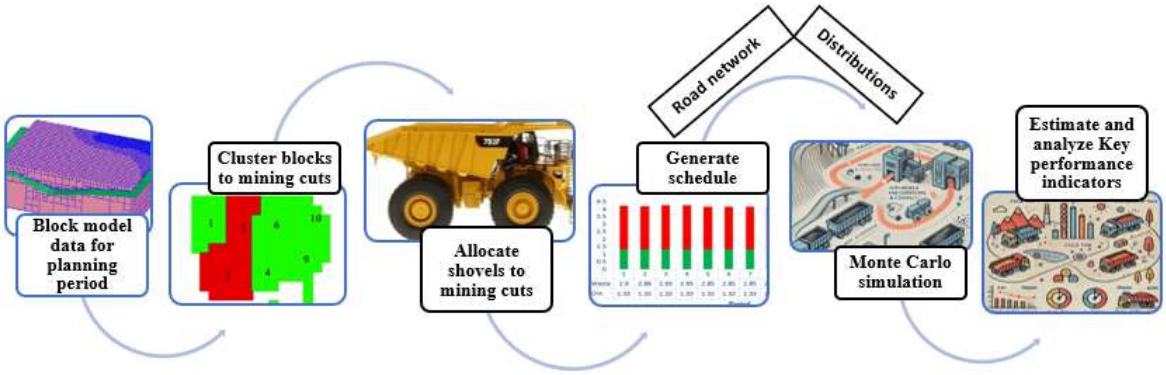

Figure 1. Outline of the proposed simulation-optimization framework.

Details on the MILP model and the Monte Carlo simulation model will be outlined in the following sections.

3.1. Mathematical Model Formulation

The proposed optimization model is a MILP model. The objective is to maximize the overall profit derived from mining activities by minimizing mining, processing, haulage, and shovel movement costs. This objective function comprises of six key components. Firstly, it calculates the mining costs associated with extracting the material. Secondly and thirdly, it computes the expenses for transporting ore to the crusher or mill, and waste material to designated dumps, utilizing diesel trucks. The fourth component determines the costs involved in conveying ore material from the crusher to the processing plant. The fifth component calculates the cost of shovel movement between mining faces. Lastly, it evaluates the net revenue by subtracting processing costs from earnings generated by processed ore. The model and the parameter values used here are the same as Habib et al. [16] except for the shovel movement cost. Hence the model and the solution methodology will be briefly discussed here. Mathematically the objective function can be represented as following,

$$\text{Minimize, } f = \text{Mining costs} + \text{Ore haulage costs} + \text{Waste haulage costs} + \text{Ore conveying costs} + \text{Shovel movement costs} - \text{Revenue from selling ore.} \quad (1)$$

Eq. (1)

Mining costs	$\sum_{p\in P,t\in T,f\in F} x_{p,f,t} \times RM_{p,f} \times TT \times M_c$
Ore haulage costs	$\sum_{p\in P,t\in T,f\in F_{ore}} x_{p,f,t} \times RM_{p,f} \times TT \times D_{f,r} \times H_t$
Waste haulage costs	$\sum_{p\in P,t\in T,f\in F_{waste}} x_{p,f,t} \times RM_{p,f}.TT \times D_{f,w} \times H_t$
Ore conveying costs	$\sum_{p\in P,t\in T,f\in F_{ore}} x_{p,f,t} \times RM_{p,f} \times TT \times C \times H_c$
Shovel movement costs	$\sum_{p\in P,t\in T} N_{p,t} \times D_{p,t} \times H_{sh}$
Revenue from selling ore	$\sum_{p\in P,t\in T,f\in F_{ore}} x_{p,f,t} \times RM_{p,f} \times TT \times (R_k - PR_c)$

The variables, parameters and indexes are detailed below.

Variable	**Description**
$x_{p,f,t} \in [0,1]$	Time percentage of period $t \in T$where shovel $p \in P$ is active in face $f \in F$
$s_{p,f,t} \in \{0,1\}$	Shovel allocation variable. Equals to 1 if shovel $p \in P$is allocated to the face$f \in F$ in period $t \in T$, 0 otherwise.
$m_{f,t} \in \{0,1\}$	Equals to 1 if face $f \in F$ is mined out in period $t \in T$, 0 otherwise.
$l_{f,t} \in \boldsymbol{R}^+$	Tonnage of face *f* at the beginning of period *t*
$N_{p,t} \in \boldsymbol{R}^+$	Shovel movement variable. Number of movements by shovel $p \in P$ in period $t \in T$

Parameter	**Unit**	**Description**
TT	hr	Total time per period
$AV_{p,t}$	%	Availability of shovel *p* in period *t*
$RM_{p,f}$	t/h	Material throughput of shovel *p* in face *f*
TM_f	Tonnes	Total material in face *f*
$D_{f,w}$	km	Distance to waste dump from face *f*
TC	Tonnes	Mill capacity per period

C	Km	Conveyor length
SR	-	Stripping ratio
$D_{f,r}$	Km	Distance to crusher/mill from face f
$D_{p,t}$	Km	Distance traveled by shovel $p \in P$ in period $t \in T$
H_t	$/tonneKm	Transportation cost per unit; $1.2/tonneKm
H_c	$/tonneKm	Conveying cost per unit; $0.25/tonneKm
H_{sh}	$/Km	Shovel movement cost; $0.4/km
M	-	A big number
R_k	$/tonne	Iron ore price; $151/tonne
M_c	$/tonne	Mining cost per unit; $3/tonne
PR_c	$/tonne	Processing cost per unit; $8.34/tonne
N^f	-	Number of precedences for face f
$c_{f,t} \in \{0,1\}$		Equal to 1 if crusher is located on face $f \in F$ in period $t \in T$, 0 otherwise

Indexes	**Description**
p	Index for shovels
f	Index for faces
t	Index for periods

The model is subject to the following constants.

$$\sum_{p \in P} s_{p,f,t} \leq 1; \forall f \in F, \forall t \in T \quad (2)$$

$$\sum_{f \in F} s_{p,f,t} \leq 2; \forall p \in P, \forall t \in T \quad (3)$$

$$\sum_{p \in P, f \in F_{ore}} x_{p,f,t} \times RM_{p,f} \times TT <= TC; \forall t \in T \quad (4)$$

$$\sum_{p \in P, f \in F_{waste}} x_{p,f,t} \times RM_{p,f} \times TT >= SR \times TC; \forall t \in T \quad (5)$$

$$l_{f,t} = TM_f; \ \forall f \in F \ \& \ t = 1 \quad (6)$$

$$l_{f,t+1} = l_{f,t} - \sum_{p \in P} x_{p,f,t} \times RM_{p,f} \times TT; \ \forall f \in F \ \& \ t = 1 \ldots T-1 \quad (7)$$

$$M \times m_{f,t} <= \text{epsilon} - l_{f,t} \quad ; \forall f \in F, t \in T \quad (8)$$

$$M \times (1 - m_{f,t}) >= -\text{epsilon} + l_{f,t} \ ; \ ; \forall f \in F, t \in T \quad (9)$$

$$m_{f,t+1} \geq m_{f,t}\ ;\ ; \forall f \in F, t \in 1 \ldots T-1 \quad (10)$$

$$\sum_{f \in F} s_{p,f,t} \leq s_{p,f,t} + m_{f,t} + \left(1 - s_{p,f,t-1}\right) + \left(1 - s_{p,f,t}\right) \times \mathrm{BM}\ ; \forall f \in F, p \in P, t \in T \quad (11)$$

$$s_{p,f,t+1} \geq s_{p,f,t} - m_{f,t};\ ; \forall f \in F, p \in P, t \in 1 \ldots T-1 \quad (12)$$

$$s_{p,f,t} \geq c_{f,t} \times BM\ \ ; \forall f \in F, p \in P, t \in T \quad (13)$$

$$\sum_{p \in P, t \epsilon T} x_{p,f,t} \times RM_{p,f} \times TT \leq TM_f; \forall f \in F \quad (14)$$

$$N^f \times \sum_p s_{p,f,t} - \sum_{f'} m_{f',t} \leq 0;\ \ ; \forall f \in F, p \in P, f' \in precednece\ set \quad (15)$$

$$\sum_{f \in F} x_{p,f,t} \leq AV_{p,t}; p \in P, t \in T \quad (16)$$

$$N_{p,t} \leq \sum_{f \in F} s_{p,f,t} - 1\ \ \forall p \in P, t \in T \quad (17)$$

Eq. (2) ensures that each face can only have one shovel assigned per period, but each shovel can be allocated to two faces within a period. This allows shovels to move to new faces once a working face is depleted. Eq. (3) combined with Eq. (10), ensure shovels can transition to new faces seamlessly.

Eq. (4) limits ore extraction per period to avoid exceeding mill capacity, aligning with the model's goal to maximize revenue without overproducing ore. In contrast, Equation 5 sets a minimum for waste material extraction to ensure all waste is mined within 12 periods, balancing the model by considering waste haulage costs.

Eq. (6) assigns the total tonnage of each face to a variable at the start of a period. Eq. (7) tracks remaining tonnage, signaling when a face is depleted, which is managed by Eq. (8) and Eq. (9). This system updates the depletion status variable, preventing shovel allocation to depleted faces as reinforced by Equation 10.

Eq. (11) refines shovel allocation rules, allowing shovels to be reassigned only when they finish mining a face. Eq. (12) minimizes unnecessary shovel movements by requiring shovels to stay at a face until it is mined out. Equation 13 prevents shovel assignment to faces where the IPCC crusher is located, defaulting to traditional allocation when the IPCC is absent.

Eq. (14) ensures shovels do not exceed the material available in a face across periods. Eq. (15) enforces mining precedence, requiring a face to be fully mined before moving to dependent faces.

Eq. (16) ensures shovel time allocation across faces does not exceed availability. Finally, Eq. (17) ensures that the number of movements made by a shovel within a specific period is one less than the number of faces it is assigned to in that period. This means that if a shovel is assigned to only one face in a period, it prevents the shovel from moving to another face during that period. Conversely, if a shovel is allocated to three faces in a period, it limits the number of movements to a maximum of two. The model has been implemented and solved in MATLAB using a rolling planning horizon technique to reduce the runtime and computational expense.

3.2. Monte Carlo Haulage Simulation

Mining haulage is a continuous and intricate process. This study uses Monte Carlo simulation to model the hauling process and capture operational uncertainties involving trucks, shovels, and the IPCC system. The goal is to evaluate total production across various scenarios, comparing IPCC and pure truck-shovel haulage under uncertain conditions. This comparison determines how each system aligns with the optimal production schedule generated by the MILP model, assessing performance in terms of production, reliability, and tonnes per gross operating hour (TPGOH).

Figure 2 illustrates the simulation flowchart for the mine haulage process. The simulation begins by reading the optimal schedules, road network, and probability distributions to ensure accurate data and realistic assumptions. These inputs reflect the variability and uncertainty in haulage operations.

Once the data is set, the simulation proceeds and differentiates tasks based on whether they involve an ore face or a waste face. The flowchart is color coded with blue color representing ore haulage and green representing waste haulage.

3.2.1. Simulation Logic Flow

Ore Haulage

1. **Excavator Assignment:** If it's an ore face, a HIT 2500 excavator is assigned to the scheduled ore face.
2. **Mining Status Check:** The system checks if the face has been mined out.
3. **Loading Process:**
    - If not mined out, an ore truck, CAT 785C, positions itself to be loaded by the shovel.
4. **Haulage Path:**
    - With IPCC: The ore truck travels to the in-pit crusher, dumps its load, and returns empty to the shovel.
    - Without IPCC: The truck travels to the mill crusher, dumps its load, and returns empty to the shovel.
5. **Face Reassignment:**
    - If the current ore face is mined out, the simulation checks if all ore faces have been mined out.
    - If not, the HIT 2500 is reassigned to the next scheduled ore face.
6. **Termination Check:**
    - If all ore faces are mined out, the simulation checks if all waste faces have been mined too.
    - If both conditions are met, the simulation terminates.
    - If all waste faces are not mined, the HIT 2500 is redirected to waste faces.

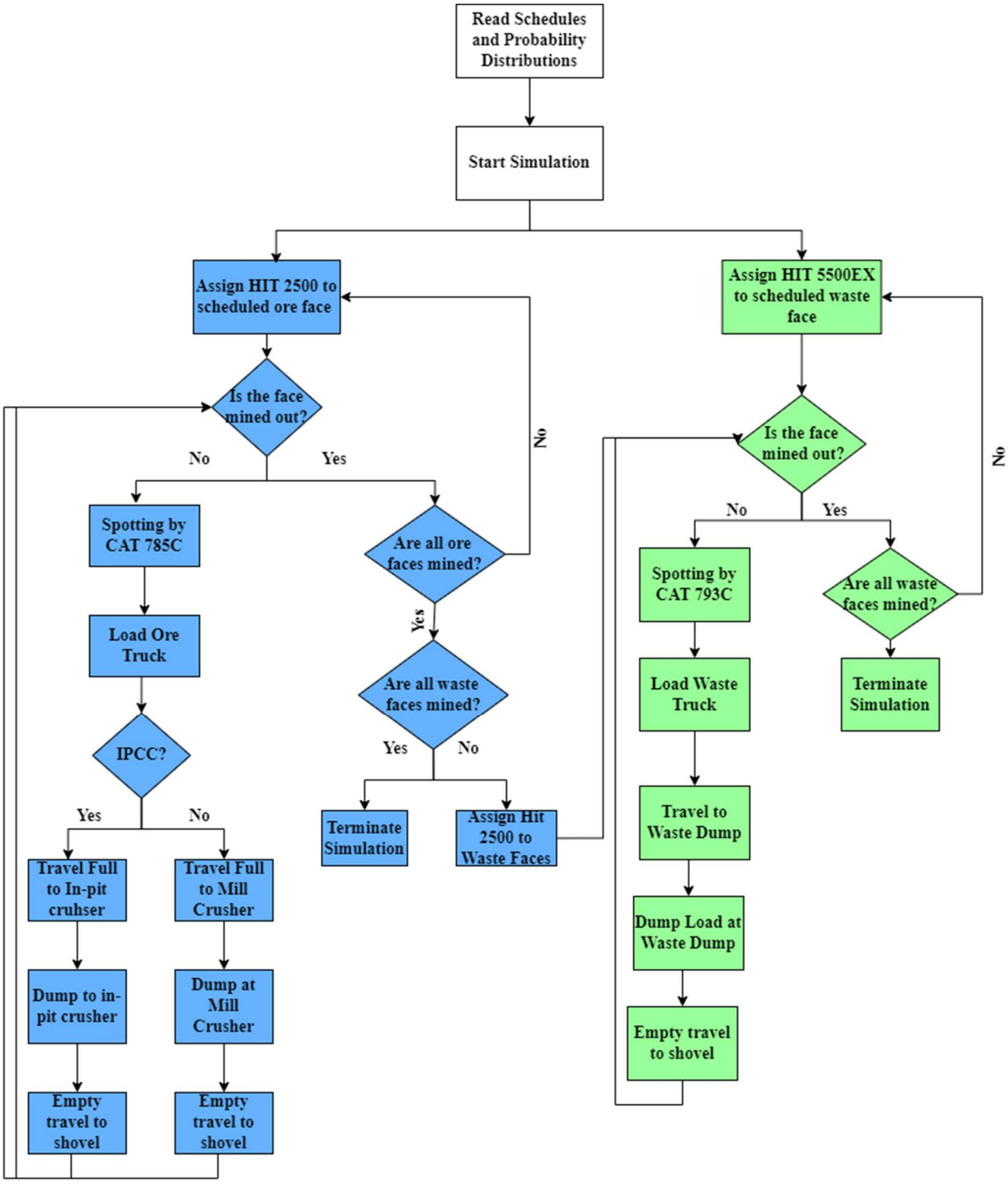

Figure 2. Haulage Simulation flowchart.

Waste Haulage

1. **Excavator Assignment:** HIT 5500EX excavators are assigned to scheduled waste faces.
2. **Mining Status Check:** The simulation checks if the waste face is mined out.
3. **Loading Process:**

- If not mined out, a CAT 793C truck positions itself to be loaded by the shovel.

4. **Haulage Path:**
   - The loaded waste truck travels to the waste dump, unloads its waste, and returns empty to the shovel.
5. **Face Reassignment:**
   - If the current face is mined out, the system checks if all waste faces have been mined.
   - If not, the HIT 5500EX is reassigned to the next waste face.
6. **Termination Check:**
   - If all waste faces are mined, the simulation terminates.
   - This simulation framework ensures efficient and continuous haulage operations, reflecting the complexities and uncertainties of real mining activities.

4. Case Study

The case study evaluates two mining scenarios in an iron ore mine: one using the IPCC system and the other with the traditional truck-shovel method, focusing on the short-term schedule for the 11th year of operation. Mining will occur on four benches at elevation 1595m, 1610m, 1730m and 1745m, extracting 16 million tonnes (MT) of ore and 35 MT of waste. The model includes one processing plant, one waste dump, and one crusher, which can be located either inside the pit or externally at the plant site. The crusher must process 2700 tonnes per hour, requiring 1.33 MT per month with two eight-hour shifts daily. The element of interest is the magnetic weight recovery of iron (MWT).

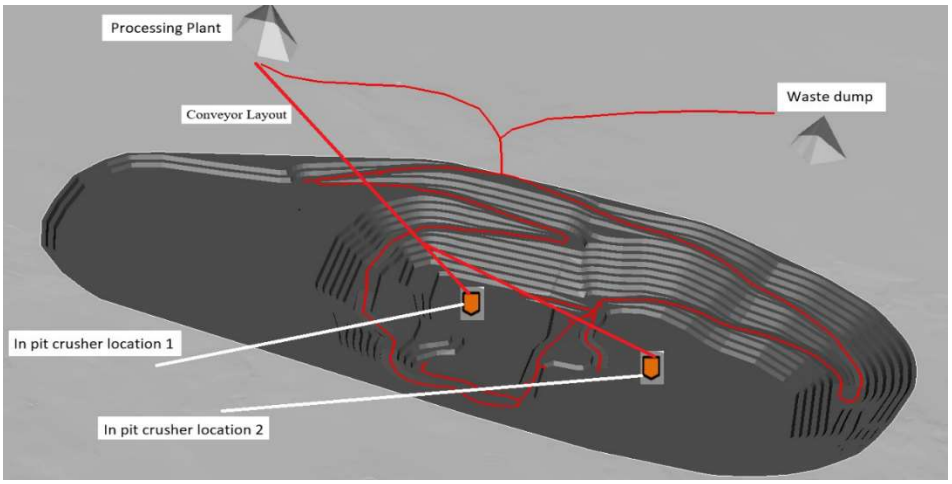

Figure 3. Mine layout for year 11.

Figure 3 shows the mine layout for the 11th year, with distances from mining faces to the waste dump, crusher, and plant calculated based on road network nodes. The mine ramps have an 8% grade, and the IPCC scenario requires a 2550-meter conveyor belt. The crusher is located on face 3 for the first six months and face 18 for the rest of the year, both at bench 1595. Although several high quality clustering algorithms have been proposed by researchers [2, 54, 62], we utilized the hierarchical clustering algorithm developed by Tabesh and Askari-Nasab [53] to aggregate 4,200 blocks into 170 mining faces across four benches due to the method's ease of use and versatility. Figures 4 and Figure 5 illustrate the clustered ore and waste faces, with face IDs numbered on benches 1595 and 1610 respectively. All the faces of the benches on elevation 1730m and 1745m are designated as waste.

The mine uses five shovels: two Hit 2500 for ore and three Hitachi 5500Ex for waste. The Hit 2500 shovels have a 12-ton bucket capacity with a 22-second cycle time, while the Hitachi 5500Ex shovels have a 22-ton bucket capacity with a 23-second cycle time. Cat 785C trucks (140-ton capacity) are paired with Hit 2500 shovels, and Cat 793C trucks (240-ton capacity) are paired with Hitachi 5500Ex shovels.

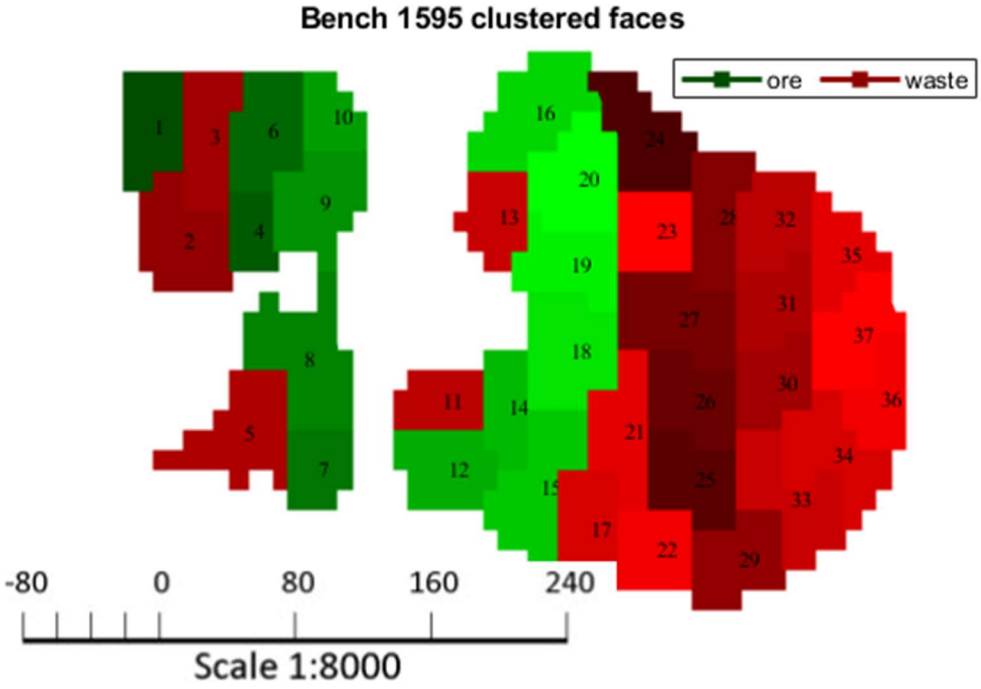

Figure 4. Clustered faces for the ore benches.

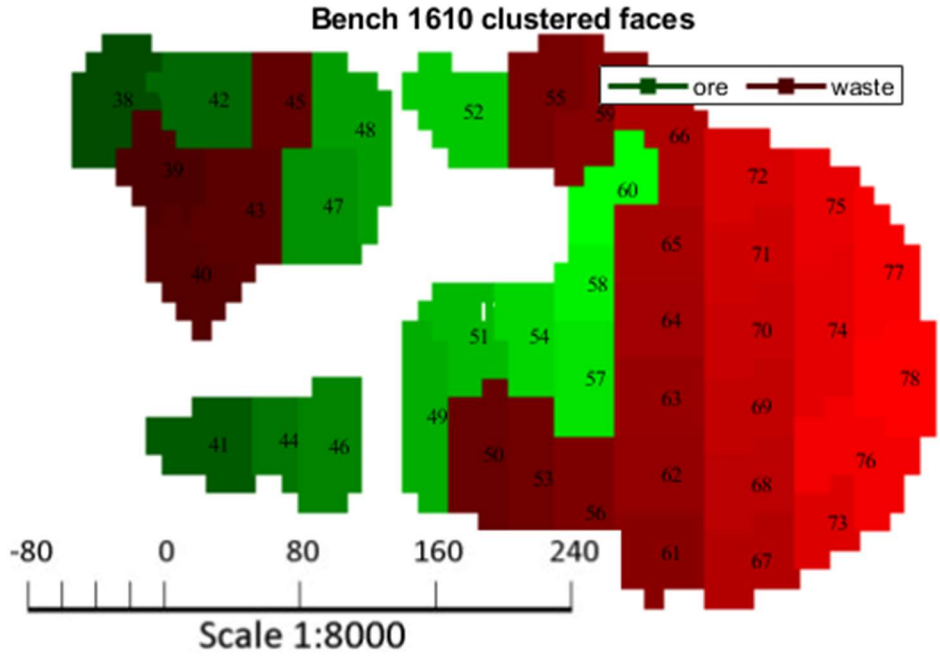

Figure 5. Ore and waste faces on bench 1610.

5. Results

The whole simulation-optimization framework has been implemented in Matlab. The MIP model has been solved for two scenarios, namely, semi-mobile IPCC and pure truck-shovel scenario. The planning horizon is 12 months, and the model is solved using a rolling horizon technique. Hence, the model operates over a twelve-month period in four steps, allocating shovels to faces for three months at a time. After each allocation, the results are saved, and the model identifies available faces for the next three months.

The model is formulated and solved using MATLAB 2021(B). Scenario 1, which excludes IPCC, took 219 seconds to run, while Scenario 2, which includes IPCC, took 237 seconds. Both scenarios were executed on a Dell XPS machine with 16 GB of RAM. The optimality gap for both scenarios is less than 0.5%.

The results from the MILP model, along with the road network and statistical distributions, are input into the haulage simulation model via a graphical user interface (GUI). The simulation is flagged with 1 for scenarios with IPCC and 0 for those without, allowing the model to run accordingly. The simulation has been replicated 100 times for both scenarios to obtain a sufficiently large sample size for reliable results and confidence intervals. Each replication takes approximately 5 minutes to run. The summary and comparison of results from the optimization model and the simulation are presented in the following section.

5.1. MILP Model Results

The mathematical model generates schedule by near optimally allocating shovels to mining faces. The shovel allocation and mining period distribution for the faces on the four available benches for scenarios with IPCC and no IPCC are delineated below.

5.1.1. Optimal Shovel Allocation

This section summarizes and compares the optimal shovel allocations made by the MILP for the IPCC and truck-shovel scenarios. Figure 6, Figure 7, Figure 8, and Figure 9 illustrate the shovel allocations for benches 1595, 1610, 1730, and 1745, respectively. As shown in these figures, the model ensures that ore shovels (indexes s1 and s2) are assigned exclusively to ore faces, while waste shovels (indexes s3, s4, and s5) are assigned to waste faces. Notably, Face 18 remains unmined in the IPCC scenario, indicating that the model considers the crusher location when allocating shovels. All the other faces have been assigned to a shovel making sure that the model fulfills the production requirements. Shovel 5 is confined to the waste benches at the 1730m and 1745m elevations, primarily because the model aims to minimize shovel movement costs. The model also does not let the shovels move across faces that are more than one bench apart.

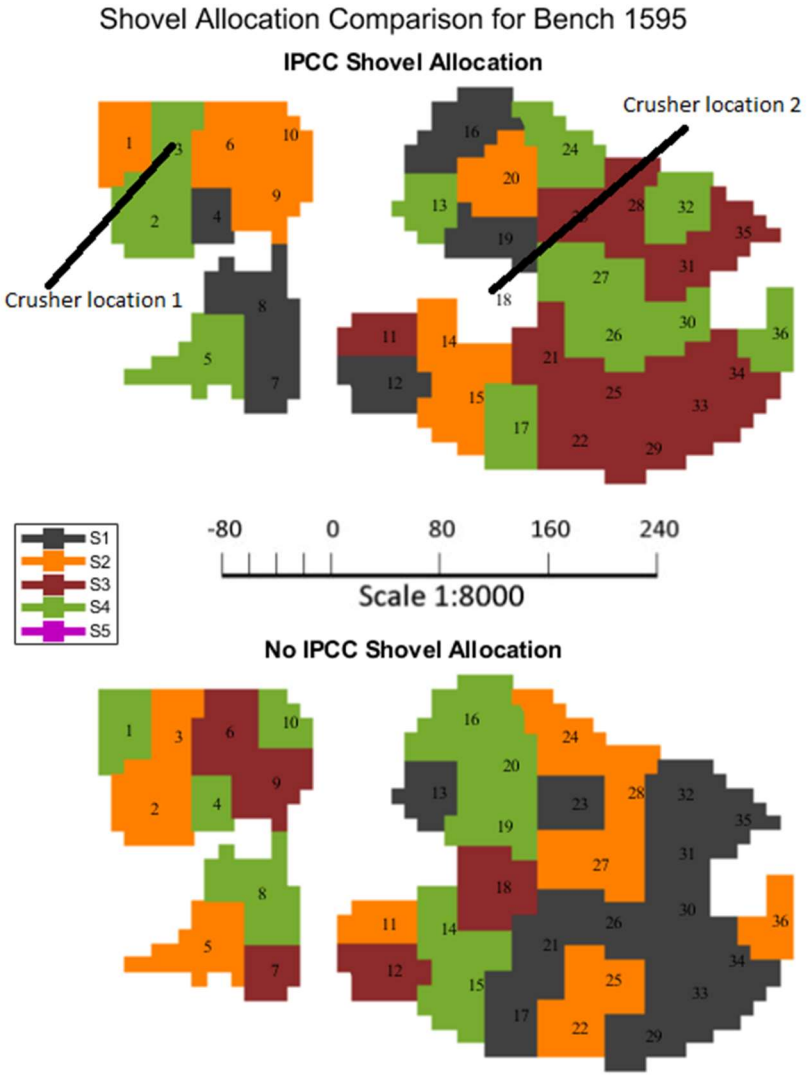

Figure 6. Shovel Allocation to bench 1595.

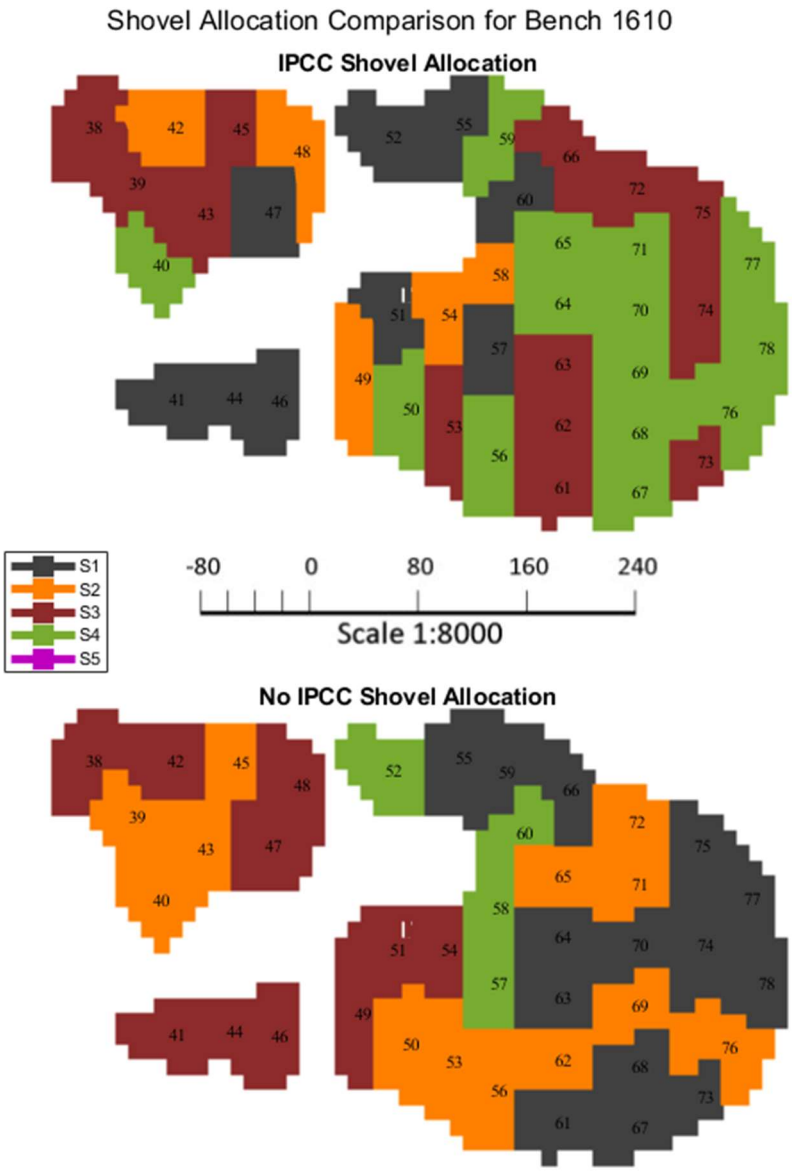

Figure 7. Shovel Allocation to bench 1610.

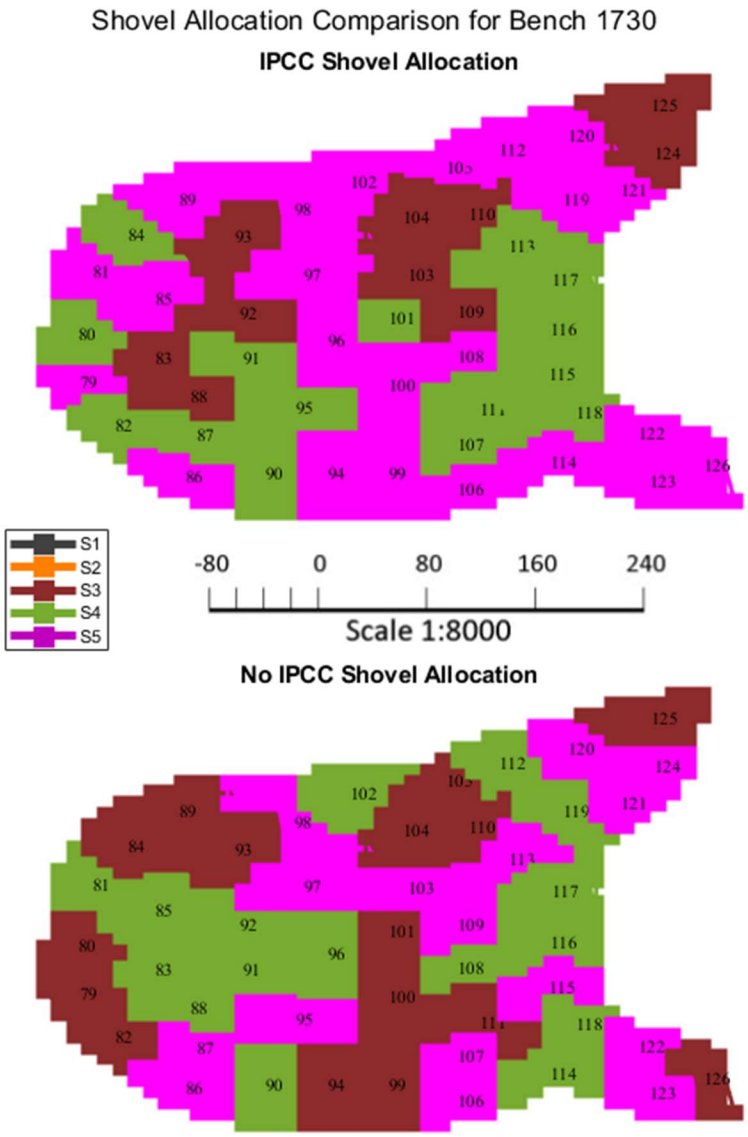

Figure 8. Shovel Allocation to bench 1730.

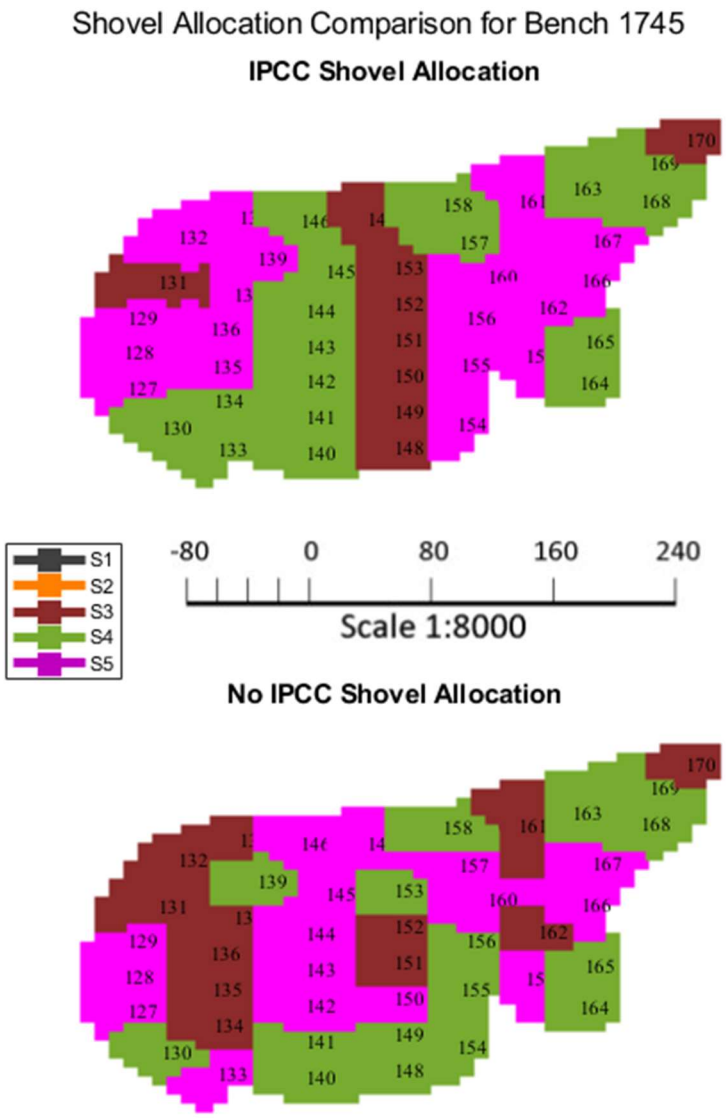

Figure 9. Shovel Allocation to bench 1745.

5.1.2. Mining Period

This section demonstrates and compares the mining period of the faces across the four benches through Figure 10, Figure 11, Figure 12, Figure 13.

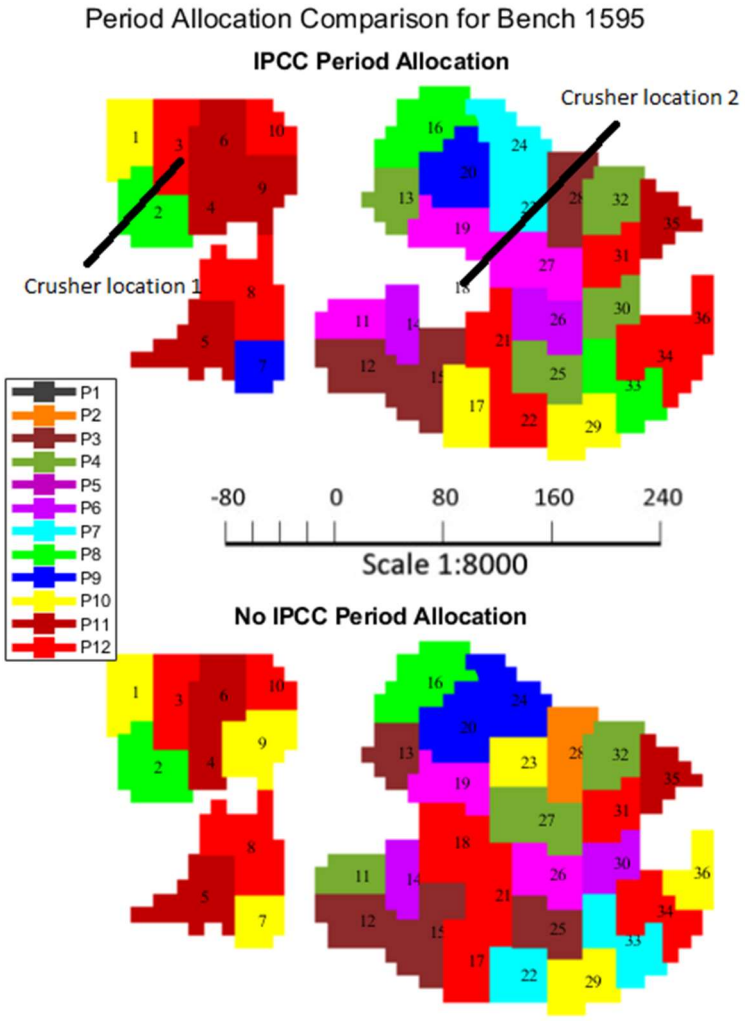

Figure 10. Mining Period for faces on bench 1595.

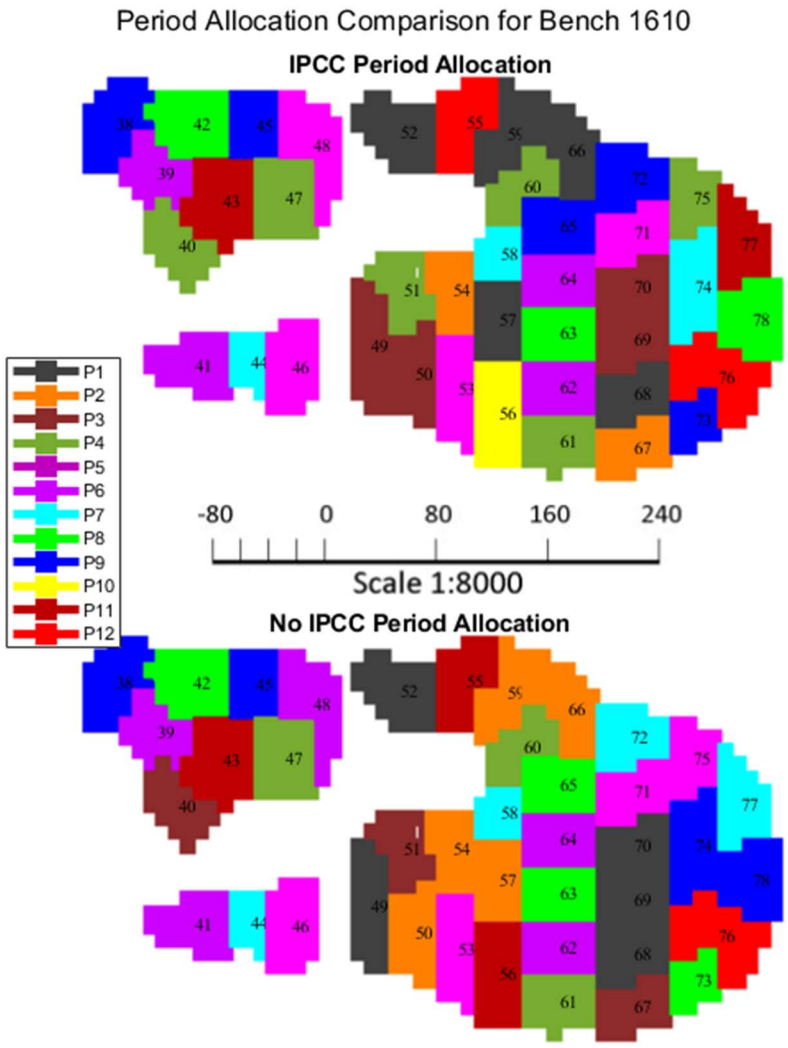

Figure 11. Mining Period for faces on bench 1610.

Figure 10 illustrates that mining face 18 remains unmined in the IPCC scenario due to the presence of the crusher during the final six months of the planning period. Conversely, face 3 is mined in the twelfth period, ensuring compliance with the crusher location constraint during the first six months of the planning horizon.

A closer examination of Figure 10 and Figure 11 reveals that mining commences in period 3 on bench 1595, whereas it begins in period 1 on bench 1610 for both scenarios. This indicates that certain faces on bench 1610 are prioritized over those on bench 1595. Thus, the model ensures that the precedence constraints are respected, with all requisite faces on bench 1610 being mined before shovels are allocated to bench 1595. Most of the faces on bench 1610 are mined within the first 11 periods, while many faces on bench 1595 are mined in the final two periods of the planning horizon. This sequence is also driven by the underlying precedence relationships among the faces of these two ore benches.

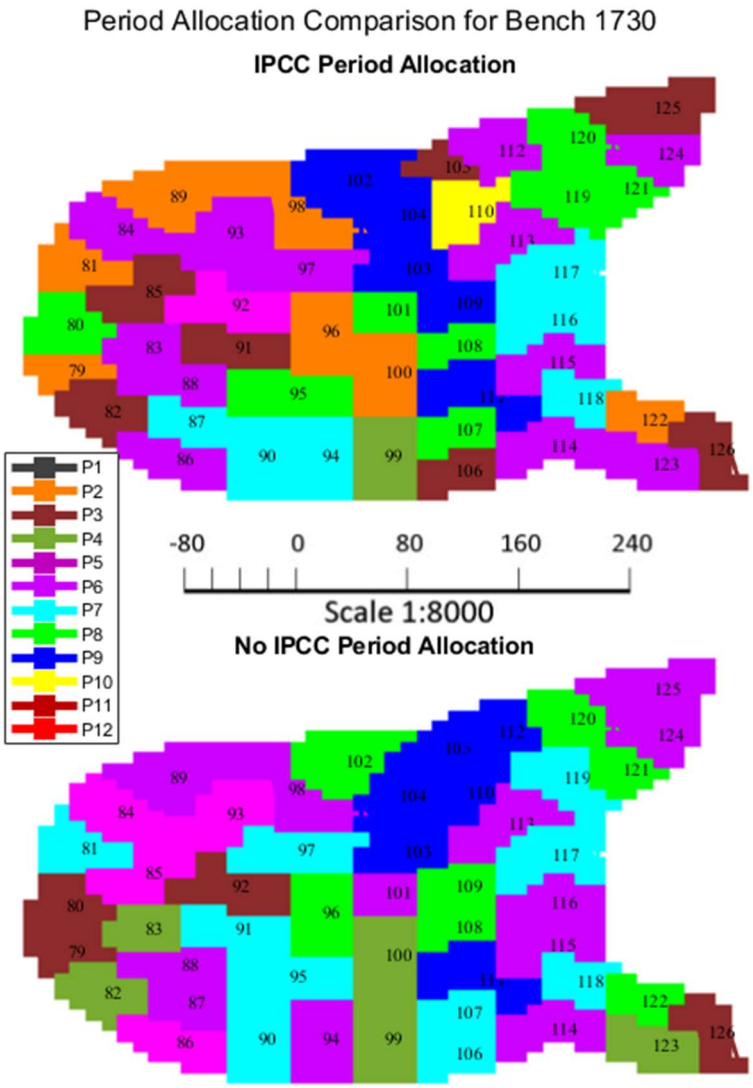

Figure 12. Mining Period for faces on bench 1730.

Mining activities on bench 1730 are concentrated in the last six months of the planning period. Figure 12 shows that mining periods on bench 1730 are distributed between periods 5 and 9 for both scenarios. The location of the IPCC does not affect the waste benches, as the crusher is always located on bench 1595. Additionally, there are minimal precedence relationships between the ore and waste benches.

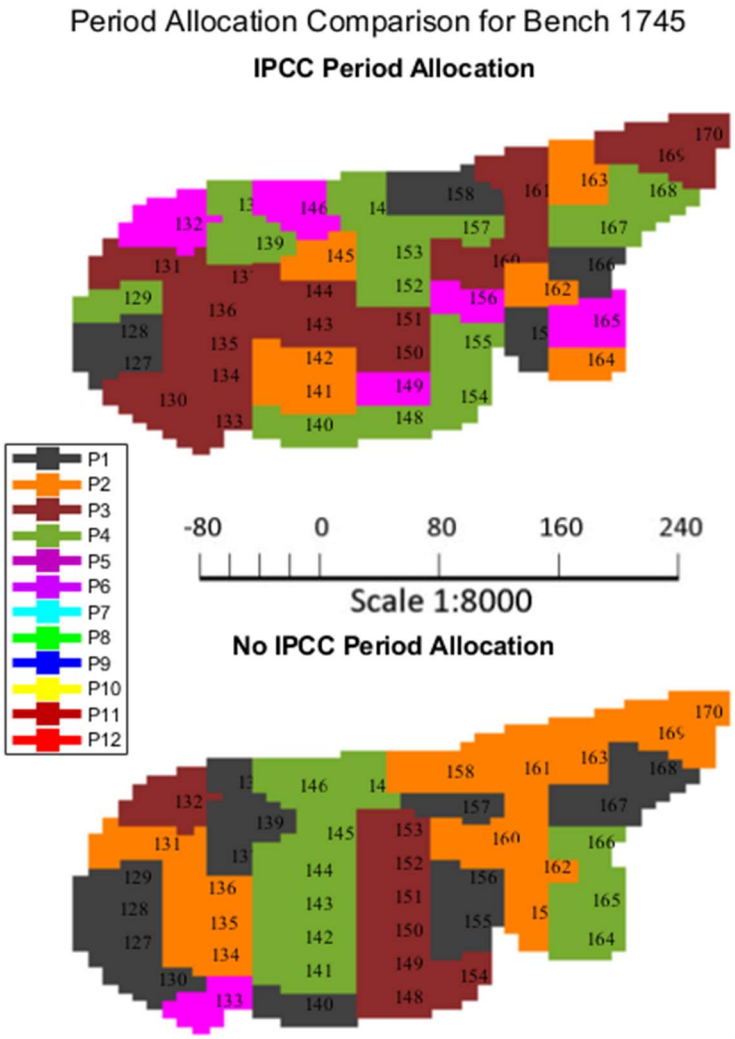

Figure 13. Mining Period for faces on bench 1745.

Mining on bench 1745 occurs between periods 1 and 5 for both the IPCC and non-IPCC scenarios. Figure 13 highlights that periods 3 and 4 are the most active for the IPCC scenario, while periods 2 and 4 are the busiest for the non-IPCC scenario. The early mining of faces on bench 1745 is driven by its precedence over bench 1730.

5.1.3. Monthly Production Schedule

Figure 14 highlights the ore and waste production for the two scenarios. The truck-shovel (TS) scenario maintains a consistent ore production of 1.33 MT per period without any variations. Waste production remains steady, with minor fluctuations between 2.85 and 2.96 MT per period. The consistent ore production in the TS scenario reflects a well-balanced approach to maintaining ore extraction. The minor variations in waste production indicate operational adjustments to manage waste efficiently.

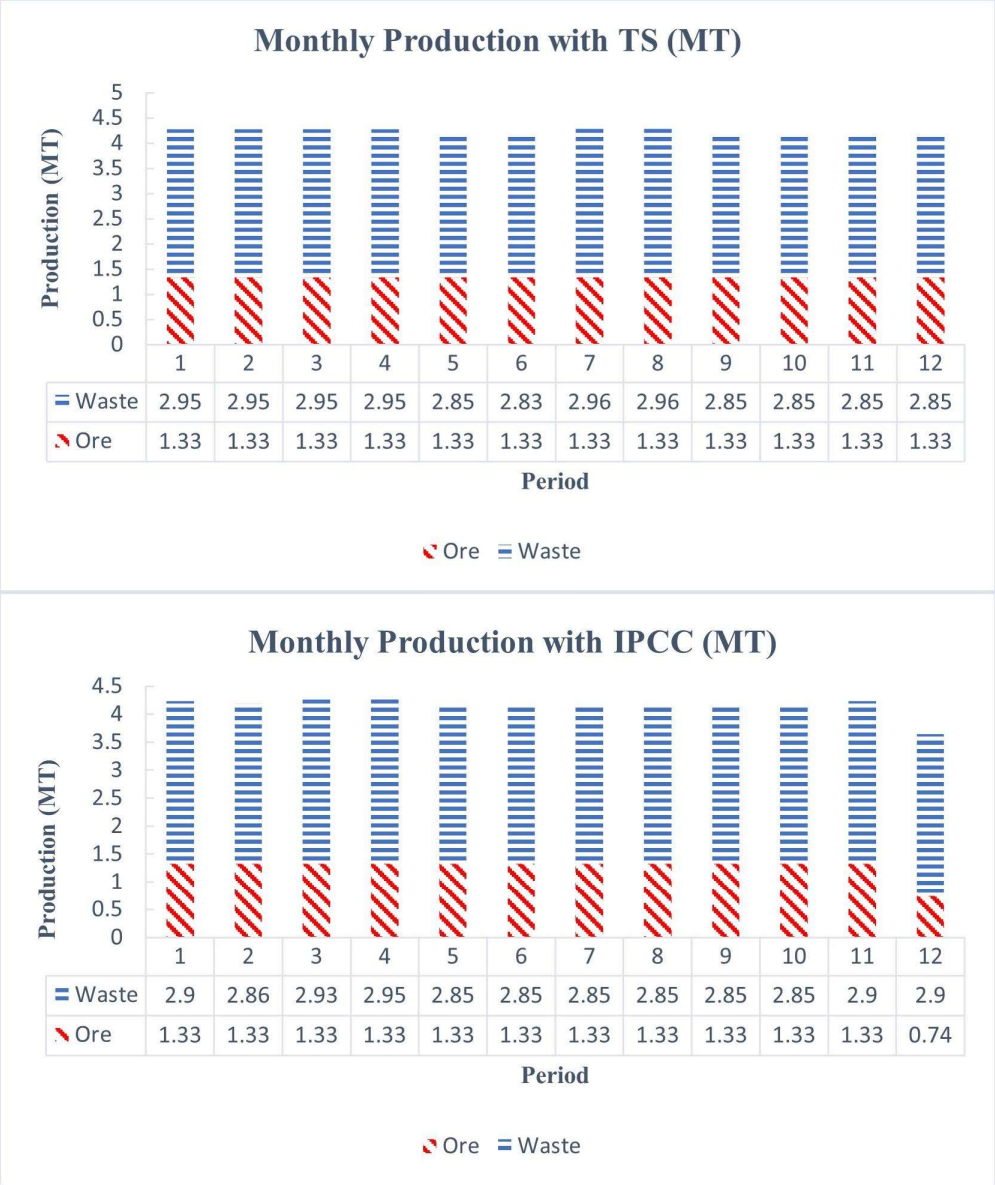

Figure 14. Monthly Production Schedule for IPCC and truck-shovel scenario.

In contrast, ore production remains constant at approximately 1.33 MT per period, with a decrease to 0.74 MT in the final period in the IPCC scenario. This drop indicates the depletion of available ore resources in the last period because of housing the IPCC. Waste production fluctuates slightly, ranging between 2.85 and 2.9 MT per period. The stability in ore production indicates a steady extraction rate facilitated by the IPCC system. However, the variations in waste production, particularly in periods 7 and 8, suggest adjustments made to meet specific operational constraints in the model, similar to those in the TS scenario.

Overall, both scenarios exhibit steady ore production, with minor variations in waste production. The consistent production of ore across all periods for both scenarios substantiates the model's capability to maintain production requirements throughout the planning horizon. While there is a dip in ore production in the final period for the IPCC scenario, it demonstrates that the model respects the IPCC location constraint, ensuring that operational adjustments are made to accommodate the presence of

the IPCC system. These adjustments are reflected in the slight fluctuations in waste production, particularly in the IPCC scenario, highlighting the model's flexibility in optimizing production while adhering to specific constraints. Figure 15 below presents a comparison of total ore and waste production for the two scenarios generated by the optimization model. Overall, both ore and waste production are slightly lower in the IPCC scenario compared to the truck-shovel scenario. The reduced ore production in the IPCC scenario can be attributed to the location of the crusher inside the pit, which imposes additional constraints on the mining operations. However, the difference in waste production between the scenarios is minimal, given the large amount of waste available to be mined. This suggests that while the IPCC system affects ore production due to its specific location requirements, it does not significantly impact the overall waste production.

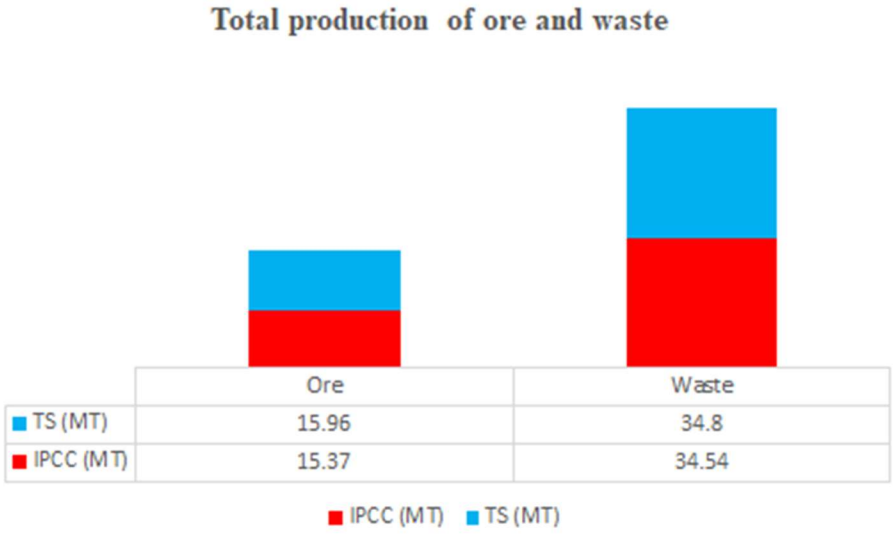

Figure 15. Total Production of ore and waste.

5.2. Comparison and Discussion of Simulation Results

The simulation model integrates data from the optimization model to effectively simulate ore and waste production, considering operational and equipment uncertainties. It evaluates the haulage performance in both the IPCC and non-IPCC scenarios, utilizing a range of variables detailed in

Table 1. The statistical properties of these variables, including averages, standard deviations, and other relevant metrics, are derived from 100 replications of the simulation model for each scenario, ensuring robust and reliable performance assessments. The distribution of the KPIs and truck-shovel failure stattistics are generated from the historical data of the iron ore mine. Because of the lack of historical data on IPCC failure, the failure distributions are adopted from Londono et al. [24].

Table 1. Key performance indicators (KPIs) to be compared.

Variable	Variable Type
Spotting time (min), Loading Time (min), Dumping Time (min), Waiting time (min), Truck traveling time (min)	Independent
Truck cycle time (min), TPGOH (tonne/hr), Total Production (tonne)	Dependent

5.2.1. Comparison of Independent KPIs

The independent variables listed in Table 1 comprise truck cycle time. A summary of the comparative statistics for the independent variables is illustrated in Table 2.

Table 2. Comparison of KPIs (independent variables) between scenarios.

Variable	Scenario	Mean	Median	St Dev	95% confidence interval
Ore Spotting time (min)	IPCC	0.585	0.56	0.25	0.585 ± 0.00015
	No IPCC	0.585	0.556	0.25	0.585 ± 0.00014
Ore Loading time (min)	IPCC	3.537	3.46	1.03	3.537 ± 0.0006
	No IPCC	3.537	3.46	1.03	3.54 ± 0.0006
Ore Dumping time (min)	IPCC	1.35	1.46	0.2	1.351± 0.0001
	No IPCC	1.35	1.46	0.2	1.351± 0.0001
Ore truck Waiting Time (min)	IPCC	1.75	1.75	0.3	1.749 ± 0.0002
	No IPCC	0.97	0.96	0.19	0.967 ± 0.0001
Waste spotting time (min)	IPCC	0.577	0.54	0.25	0.578 ± 0.0001
	No IPCC	0.577	0.54	0.25	0.58 ± 0.0001
Waste loading time (min)	IPCC	4.51	4.51	1.03	4.509 ± 0.0006
	No IPCC	4.51	4.51	1.03	4.51 ± 0.0006
Waste Dumping time (min)	IPCC	1.32	1.46	0.22	1.32 ± 0.0001
	No IPCC	1.32	1.46	0.22	1.318 ± 0.0001
Waste truck waiting Time (min)	IPCC	0.97	0.95	0.17	0.967 ± 0.0008
	No IPCC	0.97	0.95	0.16	0.967 ± 0.00008
Ore truck traveling time (min)	IPCC	2.297	2.06	1.31	2.297 ± 0.0007
	No IPCC	13.8	13.82	1.61	13.801± 0.0009

The comparison of the independent KPIs between the IPCC and no IPCC scenarios reveals that several variables exhibit identical performance across both scenarios. Specifically, ore spotting time, ore loading time, ore dumping time, waste spotting time, waste loading time, and waste dumping time all have the same mean values in both scenarios. This indicates that these aspects of the mining operation are independent of the presence or absence of the IPCC system. The consistency in these

variables suggests that the processes for spotting, loading, and dumping both ore and waste are standardized and equally efficient regardless of the scenario.

In contrast, other variables demonstrate significant differences between the two scenarios. The most notable improvement with the IPCC scenario is observed in the ore truck traveling time, where the mean traveling time significantly drops from 13.8 minutes in the truck-shovel scenario to just 2.297 minutes in the IPCC scenario. This substantial reduction underscores the efficiency of the IPCC system in minimizing the distance and time required to transport ore. The average distance to the ore crusher is reduced to 0.65 km from the ore faces in the IPCC scenario, compared to 3.8 km in the no IPCC scenario. Figure 16 shows the comparison of ore truck traveling time between the two scenarios.

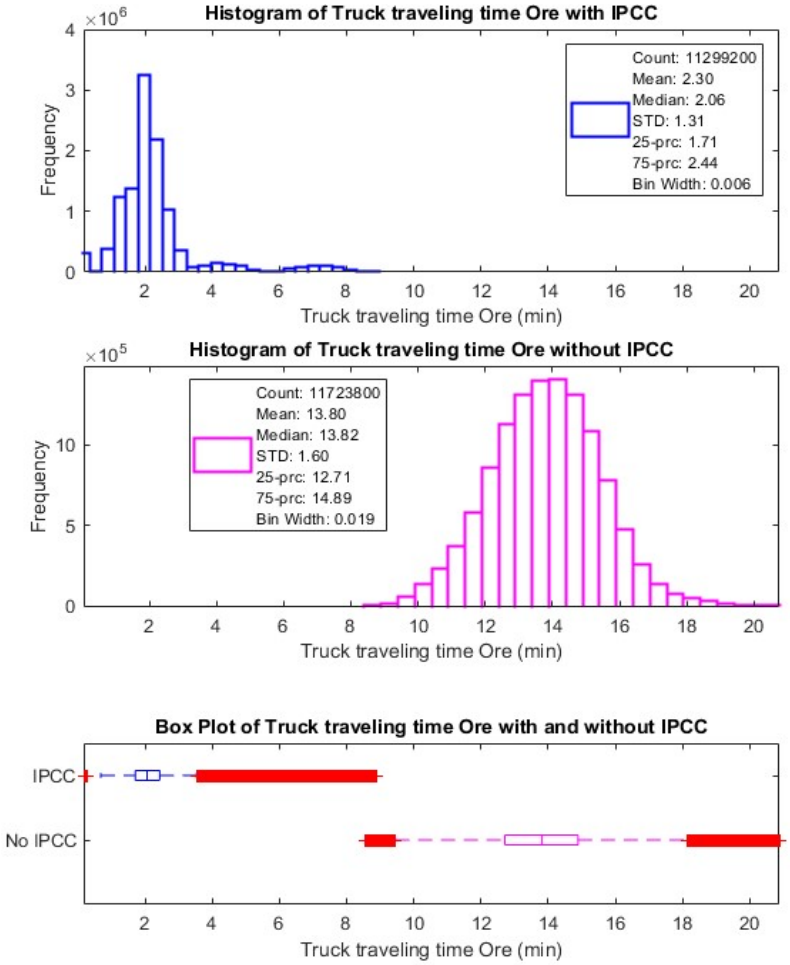

Figure 16. Comparison of ore truck traveling time.

However, this efficiency gain is accompanied by a slight increase in ore truck waiting time, with the IPCC scenario showing an average of 1.75 minutes compared to 0.97 minutes in the truck-shovel scenario. This increase is likely due to the shorter travel time and distance enabled by the in-pit crusher, which leads to longer queues of trucks waiting to be processed. Thus, while the IPCC scenario significantly enhances transportation efficiency, it necessitates careful management of truck waiting times to fully optimize the benefits, highlighting some trade-offs in operational dynamics. The waiting time of waste trucks does not vary between the scenarios because the presence of IPCC does not have any effect on the waste trucks based on the assumptions of the model. A visual representation of the ore truck waiting time is shown in Figure 17.

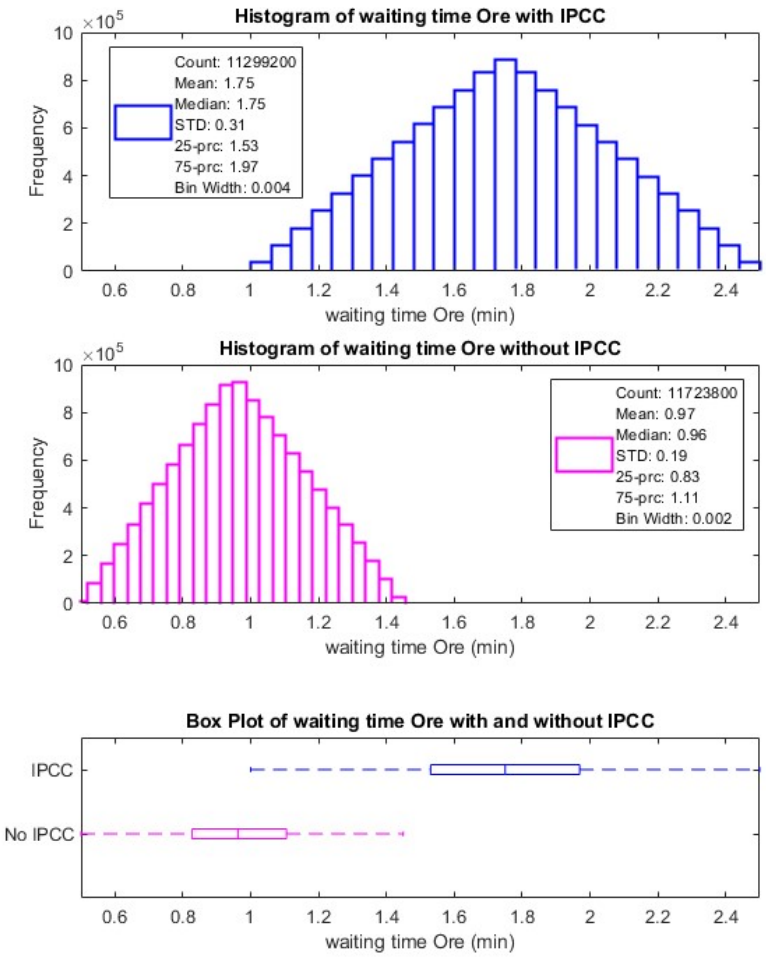

Figure 17. Comparison of truck queuing between scenarios.

The confidence intervals (CIs) for the variables in Table 2 are remarkably narrow, indicating a high level of precision in the simulation results. Given that 100 replications were run for each variable, this precision suggests that the simulation model is robust and reliable. For example, the CI for Ore Spotting time (min) under the IPCC scenario is 0.585 ± 0.00015, demonstrating minimal variability around the mean. Similarly, the Ore Loading time (min) has a CI of 3.537 ± 0.0006 for the IPCC scenario, further reinforcing the consistency of the simulation results. This high precision across different variables, whether it is ore Dumping time, ore truck waiting time, or waste loading time, underscores that the simulation outputs are dependable. The narrow CIs imply that the variability in the data is minimal, and the results are not significantly influenced by outliers or anomalies.

5.2.2. Comparison of Dependent KPIs

Truck cycle time, TPGOH (Tonnes per Gross Operating Hour), and total production are critical KPIs as they are influenced by the loading, spotting, dumping, traveling, and waiting times of trucks. The cycle time of trucks directly affects the production rate of a haulage system; a shorter cycle time indicates a higher production rate, which subsequently determines the number of trucks required. The implementation of IPCC (In-Pit Crushing and Conveying) is anticipated to reduce both the truck cycle time and the number of required trucks due to the shortened trucking distance.

The efficiency of the haulage system can be assessed by examining the production per gross operating hour and the total production during the planning period. These metrics provide insights into the overall performance and capacity of the system. Table 4 provides a comprehensive summary of the statistics for these dependent KPIs, offering a clear view of the system's performance with and without the incorporation of IPCC.

Table 3. Comparison of dependent KPIs.

Variable	Scenario	Mean	Median	St Dev	95% confidence interval
Ore Truck cycle time (min)	IPCC	9.52	9.28	1.73	9.52 ± 0.001
	No IPCC	20.26	20.25	1.93	20.26 ± 0.001
Waste truck cycle time (min)	IPCC	19.54	20.12	4.03	19.53 ± 0.002
	No IPCC	19.55	20.12	4.03	19.552 ± 0.0002
TPGOH (tonne/hr)	IPCC	2424.45	2424.66	23.70	2424.45 ± 4.65
	No IPCC	2451.84	2452	14.89	2451.84 ± 2.92
Total production (MT)	IPCC	14.16	14.16	0.138	14.16 ± 0.027
	No IPCC	14.32	14.32	0.086	14.32 ± 0.017

The stark reduction in ore cycle time between the scenarios is primarily attributed to the decreased truck travel times and distances facilitated by the implementation of IPCC. In the non-IPCC scenario, the average distance from the ore faces to the mill crusher is 3.8 km. This distance dramatically decreases to just 0.8 km with the integration of an in-pit crusher, illustrating the effectiveness of the IPCC system. Consequently, the average ore cycle time with IPCC is significantly lower at 9.52 minutes, compared to 20.26 minutes under the conventional truck-shovel haulage system. Table 3 also shows that the IPCC scenario not only has a lower average cycle time but also exhibits less variability, indicating more consistent performance. Figure 18 visually confirms that the IPCC scenario not only has a lower average cycle time but also exhibits less variability, indicating more consistent performance.

The slight decrease in TPGOH under the IPCC scenario, at 2424.45 tonnes per hour compared to 2452 tonnes per hour in the no IPCC scenario, along with the marginally lower total production, which is 14.16 million tonnes (MT) with IPCC versus 14.32 MT without IPCC, is actually a result of lesser ore availability in the IPCC scenario because of housing the crusher inside the pit. This lower availability impacts the overall output and productivity metrics.

While IPCC brings efficiency gains in truck cycle times, the constrained ore availability limits the system's production potential. The higher standard deviation for TPGOH and total production in the IPCC scenario also indicates increased variability. This variability, along with the reduced production rate, may also be attributed to the added likelihood of failures introduced by the IPCC system. Therefore, despite the operational efficiency improvements with reduced cycle times and potentially lower truck requirements, IPCC's impact on TPGOH and total production can be negatively influenced by the reduced ore availability in this scenario. The narrow confidence intervals of all dependent KPIs further substantiate the reliability and robustness of the simulation model. Figure 19 highlights the greater spread and lower TPGOH in the IPCC scenario.

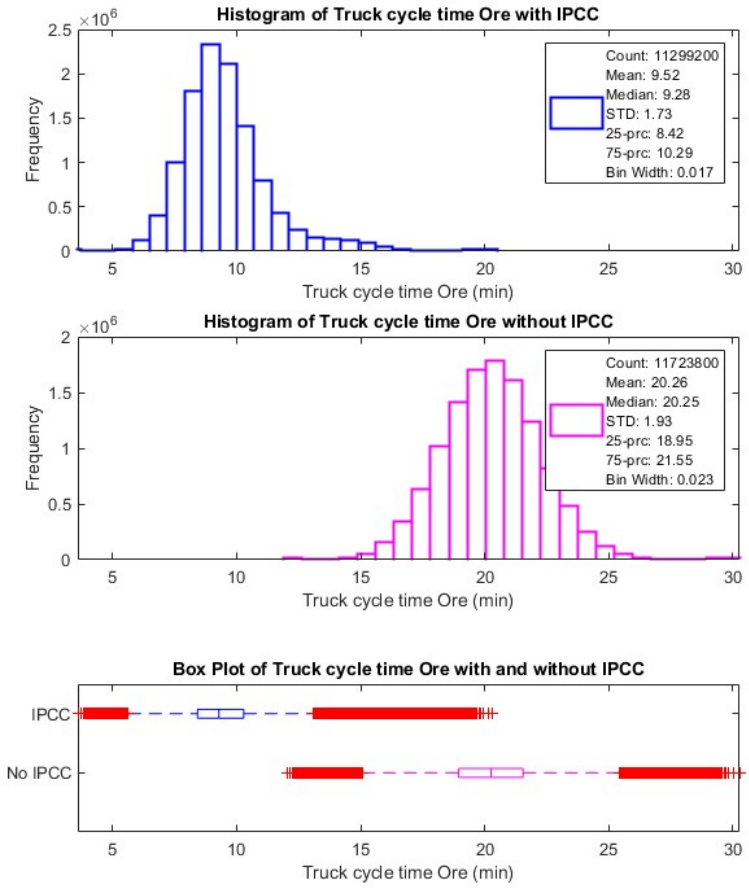

Figure 18. Ore truck cycle time comparison.

5.2.1. System Performance and Reliability

In evaluating the effectiveness of haulage systems, it is crucial to not only assess operational efficiencies but also to examine the system's performance and reliability. This section delves into the comparative analysis of failure statistics for the key components within the haulage system: trucks, shovels, and the IPCC system. We will compare the total downtime statistics of trucks, shovels, and IPCC between the two scenarios to provide insights into the system's performance and reliability. The analysis includes examining the cumulative downtime for each component and its overall impact on system availability. By comparing the failure statistics between the scenarios with and without IPCC, we aim to provide a comprehensive understanding of how the inclusion of IPCC influences system reliability and operational uncertainties. Table 4 presents a comparative analysis of downtime statistics for various components for the two scenarios.

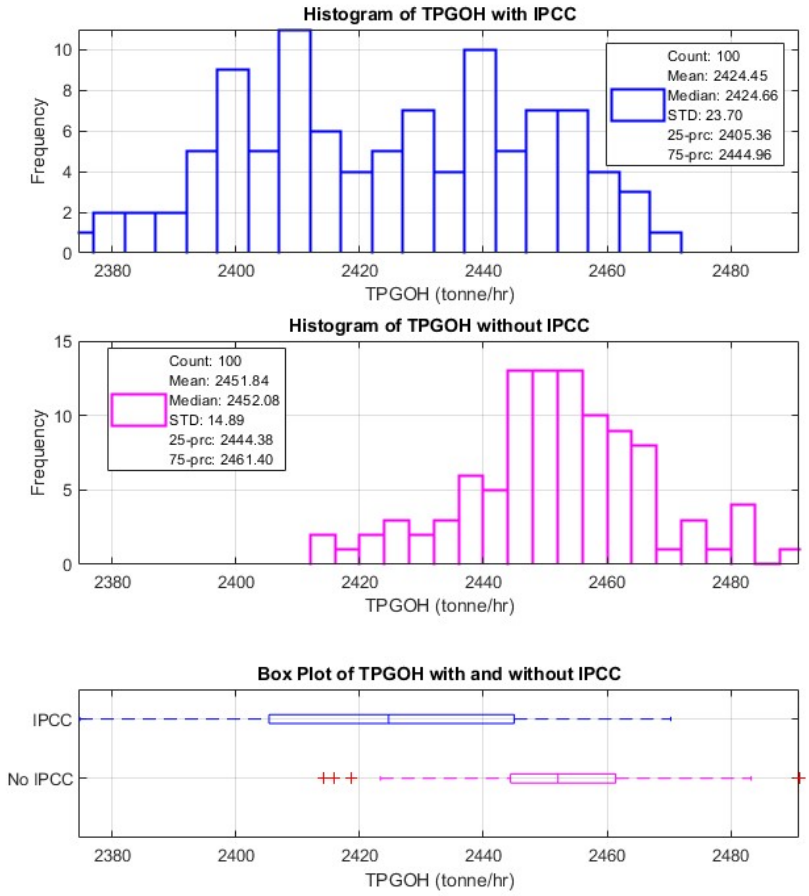

Figure 19. Comparison of simulated TPGOH.

For ore truck downtime, the IPCC scenario shows a mean failure time of 145.58 hours, significantly lower than the 330.99 hours in the no IPCC scenario. This reduction is primarily due to the decreased haulage distance and travel time, as IPCC reduces the need for extensive truck travel. The variability in downtime also differs notably between the scenarios. The standard deviation for ore truck downtime in the IPCC scenario is 14.66 hours, indicating a tighter distribution and more consistent performance. In contrast, the no IPCC scenario has a standard deviation of 19 hours, reflecting greater variability and less predictability in downtime. The median values further reinforce this observation, with the IPCC scenario showing a median downtime of 145.43 hours compared to 330.71 hours for the no IPCC scenario. Figure 20 highlights this central tendency and variability, underscoring the operational stability gained with the implementation of IPCC. However, the IPCC scenario introduces an additional downtime component, with the mean downtime for the IPCC system itself being 293.79 hours. This downtime is not present in the no IPCC scenario, highlighting the trade-off of incorporating the IPCC system.

Table 4. Comparison of downtime statistics.

Variable	Scenario	Mean	Median	St Dev	95% confidence interval
Ore truck downtime (hr)	IPCC	145.58	145.43	14.66	145.58 ± 2.87
	NO IPCC	330.99	330.71	19	330.99 ± 3.72
Waste truck downtime (hr)	IPCC	445.09	443.23	27.12	445.093 ± 5.317
	NO IPCC	437.63	439.84	26.82	437.63 ± 5.26
Ore shovel downtime (hr)	IPCC	288.65	285.08	26.71	288.65 ± 5.23
	NO IPCC	334.91	332.02	22.31	334.91 ± 4.37
Waste shovel Downtime (hr)	IPCC	447.12	446.88	22.54	447.12 ± 4.42
	NO IPCC	443.55	442.16	22.51	443.55 ± 4.41
IPCC downtime (hr)	IPCC	293.79	289.78	26.73	293.79 ± 5.24

The downtime for waste trucks shows less variation between the two scenarios, with the IPCC scenario at 445.09 hours and the no IPCC scenario slightly lower at 437.63 hours. Similarly, waste shovel downtime remains unaffected by the presence of IPCC, with the IPCC scenario at 447.12 hours and the no IPCC scenario very close at 443.55 hours. The similarity in downtime for waste trucks and shovels between the two scenarios is expected, as this case study focuses on ore IPCC only, meaning the operations of waste trucks and shovels are not directly impacted by the implementation of the IPCC system.

Ore shovel downtime is 288.65 hours in the IPCC scenario, slightly better than the 334.91 hours in the no IPCC scenario, though the difference is not as pronounced as with trucks. This suggests some operational efficiency gained with the IPCC system but not to the extent seen with ore trucks. Overall, the introduction of IPCC in the haulage system significantly reduces ore truck downtime due to shorter haulage distances. However, it also introduces additional downtime specific to the IPCC component.

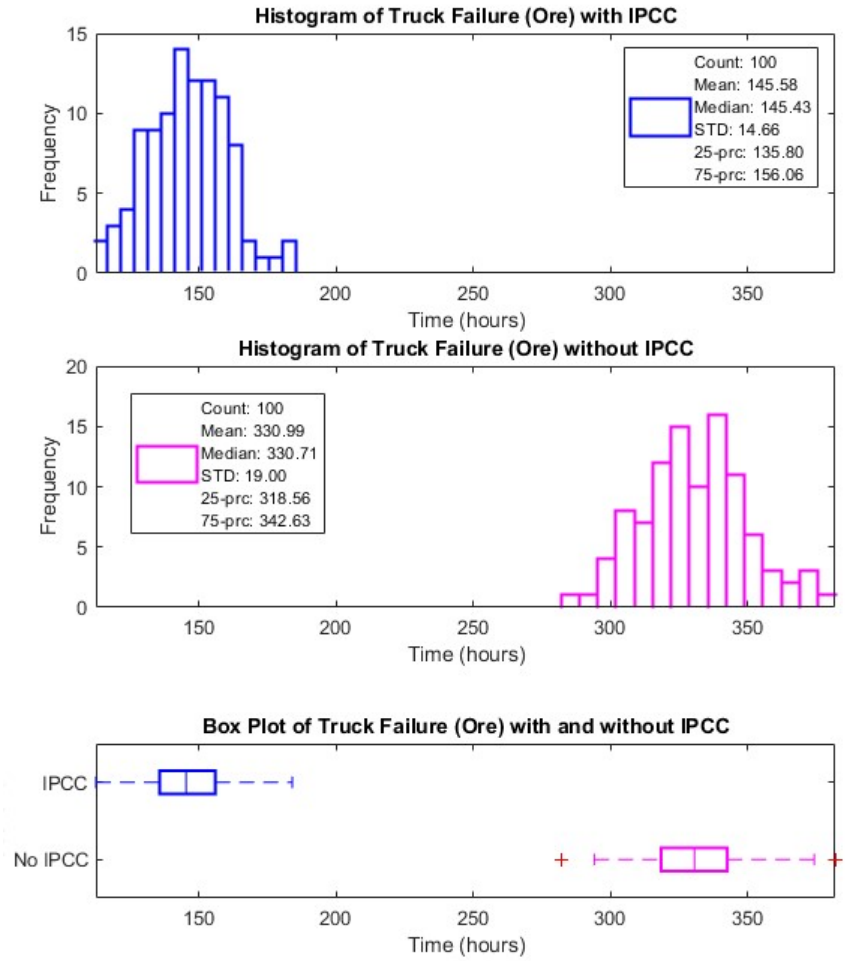

Figure 20. Comparison of ore truck downtime.

Figure 21 compares the total downtime between scenarios with and without IPCC. The scatter plot displays the total downtime across 100 simulations for both scenarios. Each blue dot represents a simulation with IPCC, while each red dot represents a simulation without IPCC. The total downtime for simulations with IPCC ranges broadly between 650 to 850 hours, while simulations without IPCC show a tighter distribution, ranging from about 600 to 750 hours. The scatter plot clearly illustrates that the IPCC scenario results in higher and more variable downtimes compared to the no IPCC scenario.

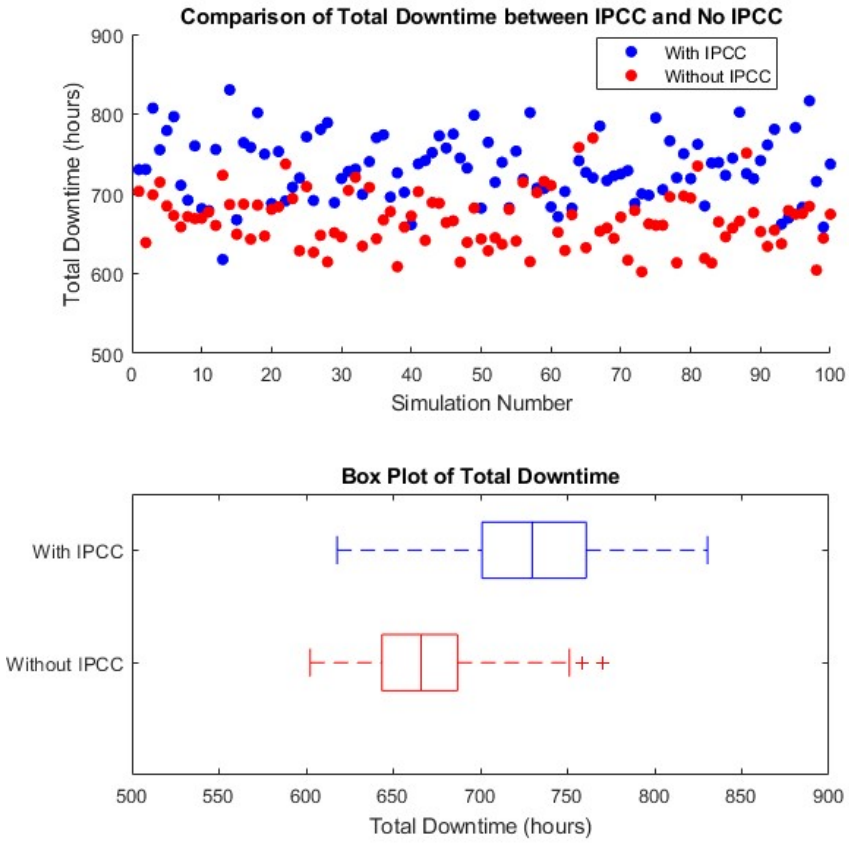

Figure 21. Total downtime comparison between the scenarios.

The box plot provides a statistical summary of the total downtime for both scenarios. The box plot for the IPCC scenario indicates a median downtime slightly above 750 hours, with the interquartile range (IQR) extending from around 700 to 800 hours. This scenario also exhibits a few outliers above 850 hours. In contrast, the no IPCC scenario (in red) shows a median downtime closer to 675 hours, with an IQR ranging from about 650 to 700 hours, and a couple of outliers just above 750 hours. The comparison highlights that the IPCC scenario leads to higher and more variable total downtimes. The increased downtime in the IPCC scenario is attributed to the introduction of the IPCC system, which adds complexity and more potential points of failure. The higher variability and overall downtime suggest that, while IPCC can improve operational efficiency by reducing truck travel times, it also brings reliability challenges that must be managed effectively. In contrast, the no IPCC scenario shows more consistent and lower downtime, reflecting a simpler system with fewer failure points. These findings are crucial for understanding the trade-offs between operational efficiency and reliability when incorporating IPCC into the haulage system.

5.3. Comparison between Simulated and Optimal Production

In this section, the simulated production will be compared to the optimal production requirements set by the MILP for scenarios with IPCC and truck-shovel haulage. The comparison aims to examine which haulage system performs better in this specific case study.

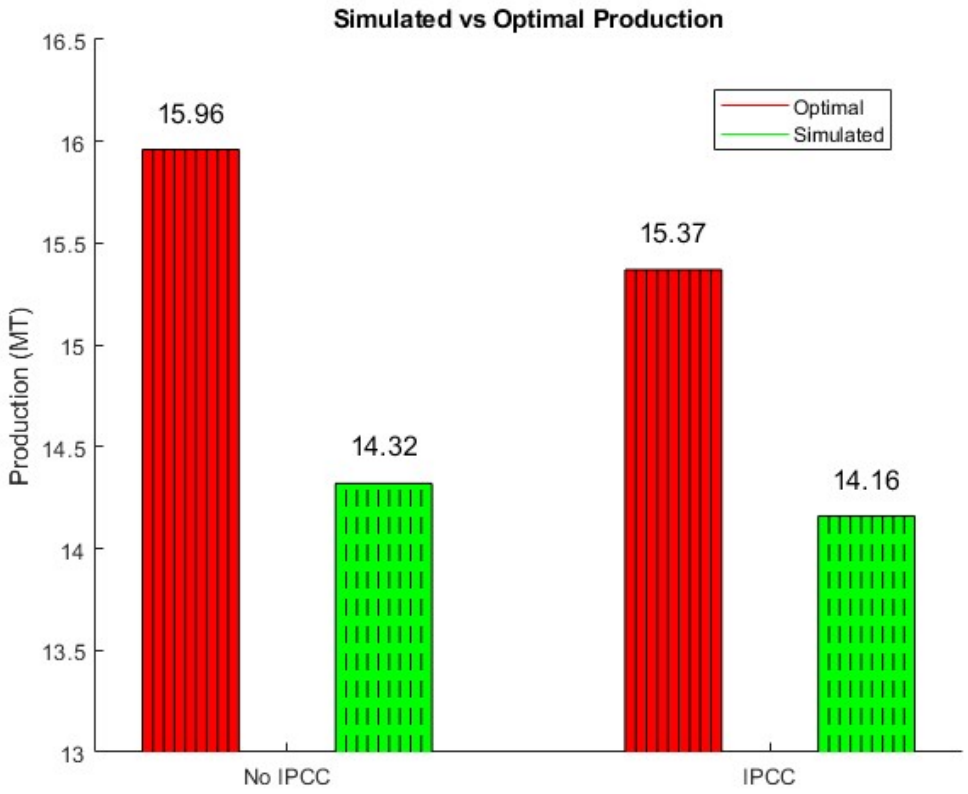

Figure 22. Simulated vs optimal production.

Figure 22 illustrates the production values for both scenarios, showcasing the gap between simulated and optimal production. In the truck-shovel scenario, the optimal production target is set at 15.96 million tonnes (MT), while the simulated production achieves 14.32 MT. This represents a shortfall of 1.64 MT from the optimal target. This discrepancy highlights the limitations of the truck-shovel system in achieving the optimal production levels due to factors such as longer haulage distances and potentially higher operational inefficiencies.

In the IPCC scenario, the optimal production target is 15.37 MT, with the simulated production reaching 14.16 MT. This results in a shortfall of 1.21 MT from the optimal production target. Although the IPCC system aims to improve efficiency by reducing haulage distance and cycle times, the additional operational complexities and potential downtime introduced by the IPCC system hinder its ability to reach the optimal production levels.

Figure 23 represents a scatter plot to provide a detailed comparison of the proximity to optimal production for both IPCC and non-IPCC scenarios across 100 simulations. Each point represents the fraction of the optimal production achieved in a specific simulation run. The blue dots indicate the performance of the IPCC scenario, while the red dots represent the performance without IPCC. The black dotted line represents the normalized optimal production target. It is evident from the plot that the IPCC scenario consistently achieves a higher fraction of the optimal production compared to the no IPCC scenario. The IPCC scenario frequently reaches production levels between 0.91 and 0.95 of the optimal production, whereas the no IPCC scenario tends to range between 0.88 and 0.92.

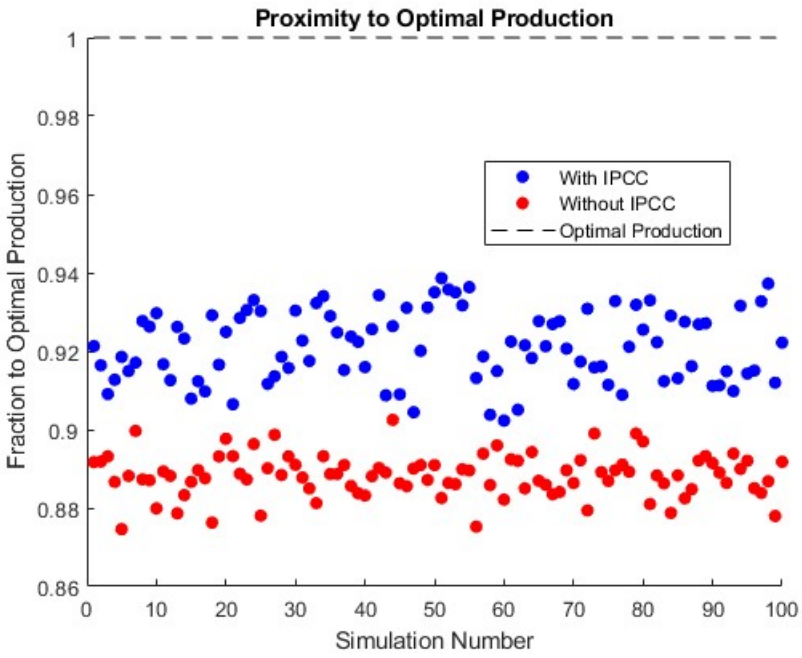

Figure 23. Proximity to optimal production.

The comparison in Figure 22 and Figure 23 reveals that while both scenarios fall short of their respective optimal production targets, the IPCC scenario has a slightly smaller deviation from the optimal production compared to the truck-shovel scenario. This suggests that the IPCC system, despite its operational complexity and potential for increased downtime, outperforms the traditional truck-shovel system in maintaining closer proximity to optimal production targets. However, both systems demonstrate the need for further improvements to bridge the gap between simulated and optimal production.

6. Conclusion

This paper provides a comprehensive analysis of short-term planning and haulage systems in open-pit mining, specifically comparing the performance of IPCC systems to traditional truck-shovel operations. The developed simulation-optimization framework effectively captures operational uncertainties, delivering reliable and realistic assessments of system performance as evidenced by the narrow confidence intervals in key performance indicators. The findings underscore that the IPCC system significantly reduces ore truck cycle time and haulage distance, thereby enhancing overall operational efficiency. The analysis reveals that housing the crusher inside the pit in the IPCC scenario limits ore availability, impacting overall production and productivity metrics. Nonetheless, the detailed examination of ore haulage demonstrates the clear advantages of IPCC in improving haulage efficiency and reducing truck requirements.

However, the study also identifies challenges, particularly the increased downtime associated with IPCC components. These findings highlight the need for robust maintenance and operational strategies to fully capitalize on the benefits of IPCC technology. The increased complexity and potential for downtime with IPCC systems underscore the necessity for further research into maintenance and reliability. Additionally, the focus on a single case study means the results may not be universally applicable across all mining operations.

Future research directions should include exploring a broader range of case studies, encompassing different mine types and operational conditions to validate the robustness and generalizability of the

simulation-optimization framework. Additionally, developing dynamic optimization models that adapt to real-time changes in mining conditions and equipment performance could significantly enhance short-term planning effectiveness. Advanced reliability analysis of IPCC components could also help in better understanding and mitigating the additional downtimes introduced by the IPCC system.

In conclusion, the integration of IPCC systems in open-pit mining presents significant operational efficiencies and challenges. The simulation-optimization framework developed in this study provides a valuable tool for mine planners, enabling informed decision-making and optimized production scheduling amidst operational uncertainties. Future research should aim to broaden the application and improve the reliability of IPCC systems, ensuring that their potential benefits are fully realized in various mining contexts.

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Different Time Scales of In-Pit Crushing and Conveying (IPCC) Enabled Open Pit Mine Planning: A Literature Review and Research Agenda

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ABSTRACT

In this paper the state-of-the-art open pit mine planning methods with In-Pit Crushing and Conveyor (IPCC) considering different time scales are reviewed. An overview is given on methods, regarding long and short-term mine planning, through a comprehensive literature review. The gaps and shortcomings of the current research are elaborated. Consequently, a specific research agenda on long and short-term mine planning with IPCC usage is stated. A research project aiming to contribute to the stated research problem is proposed. The results and observations of the literature review are discussed and evaluated. Suggestions are given for further research together with a comprehensive summary of the research findings.

1. Introduction

The demand for mineral resources is increased by a growing world population, economic growth in developing and emerging countries, and constant further innovation. The efficient planning of mining operations is vital to overcome the challenges of rising demand for mineral resources. In the face of rising fuel and labor costs, haulage is a massive part of the mining costs, representing approximately 40% [1]. Truck haulage also accounts for greenhouse gas and nitrogen oxide emissions [2,3].

In-Pit Crushing and Conveyor (IPCC) systems require accurate and detailed upfront planning. Due to the high capital costs of IPCC systems and the reduced flexibility in the mining operation and technical requirements such as the conveyor exit requirement, precise planning is crucial to guarantee a successful, economically viable operation [4].

IPCC is a haulage solution, which aims to reduce the costs of haulage and its emissions. Although the alternative usage of IPCC is widely discussed as a current trend in the mining industry [5], there are few coherent frameworks for strategic and short-term planning of IPCC [6, 7]. Currently, for example, cost estimations or mine plans with IPCC are only created based on case studies of single mining projects or based on estimates derived from empirical values [8]. These case studies are therefore not a general representative of the entire open pit mining industry. This paper aims to provide an overview of existing, related literature and to propose further research on mine planning with IPCC system.

To achieve this, some general background information about different IPCC systems is given. A structured review of the state-of-the-art open pit mine planning regarding IPCC is conducted to highlight varying long and short-term planning approaches and their relevance. Gaps and shortcomings in the current research are elaborated in Section 2. Afterward, a research agenda is

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stated that the author wants to realize in the future. Observations made during the literature review and while stating the to-be-solved research problem, are outlined. In Section 3, the results of the state-of-the-art mine planning methods and the proposal for further research are discussed. In conclusion, an outlook on further research potential is given and the findings are summarized.

2. State-of-the-Art

In the following, some general information and the classification of different IPCC systems is presented. Then, the various approaches for strategic and short-term mine planning with IPCC usage are reviewed. During the literature survey, the main objectives of long-term mine planning optimization with IPCC usage found in literature with a focus on crusher location optimization are outlined. Afterwards, research studies related to short-term mine planning with implementation of IPCC are presented.

An IPCC system is a continuous haulage system for surface mines. It consists of a crusher station or several crusher stations, which are located inside the pit. The crusher station(s) are operated in combination with a conveyor belt, which is used to transport the material out of the pit.

IPCC systems can be categorized based on their level of mobility into three categories: Fixed, semi-mobile, and fully mobile IPCC crusher systems [9]. Fully mobile crusher stations have built-in transport mechanisms such as crawlers, with which they can change their position following the mining face. Semi-mobile crusher stations have been located at one specific position for several years. Fixed crusher stations are located inside the pit and do not change their position [9].

2.1. IPCC in Strategic Open Pit Mine Planning

Long-term mine planning is considered as planning for several years to the whole mine life.

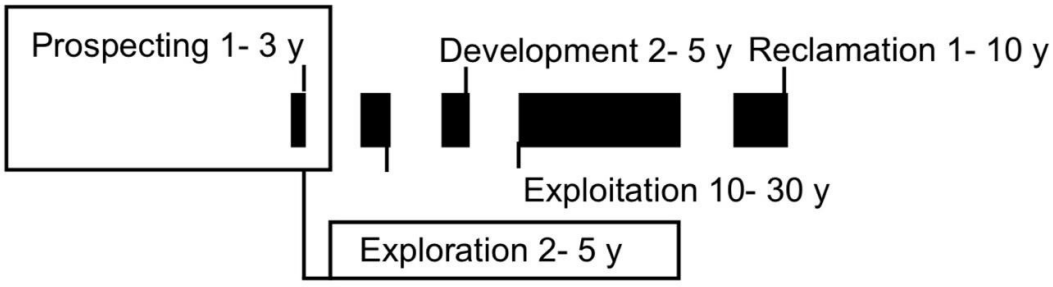

Figure 1 Stages of Mine Life (Time frames from [10])

Figure 1 depicts the stages of mine life as described by Hartmann, from prospecting to remediation. The long-term mine planning covers all time phases. Open pit mine planning with IPCC usage is important during the exploration phase and development phase. During the operation of the mine with IPCC other factors are important, which are mentioned in the short-term planning section. Before opening the mine with IPCC a detailed and socially approved closure and remediation concept needs to be planned. The usage of semi-mobile and fully mobile IPCC might hold special challenges for the remediation process because of the high amount of permanent steel structures and the major interventions into the landscape [11].

The objectives for the strategic mine planning with IPCC usage can be stated as production scheduling, location optimization, comparison to truck and shovel operations, and the optimization and assessment of various decision-making factors such as NPV.

Liu et al. [12] conducted a similar review of recent research agendas in Mining Equipment Management. Within this review, an overview is given about the current IPCC system and hybrid IPCC truck and shovel system management literature. In addition, research opportunities are pointed out. In addition to this review, four main objectives of long-term IPCC planning are summarized here with the focus on crusher location optimization.

Production scheduling optimization with IPCC usage – Few studies have been done on the production scheduling problem with IPCC usage. Production scheduling aims to find the best block extraction sequence for a mine that maximizes the net present value (NPV) and obeys certain technical and economic constraints. Technical constraints are for example geotechnical constraints such as the allowable slope angle. Economic constraints are for example commodity prices. To solve the problem a block model of discretized blocks of the modeled mineral deposit is created. To each block, an estimated tonnage and mineral grade is assigned [4, 13]. Then, mining blocks are clustered for the purpose of production sequencing. [14, 15, 16]

Long-term scheduling is composed of three steps: finding the optimal ultimate pit limit, pushback selection, and creation of production schedules [13].

In general, the techniques that can be used for production scheduling can be classified into: heuristic/metaheuristic algorithms and mixed-integer programming. To calculate an optimal solution within a reasonable time, approximation techniques should be applied [6].

Comparison of IPCC to truck and shovel system

Before developing a mining operation with IPCC usage during the feasibility study, a comparison can be done between truck and shovel equipment usage and IPCC system. Different methods are used to compare the technical feasibility and economic viability of the planned operation. One of them is discrete-event simulation. State-of-the-art studies of comparison of truck and shovel operations with IPCC operations through discrete-event simulation were for instance conducted by [17] and [18].

Optimize and access various decision-making factors regarding IPCC inauguration

It is not possible to evaluate the benefits and shortcomings of the IPCC inauguration without assessing various decision-making factors. To find out which factors are relevant, books, dissertations, journal articles and conference proceedings from 1988 to 2024 were reviewed. Each decisive factor was listed in a table. The results are presented in Table 1. Based on the reviewed literature, the most common and thus most relevant factors are economic factors such as NPV, CAPEX, and OPEX. These factors were mentioned most often within the reviewed literature. Some factors were considered neglected because of the number of occurrences in literature but considered important for the decision-making process. These factors include mostly environmental and social factors.

Table 1 Overview of decisive factors found in literature.

Category	Decisive factor	Count	Citations				
Economic	Operating Cost (OPEX)	10	[19]	[5]	[8]	[20	[21]
			[22]	[23]	[24]	[25]	[26]
	Capital Cost (CAPEX)	4	[19]	[8]	[24]	[5]	
	Economic Index (EcI)	1	[24]				

Category	Decisive factor	Count	Citations				
	Net Present Value (NPV)	10	[27]	[28]	[19]	[29]	[30]
			[18]	[5]	[31]	[30]	[32]
	Other economic analysis, cost analysis, sensitivity analysis	7	[17]	[33]	[34]	[8]	[35]
			[36]	[37]			
Performance	Mine Life	3	[24]	[18]	[8]		
	Mining Capacity	3	[28]	[3]	[9]		
	Utilization	2	[9]	[36]			
	Availability	5	[38]	[9]	[18]	[36]	[39]
	Productivity	2	[38]	[36]			
	Mine Productivity Index (MPI)	2	[40]	[41]			
	Resource Recovery	1	[27]				
	Major shortcomings of truck usage*	1	[8]				
Environmental	Pollutants	5	[3]	[38]	[19]	[2]	[42]
	Energy consumption	2	[43]	[44]			
	Life Cycle Assessment (LCA)	3	[3]	[45]	[46]		
	Other environmental study	6	[47]	[23]	[48]		[49]
			[50]	[51]			
Social	Safety	3	[52]	[5]	[23]		
	Other social concerns	1	[52]				

*Major mine specific shortcomings of truck usage for instance insufficient climatic conditions for road conditions, dust, wash holes, etc. ** The methodology used to create this table is presented in [53]. The table was updated after this publication.

Crusher location optimization:

Most of the research on semi-mobile IPCC system optimization has been focused on the optimal position of the crusher in the pit. The objective of the operations research approach is to minimize the total transportation and associated costs by selecting the optimal location from a given set of potential crusher sites [6, 29]. These studies can be static or time-dependent. Other methods of solving the crusher location and relocation problem are for example simulation and heuristic algorithms. Another task is the optimization of the conveyor location.

Table 2 Overview of crusher location optimization studies.

Summary of approach	Shortcomings
Konak et al. [54] evaluated the selection of an optimal crusher location. The study is for an aggregate production quarry in Turkey. The decision was made based on the haulage distance. Both stationary and semi-mobile crushers were analyzed. An algorithm was developed to calculate the average haulage distance to the crusher from the mine. Up to three relocations during the mine life were considered.	The only decision variable considered is the haulage distance. Capital or relocation costs for the in-pit crusher are not included, this impacts the cost savings shown by the study [54].
Taheri et al. [55] used a simple approach to determine the optimum location of stationary crushers in deep open pit mines. The NPV of the haulage and installation costs is calculated for three candidate locations by the model. Then the location with the lowest costs is selected.	The model does not account for uncertainties in costs caused by crusher breakdowns or shovel downtimes. Candidate locations are selected randomly [55].
Rahmanpour et al. [56] studied the optimal in-pit crusher location selection as a trans-shipment problem with single hubs. An analytical hierarchical process was used to select candidate locations. Six economic and eleven technical factors were considered. The Hub-spoke network connected all destinations to source locations to increase haulage capacity.	No delays and queuing during trans-shipment at hubs were considered [56].
Roumpos et al. [57] suggested an iterative model to minimize the total transportation cost of continuous surface mines. The best location for a belt conveyor distribution point is found using simulation.	The model is only valid for continuous operating surface mines. Only operating and capital costs are considered, operational uncertainties such as conveyor downtime are not considered [57].
Paricheh et al. [58] developed a heuristic model in 2018 to hierarchically find the optimum in-pit crusher locations in open pit mines and the optimal relocation moment. The crusher location is optimized by an iterative, linear dynamic facility location model which minimizes the cost of haulage. The relocation moment of the crusher is optimized by maximizing the discounted cash flow throughout the life of mine.	Strictly deterministic model [58].
Summary of approach	Shortcomings
In 2017 Paricheh et al [59] proposed another model modeling the location problem dynamic based on primary factors like the	A strictly deterministic model with a hypothetical case study [59].

haulage distance. The objective of the model was to minimize the haulage costs.	
Paricheh and Osanloo [60] used a stochastic facility location model in 2016 to find the optimal crusher location in open pit mines. Production and haulage cost uncertainty was considered. The model was formulated as a P-median problem.	The model does not work well in all cases [60].
Paricheh and Osanloo [61] developed a search algorithm in 2019 to find the optimal crusher locations from a set of candidate locations. The optimal candidate locations are practical and cost-effective. Six specific rules were used in addition to conventional rules based on topography and ramp intersection as well as block aggregation policies. The number of candidate locations in a case study of the Sungun mine in Iran could be reduced from 283 to 23.	No geotechnical or shape restrictions are considered when defining candidate locations [61].

Some of the Disadvantages of current crusher location optimization models include [62]:

- The mine plan and sequencing of mining are not considered for the location optimization. Therefore, economic optimization cannot be guaranteed in the long term.
- The case study results of Kamrani [6] are unreliable due to hypothetical mine data with simplified geometrical assumptions.
- Most models choose locations without taking a real road network into account.
- Geometric IPCC design parameters must be considered.

IPCC in Short-Term Open-Pit Mine Planning

In this section, the different approaches for Short-term planning are reviewed. Short-term planning is referred to as a term for planning operations with a period of weeks to several months. Operational planning is the task of allocating short-term plans to day-to-day mining operations. Objectives of the short-term planning are to synchronize the long-term production plan by generating feasible short-term production schedules. Short-term schedules need to account for the effects of the IPCC location such as effective production capacity and haulage distance. In addition, the location(s) of the hauling equipment(s) need to be planned to ensure product quality (grade blending) and quantity for the mine to be profitable and produce an ore concentrate [7,62,63, 64, 65].

Short-term to mid-term planning is about both operation and downtime scheduling. Maintenance scheduling and timed replacement of loading, hauling, and crushing equipment is as important as production quantity and grade control. Geotechnical and environmental circumstances influence the mid-term mine design.

This section covered information about production scheduling, location optimization, comparison to truck and shovel operations, and the optimization and assessment of various decision-making factors. Through this, some general information about IPCC planning was presented.

3. Statement of Research Agenda

The author proposes a research methodology for further research on short and long-term mine planning with IPCC usage. For the statement of this research problem, the research questions are: 1) How can short-term mine planning with IPCC usage be optimized and simulated? and 2) How can the optimal crusher locations for a semi-mobile IPCC be chosen? The objective of the

research is to create a comprehensive tool for short-term production planning and analysis options for semi-mobile IPCC usage. In addition, the long-term mine plan must be fulfilled by the optimal chosen crusher locations. The creation of a separate mathematical optimization tool is a second objective. The underlying model needs to be pragmatic and able to capture uncertainties. In the future, the grade of detail and properties of the model must be defined. For example, about the operational constraints, requirements, and costs, associated with implementing the IPCC system. A comprehensive research methodology must be determined before creating a model that can consider operational uncertainty. For the determination of the optimal crusher location, uncertainties might be neglectable.

A mathematical optimization algorithm is designed to optimize the long-term crusher locations. The Scope of the Optimization Model experimental design to optimize the crusher locations:

- Collection and analysis of data
- Establishment of a road network and block model sequenced into mining cuts to generate insight into the tabular oilsands deposit.
- Development of a mathematical formulation and framework for the crusher location optimization. Improvements to existing research work are discovered and existing work is adjusted based on industry needs. For example, the bench height for crusher panels must be based on technically specified crusher heights [6].
- Development, training, testing, and validation of an effective optimization model for optimized crusher location calculation [23].

Discrete Event Simulation is chosen to optimize the short-term mine haulage management. Before the designing of the simulation model, the scope and objective of each analysis needs to be defined [28]. Successful performance of discrete event simulation includes quality control procedures. Important are verification (a check whether the simulation model works as intended) and validation (a check whether the simulation model reflects the real system sufficiently) [66].

In the following research study, the next step is the statistical analysis of input data for the simulation model. An action plan formulation is a detailed plan outlining the actions needed to reach the defined goals for IPCC scheduling and haulage simulation. The action plan is a sequence of steps that must be performed for the model to succeed. Next a model, a depiction of the real mine must be defined. The model must be verified and tested. After the creation of the underlying model, it can be implemented into suitable simulation software. With the simulations, scenarios are performed to solve the defined analysis questions. The results of these simulations need to be validated.

The main steps of developing and implementing a simulation framework include:

- Statistical analysis of input data for the model
- Action planning
- Developing the model (as a prototype program or in a simulation software)
- Model verification and simulation validation.
- Running of scenarios, to solve defined analysis questions

Suggestions to consider in future research:

Further research should focus on the systematic reporting of benchmarking parameters of IPCC operations and the implementation of the described neglected decisive factors into calculation or simulation models. Such neglected factors include but are not limited to: safety indexes, lifecycle assessments, and other environmental analyses like studies about the decrease of energy consumption or emissions. Especially analyzing and considering data from smaller IPCC operations is relevant for the future, successful implementation of the technique in the industry. Each mining company should have its own confidential record of historical data and is obligated

by law and order to keep records to have an official permit to operate. These records should be made available for research. Different stakeholders must engage and cooperate to strengthen rural and central governance in the mineral sector to increase awareness about sustainable decision factors. A modern research approach should capture uncertainty in mining equipment management.

4. Observations and Discussions

The results obtained from the review of the state-of-the-art mine planning methods for IPCC and the proposal for further research are discussed here. Today, the relevance of the economic decisive factors is significant. Other factors like social life cycle analysis are often neglected when considering how seldom they were mentioned in the latest literature. Economic factors are important for the success of the IPCC inauguration, but other factors like performance, environmental, and social factors should not be neglected during decision making. The neglect of these factors leads to a lack of knowledge about both the decisive factors of IPCC and its constraints regarding long-term mine planning.

The scope of the research problem is vague. The exact research methodology must be explained in more detail. Ethical approval is an important lack of the research proposal. Input data from a real mine must be collected to be able to start the proposed research.

5. Conclusion

A comprehensive literature review about open pit mine planning with In-Pit Crushing and Conveying usage is outlined. Different time scales of mine planning are analyzed. Strategic open-pit planning is planning with a time span of several years to the whole mine life. There are some main objectives of long-term IPCC planning. These objectives include the optimization of the production schedule, the selection of the best crusher location and relocation position in the mine layout, and the comparison of the economic and technical feasibility of truck and shovel and IPCC usage when conducting the feasibility study and technical mine planning.

In comparison to long-term, short-term planning is referred to as a term for planning operations with a period of weeks to several months. Short-term mine schedules need to account for the effects of the current IPCC location such as effective production capacity and haulage distance. In addition, the location(s) of the hauling equipment(s) need to be planned to ensure product quality (grade blending) and quantity for the mine to be profitable and produce an ore concentrate with constant chemical properties.

After the literature review, a research agenda is described. The statement describes the approach of performing a scenario analysis to answer questions about the ideal design of an IPCC system before the inauguration of this haulage method at a mine site. The scenario analysis, with Discrete Event Simulation, is a decision-making tool helping to quantify capacities, layout, and type of IPCC equipment. In this section, the basic methodology and procedure of action for the realization of this planning approach are outlined. In addition, the methodology to create an effective optimization model for the calculation of the optimal semi-mobile crusher location is described. The methodology includes a case study within a tabular oil sand deposit.

In future research, input data from a real mine must be collected to be able to start the proposed research. Additionally, increased consideration of the described neglected decisive factors in calculations or simulation models is important.

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Quantifying Operational Uncertainty: An Integrated Framework for Enhancing Efficiency in In-Pit Crushing and Stockpiling vs. In-Pit Crushing and Conveying Methods

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ABSTRACT

Conveyor operations have demonstrated significant cost advantages over truck systems for long-distance transportation, leading to the adoption of the In-Pit Crushing and Conveying (IPCC) method as a superior alternative, particularly at greater mining depths. Recently, the In-Pit Crushing and Stockpiling (IPCS) method, or near-face stockpile (NFS) mining, has emerged, separating the process into truck-to-stockpile and stockpile-to-crusher stages, which reduces the impact of mining rate fluctuations on milling and enhances system resilience. Studies indicate IPCS improves equipment utilization, stabilizes the mining system, and boosts production compared to traditional methods, but its specific enhancements over IPCC in risk resistance have not been quantified. This paper addresses this gap by developing an optimization model for IPCC using mixed integer linear programming and a discrete event simulation using Arena to simulate operations and incorporate uncertainties. Comparative analysis with real mine data shows IPCS increases equipment utilization (1.67% for shovels, 1.94% for crushers), annual output (2.28%), and reduces truck utilization (2.03%), highlighting its efficiency in managing operational uncertainties. In conclusion, IPCS enhances mining system efficiency and resilience compared to IPCC, particularly in managing uncertainty, warranting further research to refine and apply this framework across different mining environments.

***Keywords**: IPCC, IPCS, stockpile, near face stockpile, discrete event simulation*

1. Introduction

Conveyor operation costs have consistently demonstrated significant advantages over trucks in long-distance transportation, as evidenced by numerous past operations and studies [1, 2]. Building on this foundation, the in-pit crushing and conveying (IPCC) mining method has emerged as the predominant alternative to the traditional truck-shovel system. Despite certain drawbacks, such as high initial investment and complex management, the appeal of IPCC increases as mining depths grow deeper, rendering truck investments less cost-effective. Consequently, IPCC has gained widespread adoption due to its superior investment returns over the mine's entire life cycle [3].

In recent years, an innovative approach combining the IPCC method with in-pit stockpiling—referred to as the In-Pit Crushing and Stockpiling (IPCS) method or near-face stockpile (NFS) mining method—has garnered attention. The layout of IPCS is illustrated in Figure 1. Unlike the IPCC

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method, in which the mining and milling systems are directly connected through the interaction of trucks and shovels to form an integrated whole, IPCS differentiates this interaction into two independent stages: truck-to-stockpile and stockpile-to-crusher. This separation significantly mitigates the impact of mining rate fluctuations on the milling system and enhances the mining system's resilience to uncertainty.

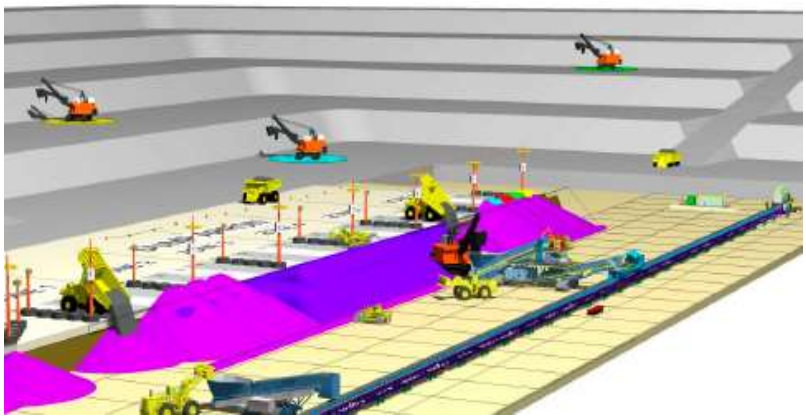

Figure 1. Pit bottom layout of IPCS mining method [4].

Previous studies indicate that IPCS, compared to the traditional truck-shovel method, improves equipment utilization, stabilizes the entire mining system, and boosts mining production [5, 6]. However, the specific enhancements in risk resistance offered by IPCS over IPCC have not been quantified. This paper aims to address this gap by quantitatively verifying the improvements of IPCS over IPCC under operational uncertainties. To achieve this, we propose a framework that integrates optimization and simulation, providing a comprehensive analysis of IPCS's advantages.

2. Literature Review

IPCC is a crucial innovation in the field of mining engineering, designed to enhance efficiency, reduce costs, and minimize environmental impacts by replacing conventional truck haulage with conveyor belt systems. The concept of IPCC dates back to the early 20th century, with initial implementations focused on reducing the reliance on haul trucks. Early systems faced significant technical and economic challenges, such as inadequate technology for efficient material handling and high initial capital costs [7]. Early studies highlighted these early challenges, emphasizing the limitations in conveyor technology and the lack of automation, which hindered the widespread adoption of IPCC systems [8].

Significant advancements in technology during the latter half of the 20th century and into the 21st century have revitalized interest in IPCC. Improvements in conveyor belt technology, automation, and control systems have addressed many of the initial challenges. Research by [9] underscores the role of these technological advancements in enhancing the efficiency and reliability of IPCC systems. For instance, modern conveyors can now handle higher capacities and longer distances, making IPCC a more viable option for large-scale mining operations.

The integration of automation and sophisticated control systems has been pivotal in enhancing the operational efficiency of IPCC. Automated control systems enable real-time monitoring and adjustments, optimizing material flow and reducing downtime. In 2015, a study [10] discussed how these advancements have made IPCC more viable and attractive for large-scale mining operations.

Several case studies demonstrate the successful implementation of IPCC systems in diverse mining operations. An early study [11] documented a copper mine where IPCC significantly reduced operational costs and enhanced productivity. Another study showed that the overall NPV of IPCC

can be improved by more than 3% compared with the traditional truck-shovel hauling system [12]. A simulation study in large-scale mining operations showed that semi-mobile IPCC achieved better performance than fixed layout [13]. On top of that, some scholars have proposed a mathematical model for semi-mobile IPCC to further reduce its transportation cost [14]. In addition to the cost reduction, through conducting a Fuzzy decision-making trial evaluation laboratory, it is proved that the deployment of IPCC can significantly reduce the number of traffic accidents [15].

The focus on sustainability has driven further innovations in IPCC. Modern IPCC systems are designed to minimize environmental impact by reducing greenhouse gas emissions and energy consumption. An iron ore mine using IPCC was declared that it achieved substantial reductions in greenhouse gas emissions by replacing diesel trucks with electric conveyors [16]. Studies by [17] and [18] emphasized the environmental advantages of IPCC. Comprehensive econoamic analyses and cost-benefit studies have underscored the long-term financial advantages of IPCC systems. Despite the high initial capital expenditure, IPCC can lead to significant cost savings over time. In 2017, research [19] provided a detailed cost analysis, demonstrating the potential for substantial economic benefits, particularly for large-scale mining operations. Some scholars are committed to the optimization of mining sequence in IPCC via varied time resolution and have proposed some linear models to improve NPV and algorithm for fleet control for higher efficiency [20–28].

Although modern IPCC systems offer substantial operational and environmental benefits, making them an attractive alternative to traditional truck haulage for large-scale mining operations, high initial investment costs, lack of flexibility, and maintenance challenges remain significant barriers to widespread adoption. IPCS is a new mining method proposed based on IPCC that can partially solve the lack of flexibility and risk resistance of IPCC. Although some studies have shown that IPCS has obvious advantages over the traditional truck-shovel mining method, a direct comparison between IPCC and IPCS is still missing, which is also the gap that this paper attempts to fill.

3. Methodology

The first part of this section provides a detailed overview of the establishment of IPCC and IPCS simulation models, along with the software and technology that support them. The second part discusses the selection and introduction of case studies. The final part focuses on the verification of the simulation model, which is crucial for enhancing the credibility of the subsequent result comparison.

3.1. Simulation Modeling

This section begins by elaborating on the process of establishing simulation models for the IPCC and IPCS methods. It starts with summarizing and generalizing the similarities and differences between these methods in their operational activities, leading to the creation of corresponding frameworks. Following this, the section introduces the use of macros—a technology that addresses the limitation of the simulation models being case-specific. The application of macros allows for modular and automated construction of various components within the simulation models.

3.1.1. Framework

In a conventional surface mining system, the working area typically comprises the following elements: polygons (also known as blocks or faces to be moved), several electric shovels, a fleet of trucks, an expanding road network, crushers, processing plants, and stockpiles (positioned at various locations based on needs). Mining, therefore, is not a singular activity but rather the sum of all activities performed by these elements, which are interconnected primarily through the trucks and influence each other. For example, in an oil sands mine using the conventional IPCC method, the main activities can be summarized as follows:

1. Shovels are allocated to working polygons and request trucks by following a predetermined mining schedule.
2. Trucks haul material to shovels.
3. Shovels begin digging the assigned polygons and loading the trucks.
4. Full trucks travel to determined destinations (crusher in the pit bottom or waste dump) based on materials grade.
5. Trucks unload material carried at the designated location.
6. Trucks are assigned to a shovel for an empty return trip and are reloaded at the shovel locations.
7. The crusher processes the ore material to an acceptable particle size.
8. Crushed ore is conveyed to the slurry plant.
9. The slurry plant grinds the minerals into smaller sizes and prepares a slurry.
10. The slurry is transferred to the processing plant to produce the final product.
11. The crude oil from the processing plant is either sold in the market or sent to a refinery.

The IPCS method involves some variations in these steps. Specifically, in step 5, dumping trucks deposit material into a stockpile located in front of the crusher. As a result, trucks no longer directly feed the crusher, and an additional shovel is required to manage feeding the crusher as needed. Figure 2 illustrates the framework of the IPCS method. In the generated IPCS simulation model, there is only one stockpile divided into three zones, with four dumping spots available for each zone. A reclaim shovel retrieves materials from the stockpile zones in a specified order. These materials then proceed through the crusher, conveyor belts, and slurry plant before being pumped out of the pit.

3.1.1. Macros

A common disadvantage of simulation models is their case-specific nature and 'hard coding,' making it nearly impossible to transfer them to different scenarios. This limitation arises from various factors, including the vastly different burial conditions and physical properties of minerals in different regions. Additionally, equipment choices can significantly impact the final extraction boundary. Other influencing factors include variations in environmental policies, mining methods, capital costs, worker capabilities, and engineers' experience. As a result, automatically generating a corresponding simulation model by defining just a few key parameters is challenging. While complete automation remains unrealistic at this stage, semi-automation can enhance simulation efficiency and reduce the case-specific nature of simulation models. Given the common bottom structure of the IPCS method compared to the IPCC method, this study developed a semi-automatic model to simulate both IPCS and IPCC methods by varying stockpile capacities (either zero or a specified number) and incorporating dumping and loading logic.

Considering this, Arena, a well-established discrete event simulation software, is utilized in this research to build the simulation models due to its ability to manage both the discontinuous and continuous nature of mining activities. Additionally, its compatibility with macros and its capability to read and store data externally greatly enhance the model's establishment and operation. The macro in Arena reads equipment parameters, quantities, and road information from an Excel spreadsheet, allowing the model to be easily adapted to other mining scenarios using the same methodology. The macro performs the following functions:

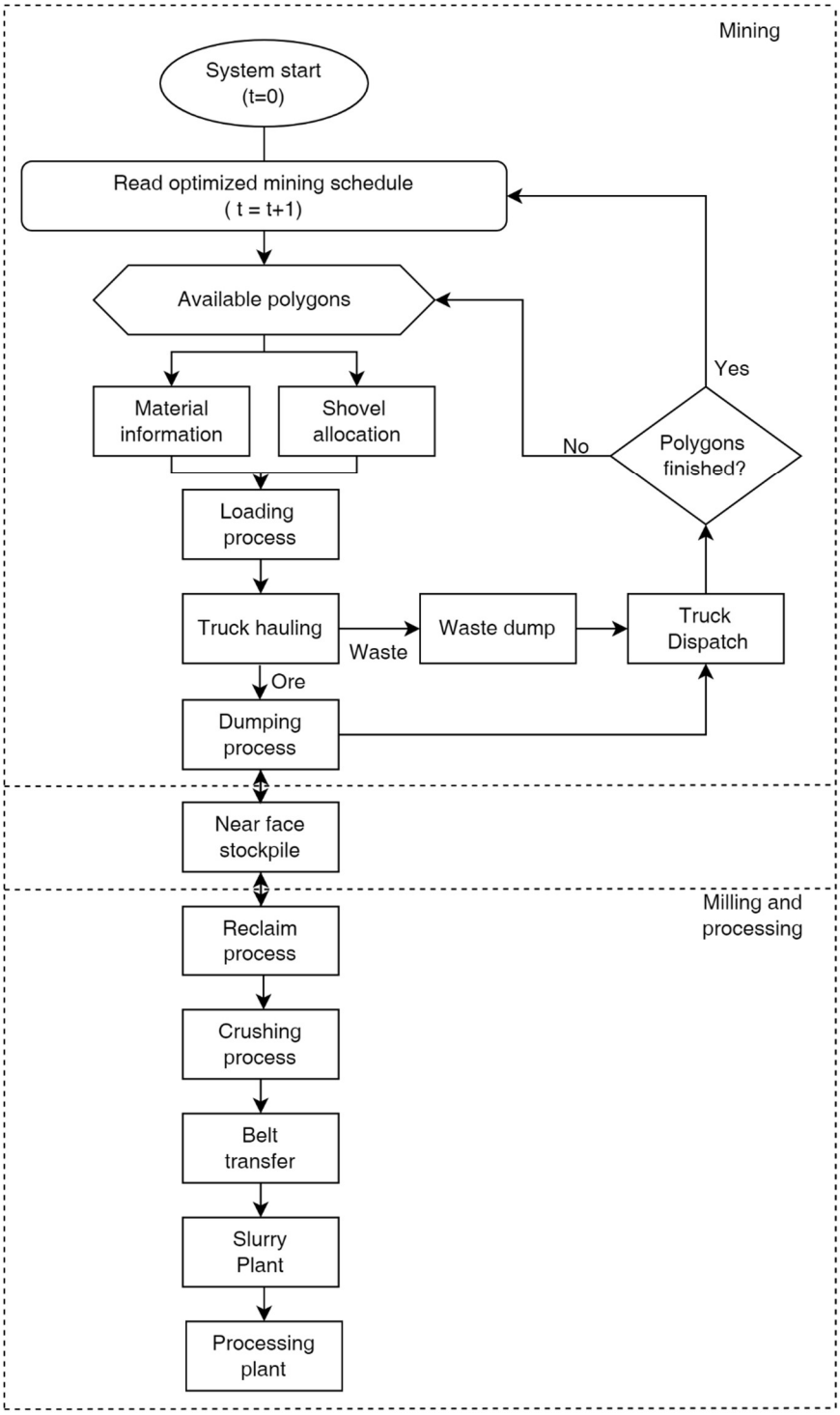

Figure 2. Framework of IPCS mining method.

1. Reads polygon data (including tonnage, grade, rock type, sequence, and coordinates) to build the polygon set.
2. Reads related data to construct 'tanks' for dumping zones, crushers, and slurry plants, and establishes corresponding regulators based on capacity and other factors.
3. Create variable sets for each dumping point to track status.
4. Develops a mining shovel resource set for the mining process.

5. Constructs a sub-model for dumping decision-making.
6. Builds a sub-model for the reclaiming process and corresponding level changes (IPCS model only).
7. Constructs a sub-model for checking the status and level changes of crushers and dumping zones.
8. Develops the conveyor system and processing system.
9. Creates stations for each mining, dumping, and processing location, establishing station sets for each branch system and classifying these stations into different sets.
10. Constructs the road network system and inputs the distances between stations.

In ARENA software, conveyors are modeled using the incorporated ready-to-use module. However, specialized simulation constructs are not always necessary for conveyor modeling. Instead, conveyors can be effectively represented using either a PROCESS module or a DELAY module with a deterministic delay. This delay parameter accurately reflects the time required for an entity to move from one location to another during sliding. The simulation models also account for uncertainties such as truck and crusher failures, which significantly contribute to operational uncertainty.

3.2. Case Study

To effectively compare the IPCS and IPCC methods, we selected an oil sand mine instance with an annual output of 93.1 Mt, of which 60.7 Mt is derived from mining, as the simulation subject. Figure 3 illustrate the road network of the chosen mine instance.

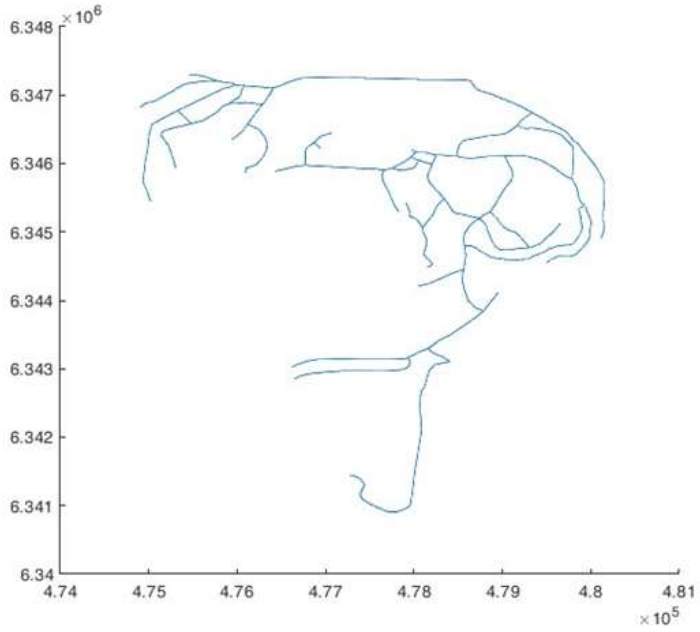

Figure 3. Road network of the oil sands mine.

While this paper primarily focuses on simulating the IPCC and IPCS methods, the mining sequence has a critical impact on mining output and can significantly affect the evaluation of a mining method. To ensure a fair comparison between the IPCC and IPCS methods, it is essential that both methods operate under an optimal or near-optimal mining sequence to enhance the credibility of the simulation results. To determine the best mining sequence, this study utilizes the mixed-integer linear programming optimization method outlined in the authors' previous work [6]. The optimized mining sequence will serve as the input for both simulation models, which will be constrained by the

underlying logic to operate within an effective mining sequence, thereby ensuring credible simulation results.

By comparing the simulation results of the IPCC and IPCS methods, this study aims to quantitatively demonstrate the improvements of the IPCS method over the IPCC method while considering operational uncertainties.

3.3. Verification

Although the two methods share significant similarities and utilize the same input parameters, the software itself introduces randomness during the simulation process. Consequently, before further comparing the simulation results of the two methods, it is essential to verify the accuracy and reliability of the simulation models. This section focuses on analyzing the effectiveness of the simulation results by examining five independent variables in both models.

Table 1. Independent variables comparisons of two models.

Category	Range	Mean	Summation
Average loaded tonnage/truck(ton) - IPCC	470 ± 0	336 ± 0.45	62334106 ± 194852
Average loaded tonnage/truck(ton) - IPCS	470 ± 0	336 ± 0.28	63741722 ± 83067
Difference	0.00%	0.00%	2.26%
Loading time(min) - IPCC	5 ± 0	2.89 ± 0	536066 ± 1592
Loading time(min) - IPCS	5 ± 0	2.89 ± 0	548306 ± 1274
Difference	0.00%	0.00%	2.28%
Dumping time(min) - IPCC	1.62 ± 0.19	0.95 ± 0	176691 ± 591
Dumping time(min) - IPCS	1.64 ± 0.09	0.95 ± 0	180767 ± 361
Difference	1.23%	0.00%	2.31%
Empty speed(km/h) - IPCC	63.2 ± 5.0	28.6 ± 0.05	5309683 ± 20592
Empty speed(km/h) - IPCS	64 ± 3.3	28.6 ± 0.04	543009 ± 12366
Difference	1.31%	0.00%	2.27%
Full speed(km/h) - IPCC	58.4 ± 0.8	26.1 ± 0.03	4839876 ± 12161
Full speed(km/h) - IPCS	58.5 ± 0.6	26.1 ± 0.04	4951775 ± 7113
Difference	0.26%	0.04%	2.31%

Figure 4 presents the QQ plots for the simulation results of truck payload per cycle, truck dumping time, truck loading time, and truck empty speed for both simulation models. When combined with the data described in Table 1, it is evident that the simulation results for these independent variables are highly consistent between the two models, thereby verifying the effectiveness of the simulation models.

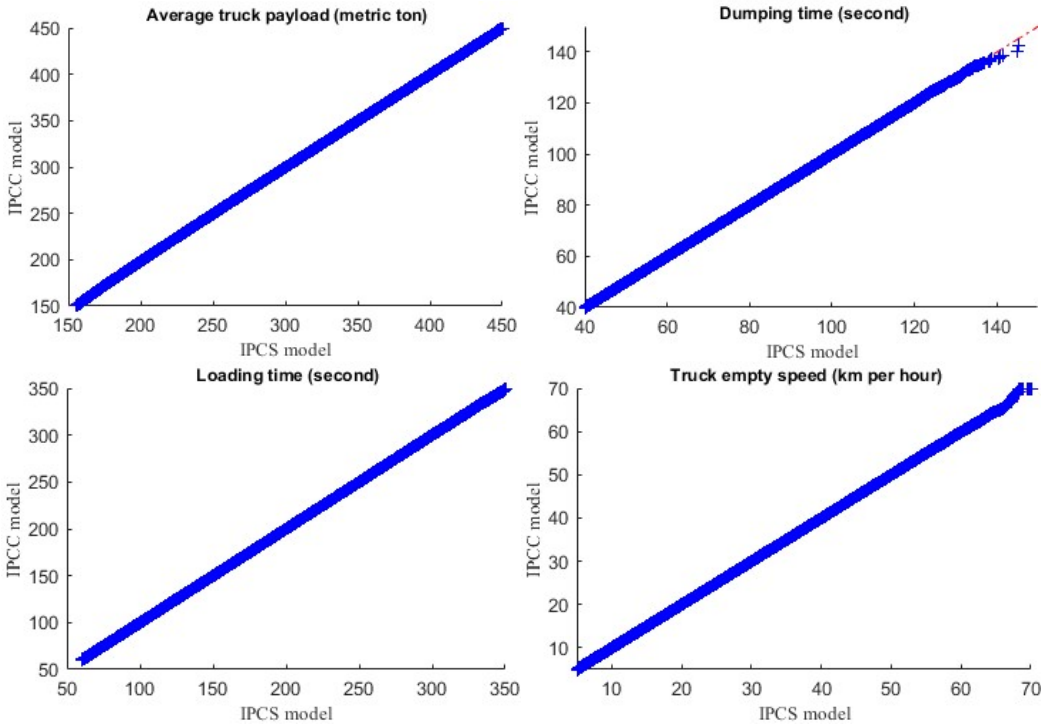

Figure 4. QQ plots of some independent variables in two models.

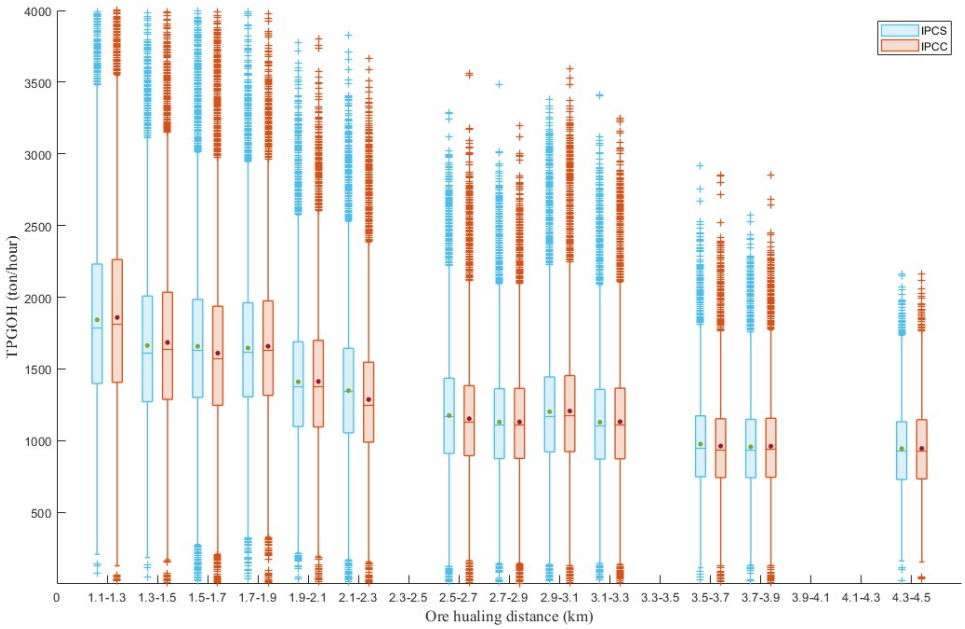

Figure 5. Simulated TPGOH of IPCC and IPCS mining methods.

In addition to independent variables, it is crucial to compare the simulation results of certain dependent variables to ensure that the simulation models accurately represent the two different mining methods. Common dependent variables include truck queuing time before shovels, empty/full truck hauling time, truck cycle ready time, and tons per gross operating hour (TPGOH), among others. For illustration, TPGOH is used to compare the simulation results of the two models. As shown in Figure 5, both the IPCS and IPCC methods exhibit a significant downward trend in TPGOH with increasing transportation distance. This trend confirms that the simulation results are consistent with actual operating results, expert assessments, and engineering expectations. Therefore,

the established simulation models accurately simulate the real activities in a mine, thereby verified the correctness of the models.

4. Results

4.1. Equipment Utilization

The utilization rates for shovels and crushers exhibit some improvements in the IPCS scenario compared to the IPCC scenario. Specifically, the average utilization rates for shovels and crushers in the IPCS scenario increased by 1.67% and 1.94%, respectively, as depicted in Figure 6. These results underscore IPCS's enhanced capability to manage equipment effectively under uncertain operational conditions. Conversely, Figure 6 also shows that the utilization of trucks in the IPCS scenario declines by 2.03%. This decrease is attributed to IPCS's effectiveness in mitigating truck queuing at crusher sites and reducing overall truck occupancy rates. As a result, IPCS demonstrates a reduced dependency on trucks compared to the IPCC scenario, further emphasizing its operational efficiency amidst uncertainty.

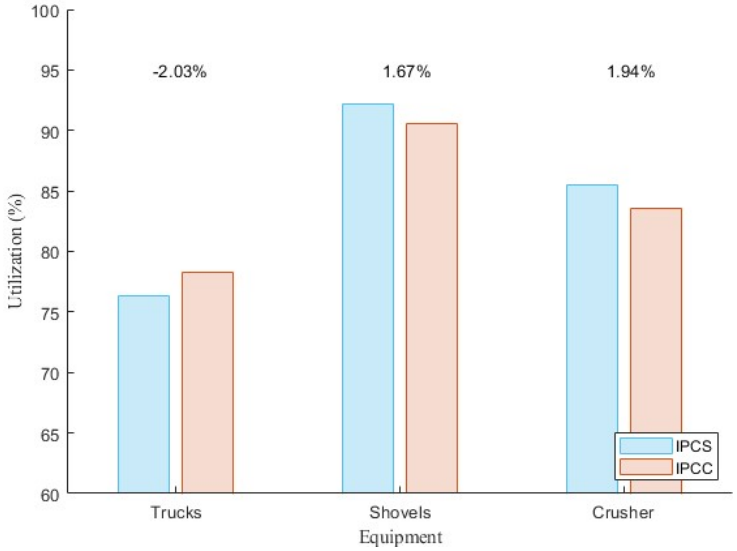

Figure 6. Trucks, shovels, and the crusher's average utilization of IPCC and IPCS scenario.

4.2. Crusher Output

This section evaluates the performance of the crusher under the IPCC and IPCS mining methods, focusing on production, defined as the output from the crusher. Figure 7 presents a comparison of crusher output performance on a yearly basis between the IPCS and IPCC methods. It is evident that the IPCS method consistently surpasses the IPCC method in crusher output, with an average annual increase of 2.28% across ten replications.

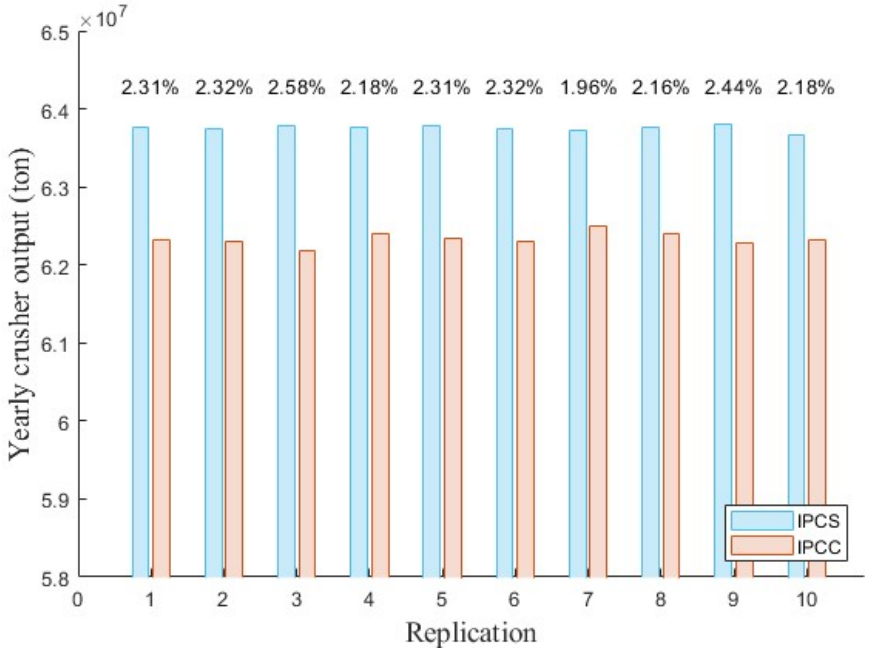

Figure 7. Shovels' annual productivity comparison of two methods.

Given that the same equipment, parameters, and mining sequence are used, the observed improvement in simulation results is primarily attributed to the inclusion of a stockpile in the IPCS method. This enhancement confirms that IPCS offers superior production and, consequently, better returns compared to the IPCC method.

4.3. Stockpile

Figure 8 illustrates the daily differences between the input and output of the near-face stockpile in the IPCS mining method, as well as the difference between the input and output of the crusher in the IPCC mining method. A positive difference indicates that the stockpile feeding tonnage exceeds the crusher's productivity, while a negative difference means the crusher's productivity is higher than the stockpile feeding rate.

In the IPCC method, which lacks a stockpile, the crusher's productivity per unit of time is expected to be less than or equal to the feeding rate. Consequently, crusher productivity will fluctuate in tandem with the feeding rate, unless a stable feeding rate is ensured. The simulation results for the IPCC method, depicted by the orange dotted line, confirm this pattern, showing a small difference between the feeding rate and productivity that fluctuates around zero, within one or two loads.

This characteristic is a common limitation of current mining methods, including IPCC, and is a problem that the IPCS method seeks to address. The IPCS method incorporates a pre-crusher stockpile, which acts as a buffer between the mining and crushing systems. The results, represented by the blue line in the figure, show noticeable volatility, indicating that the pre-crusher stockpile is functioning as intended. When the difference is positive, the stockpile holds excess ore material, while during periods of reduced feeding rates, it releases stored materials to ensure consistent crusher operation. This buffering process enhances the system's ability to manage uncertainties, significantly improving the crusher's capacity to maintain stable productivity.

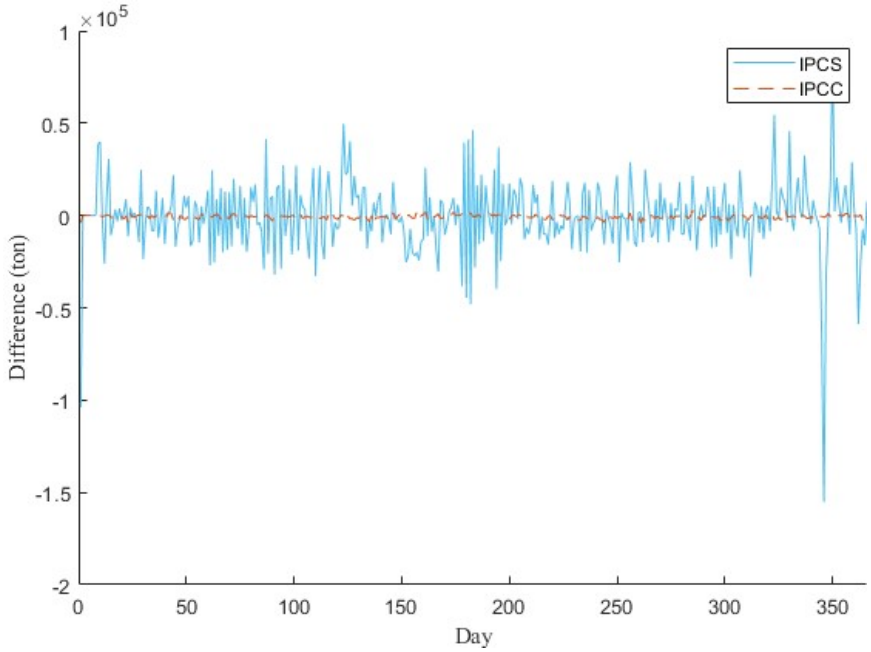

Figure 8. Stockpile/crusher input tonnage minus output tonnage on daily basis.

This stability is a key reason the IPCS method achieves higher production rates compared to the IPCC method, given the same crusher capacity. The IPCS method benefits from its ability to buffer and manage uncertainties, resulting in more consistent production rates. In contrast, the IPCC method, due to the direct linkage between the mining and crushing subsystems, lacks the capacity to effectively handle uncertain events, leading to less stability and lower production rates.

5. Conclusions

This study validates the effectiveness of the IPCS method in enhancing the operational efficiency and resilience of mining systems compared to the traditional IPCC method, with a focus on quantifying and managing operational uncertainty. By integrating a mining sequence optimization model with a discrete event simulation model, the authors developed a comprehensive framework for assessing the performance of both IPCC and IPCS methods under varying operational uncertainties.

Simulation results, based on ten replications per scenario, show that the IPCS method enhances the utilization of shovels and crushers, with average increases of 1.67% and 1.94%, respectively. Additionally, the IPCS method leads to a 2.28% improvement in annual output, underscoring its potential for greater operational efficiency in uncertain conditions. Moreover, truck utilization decreased by 2.03% under IPCS, reflecting a reduced demand for trucks and improved logistical efficiency.

These findings highlight the IPCS method's superior ability to manage and mitigate operational uncertainties, presenting a more robust and efficient alternative for future mining method selection. Future research should aim to validate the credibility of the developed model through comparison of the simulated results against historically recorded data, refine this framework and explore its applicability in diverse mining environments and conditions, further quantifying the impact of various uncertainties on operational performance.

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Semi-Mobile In-Pit Crushing and Conveying vs. Truck-Shovel Systems: Long-Term Scheduling with Road and Conveyor Networks Integration

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ABSTRACT

In-pit crushing and conveying systems (IPCC) integrate crushing and conveying directly from the pit, minimizing the need for extensive truck fleets and haulage infrastructure that is typical in Truck Shovel systems (TS). This approach reduces truck-related costs and environmental impacts while enhancing operational efficiency. The current study optimizes long-term scheduling in open-pit mining operations by comparing IPCC and traditional TS systems. Our methodology employs a two-step mathematical optimization model to determine optimal crusher locations or crusher panels and establish a practical long-term extraction sequence. Through a comprehensive case study involving pushbacks with roads and conveyor ramps and analyzing different road and conveyor network configurations, we examine the capital and operational costs across four scenarios for the in-pit crusher: without a crusher, with an ore crusher, with a waste crusher, and with both ore and waste crushers. Results include comparisons of Net Present Value (NPV), tonne-kilometers traveled, total kilometers traveled, and the number of trucks required. Significant improvements in NPV are observed in scenarios with both ore and waste crushers, reflecting reduced hauling distances and operational costs. The waste crusher scenario also demonstrates substantial savings, while the ore crusher scenario shows moderate improvements compared to the base case without a crusher.

Keywords: *IPCC, Long-term planning, MILP, Crusher Panel, Road Network, Conveyor Network*

1. Introduction

Open-pit mining operations are constantly evolving to meet the demands of efficiency and cost-effectiveness in material handling. Traditional truck shovel systems (TS), although prevalent, face challenges such as high operating costs, operational efficiency, economic viability and environmental impacts. A promising solution to these challenges is the In-Pit Crushing and Conveying system (IPCC), which integrates the crusher within the mining pit and employs conveyor belts for material transport. This approach not only minimizes truck dependency but also enhances operational safety and efficiency and it could bring about a huge financial advantage through reduced operating costs, lower energy consumption, lower emissions and improved productivity. Nevertheless, the implementation of IPCC systems is complex, requiring meticulous planning regarding the crusher's location, capacity, and integration within the mine's overall design. Failing to properly plan for the IPCC's locations can disrupt the mining sequence and adversely affect the ultimate pit limit (UPL) design. This paper aims to address these challenges by proposing

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a comprehensive long-term planning methodology that optimizes the open-pit mine extraction sequence under four scenarios: full IPCC implementation, partial IPCC implementation for either of ore or waste material, and without IPCC.

In-pit crusher is an expensive option in the capital-intensive field of open pit mining making meticulous planning inevitable. The objectives of a precise production planning study are to optimize net present value (NPV) while minimizing net present cost (NPC). Mine planning is typically divided into two primary phases: long-term and short-term, with additional subphases such as medium-term and operational planning. Therefore, the adoption of IPCC technology demands comprehensive evaluation across both long-term and short-term planning horizons to ensure its effective implementation.

According to Al Habib et al., there are five types of IPCC studies published, including: 1) finding the optimal location for the IPCC, 2) industry-related research and viewpoints, 3) economic and environmental comparative studies, 4) mine planning optimization in the presence of the IPCC and TS systems, and 5) other related studies [5-6]. These categories encompass a broad range of research efforts aimed at enhancing the efficiency and sustainability of mining operations. For instance, studies focusing on the optimal location for IPCC systems delve into spatial analysis, pit alteration layout, pit slope adjustments, and the strategic placement of crushers to maximize operational efficiency. This topic has received considerable attention over time, ranging from early studies in the 20th century to more recent publications [2, 4, 20, 34, 54, 61].

Industry-related viewpoints studies from professionals and stakeholders, can be investigated through various aspects such as productivity issues, failure stories and detailed risks and challenges followed by implementation examples presented by in addition to the deep open pit mine application of IPCC system [19, 39, 41-42]. These perspectives provide an understanding of the practical implications and operational challenges associated with the IPCC system.

The studies explore the environmental impacts of mining haulage systems using Life Cycle Assessment (LCA) including comparative studies between TS and IPCC or conveyor systems. Awuah-Offei et al. developed a methodology to evaluate the environmental impacts of belt conveyors and truck haulage systems in a hypothetical hard rock gold mine in Alberta, Canada [10]. The study considered a 20-year mine lifespan, productivity of 4,000 tonnes per hour, and haul distances of 4 km to the waste dump and 15 km to the run-of-mine (ROM) pad. They used ISO 14040 standards for LCA and Monte Carlo simulations for uncertainty analysis, finding that truck haulage had lower global warming potential (GWP) and acidification potential (AP) compared to belt conveyors. Norgate and Haque conducted an LCA to estimate the greenhouse gas (GHG) emissions reduction potential of IPCC and ore sorting technologies in a hypothetical copper mining operation [45]. The study, focused on processing one tonne of copper ore, showed that IPCC could reduce GHG emissions by 4% to 22%, depending on the electricity source, while ore sorting offered greater GHG reductions with coal-based electricity but was less effective with natural gas. Erkayao and Demirel evaluated the environmental impacts of off-highway mining trucks and belt conveyors in a coal mining operation with a daily production of 20,000 tonnes transported over a 5 km distance [23]. Using SIMAPRO 7.3 software and data from equipment manufacturers, they found that trucks had higher acidification impacts due to diesel combustion, while conveyors had higher climate change impacts from coal-fired electricity. These LCA studies showed that trucks have lower acidification impacts than conveyors due to fuel combustion, but the environmental benefits of conveyors depend on cleaner electricity sources, with IPCC showing significant greenhouse gas reduction potential compared to trucks when natural gas is used instead of coal for electricity production.

Klanfar and Vrkljan compared stationary and mobile processing models for quarrying crushed dolomite for concrete aggregates, finding that mobile processing offers distinct advantages in reducing transport costs, environmental impact, and energy consumption [29]. Mobile plants process material directly on-site, reducing infrastructure needs and costs, especially effective in protected or spatially constrained fields. A case study at surface pits in Hercegovac and Oršulica Kosa demonstrates mobile plants' lower costs (€7.23/m³) compared to stationary ones (€8.03/m³) due to reduced transport distances. Similarly, Londoño et al. explore alternative In-Pit Crushing and Conveying (IPCC) configurations in an open cut coal mine in Central Queensland, Australia, highlighting the benefits of parallel conveyor lines with spreaders, which, despite higher Equivalent Unit Costs (EUCs), increase productivity by up to 12.6%, leading to an additional AUD 376 million over ten years [33]. Rahmanpour et al. applied a hub location model to minimize haulage costs in the Sarcheshmeh Copper Mine in Iran, suggesting the optimal location for an IPCC system at level 2450 [53-54]. The study emphasizes cost efficiency and environmental benefits, noting reduced truck requirements and overall lower operating costs. Roumpos et al. optimized the location of the belt conveyor distribution point (BCDP) in a lignite surface mine to minimize transportation costs [55]. Using a Matlab-based optimization algorithm, the study determines the BCDP location considering mine geometry and excavation sequences, showing significant cost savings influenced by optimal BCDP placement. All studies show the importance of IPCC placement to enhance operational efficiency, reduce costs, and mitigate environmental impact.

Paricheh and Osanloo employed a facility location model to address uncertainties in production and operating costs by focusing on scenario investigation for determining the optimal location of in-pit crushers at the Sungun Copper Mine in Iran [48]. The study aimed to minimize haulage costs and maximize NPV, using a semi-mobile crusher with a 2000 tons/hour capacity. This research simplifies the candidate location of the crusher to the gravity center of each extracting level. Additionally, the uncertainty handled through searching some known scenarios which can not be generalized. Paricheh et al. further investigated optimal placement and relocation of crushers at Sungun, utilizing a dynamic location-relocation problem model, and estimated a $150 million saving from the 6th year of operation by optimizing crusher locations and reducing haulage distances [50]. Paricheh et al. extended this research by addressing the optimal time and location problem for implementing IPCC systems in large open-pit mines [51]. Their heuristic approach divided the problem into determining the optimal location for the crusher and the optimal time for its application, resulting in a $150 million improvement in NPV by implementing the IPCC system in the 17th year of mine life. The case study at Sungun Copper Mine demonstrated a 1% NPV improvement by transitioning to IPCC at the optimal time and location. The focus of these two mentioned study by Paricheh et al. is to find the best locations and relocation time and maximizing NPV by minimizing haulage cost. As a result, the mine plan remained the same even by incorporating the in-pit crusher. Yarmuch et al. concentrated on Chuquicamata mine in Chile, using Markov chain models to determine optimal locations for a third crusher, considering equipment failure probabilities [72]. They concluded that an in-pit crusher configuration, although more expensive, was more reliable and cost-effective, influencing haulage distances and truck requirements over four years.

Abbaspour et al. explored safety and social impacts of different transportation systems in open-pit mining, comparing TS and various IPCC systems through system dynamics modeling [1, 3]. The study revealed that Fully Mobile IPCC (FMIPCC) had the highest safety index due to zero traffic density, while TS ranked highest in social indices because of higher employment and training rates. Abbaspour et al. formulated a transportation problem to determine optimal locations and relocation plans for Semi-Mobile IPCC (SMIPCC) systems in open-pit mines, demonstrating cost efficiency through minimized operating and relocation costs [2, 4]. The SMIPCC system is used exclusively

for ore and the relocation of the SMIPCC is analyzed at various intervals (every 12.5m to 75m). de Werk et al. conducted a comprehensive cost analysis comparing TS with IPCC in an iron ore prefeasibility study, finding that despite a 41% higher investment cost, IPCC reduced unit operating costs by 13.6%, making it more cost-effective long-term [18]. Nehring et al. investigated strategic mine planning approaches for IPCC versus TS systems in a conceptual simplified Australian copper orebody, finding significant economic benefits and improved resource recovery when using IPCC [43]. Nunes et al. evaluated the feasibility of SMIPCC in a Brazilian copper-gold mine, showing that despite higher initial CAPEX, SMIPCC had significantly lower OPEX, reducing life-of-mine costs by 28% and offering environmental benefits [47]. This substantial cost reduction and lower environmental impact highlighted the advantages of adopting SMIPCC over conventional truck haulage.

Table 1 presents an ample overview of post-2010 studies on the IPCC system. The table systematically categorizes each paper based on their case study and their critical parameters such as crusher types, crusher capacity, the presence of a road or conveyor ramp design, investment and operating costs of crushers and conveyors, and the type of material handled (ore, waste, or both). By consolidating this information, we highlight the key aspects that have been explored in recent research, providing a foundation for what we will present in this current research about the IPCC system implementations.

According to Table 1, a prominent effort in size reduction is evident in the case studies of the investigated research, particularly where mine planning and IPCC are modeled using mathematical methods due to the complexity of managing large open pits with numerous sophisticated constraints. There are constant indications of either haul truck roads, conveyor ramps, or both being ignored, leading the models to adhere to undesigned block models for optimization purposes, resulting in impractical outcomes. Additionally, there is a significant lack of knowledge regarding the capital and operating costs of IPCC systems, causing any trade-off studies between TS and IPCC to suffer from a lack of precision. Furthermore, some studies either did not provide or did not consider the capacity of the assumed operation and/or crusher, resulting in oversimplification of their cases.

When examining the studies that focus on mine planning in the context of applying IPCC systems, the following works can be mentioned. Paricheh and Osanloo, who developed a new mixed-integer linear programming (MILP) model to optimize the concurrent planning of open-pit mine production, truck fleet sizing, and IPCC systems [49]. Their objective was to enhance the net present value (NPV) and overall cash flow by integrating these aspects into a single optimization framework. Their case study, focusing on a copper deposit, employed hypothetical instances geometrically similar to real mines using semi-mobile IPCC systems. Shamsi et al. proposed a mathematical integer programming model to optimize open-pit mine production scheduling by selecting the optimal transportation system and SMIPCC [60]. Their case study on a copper reserve demonstrated that despite higher capital costs, the SMIPCC system significantly improved NPV to the traditional TS system. In these two instances, their models, though similar to real mines, were hypothetical. There is no indication of having roads or ramps in the model, so the distances were calculated based on the minimum distance rather than the shortest road or path, making it difficult to resemble a realistic scenario.

Table 1. IPCC research case studies comparison

		Case Study	Production Capacity (Million Tonnes per Year)	Crusher Type & Capacity	Road Design	Conveyor ramp	Investment Costs Crusher/ Conveyor	Operating Costs Crusher/ Conveyor	Ore/ Waste/ Both
1	Awuah-Offei et al. [10]	A hypothetical hard rock gold mine located in Alberta, Canada.	21 (Ore & Waste)	Not specified 4,000 tph	-	-	-	-	Both
2	Klanfar and Vrkljan [29]	The surface pits of dolomite for concrete aggregates named Hercegovac and Oršulica kosa near Orahovica.	-	Mobile impact crusher 110 - 300 m3/h	-	-	Stationary Crusher: €400,315 or €8.03/m³ crushing and screening operations and 1.8 km of conveying	Mobile Crusher: €361,487 or €7.23/m³ crushing and screening operations	Both
3	Londoño et al. [33]	Multiseam open-cut coal in Queensland, Australia	20-24 (Overburden)	Fully mobiled 10,000 tph	✓	✓	-	1.22 - 1.39 $/t (Equivalent Unit Cost)	Waste
4	Norgate and Haque [45]	A hypothetical copper mining and mineral processing operation	3.6	- -	-	-		Reduction by 0.18 - 0.82 $/t compared with TS option	Ore

5	Rahmanpour et al. [53-54]	Sarcheshmeh Copper Mine, Iran	40 (Waste)	Mineral Sizer (semi-mobile)	-	-	-	-	Waste
6	Roumpos et al. [55]	A Simplified lignite surface mine with 4 benches	8 - 10 (Different in different benches)	- -	✓	✓	€3520 per meter of conveyor length	-	Both
7	Dean et al. [19]	deep open pit metalliferous mine from various cases including a Brazilian iron ore mine and the Yimin He Mine in China	-	Fully mobiled 4,000 to 10,000 tph	-	✓	U$180-250 Million Fully mobile unit with conveyor components	-	Both
8	Erkayao & Demirel [23]	A conceptual production capacity of 20,000 tons/day of coal transported for 5 km. The comparison includes 23 off-highway trucks and 8 belt conveyors.	20,000 tonne per day	- -	✓	-	-	-	Ore
9	Paricheh and Osanloo [48]	The 10th year of the mine life, based on the Sungun Copper Mine	7 - 14	Semi-Mobile 2000 tph	-	-	-	-	Both

10	de Werk et al. [18]	An iron ore deposit. The mine model assumes a 500-meter diameter conical-shaped pit with constant bench heights of 20 meters.	8,000 tonne per day (ore) 12,000 tonne per day (waste)	Semi-Mobile 907 tph	✓		$1.6 to $3.3 Million - with additional costs of $1,300 to per meter based on in-pit or overland conveyors. $23.9 Million in Total for conveyors.[1]	$47.91 to $97.88 per hour, with labor costs of $67.43 to $137.71 per hour based on in-pit or overland conveyors	Ore
11	Paricheh et al. [50]	Sungun copper mine in Iran.	7 - 14	Semi-Mobile 4,000 tph	✓	Uses the haul road ramp for conveyors	$3000 per meter for conveyor	-	Ore
12	Yarmuch et al. [72]	The Chuquicamata copper mine examining the addition of a third crusher to improve the reliability	-	gyratory type 5,600 tph	-	Conveyor is installed in the tunnel	Crusher: approximately U$15 million, with an additional U$35 million for installation. Conveyor belts: approximately U$2500 per meter.	-	Ore

[1] Not Specified (-) in the road design and conveyor design might be assigned even for a case study that considered a road or conveyor ramp but not mentioned anything in the study or not provided any details about the design.

13	Abbaspour et al. [1, 3]	A hypothetical copper open pit mine with a total ore reserve of 700 million tonnes.	21.52	All crusher types	-	-	-	-	-
14	Nehring et al. [43]	A two-dimensional vertical cross-section, 25 blocks wide and 8 blocks deep. Each block contains 5 million tonnes of material.	15 for processing and 20 for mining	Semi - Mobile & fully - Mobile	-	-	$200 Million	$2.5 to $2 per tonne with 10% to 5% increasing rate for each lower level	Both
15	Paricheh et al. [51]	Sungun copper mine in Iran.	7 - 14	Semi - Mobile 4,000 tph	✓	Uses the haul road ramp for conveyors	the crusher relocation estimated at $1.5 million	-	Both
16	Rahimdel and Bagherpour [52]	Kahnuj titanium mine in Iran	4	fixed, semi-mobile, and fully mobile crushing systems 1333 tph	✓	-	-	-	Both Ore Crusher & Waste sizer

17	Abbaspour et al. [2, 4]	A hypothetical copper mine where the ore is extracted over five years across seven levels.	17.4	Semi - Mobile 3,000 tph	-	-		$0.2 to $0.42 per tonne	Ore
18	Nunes et al. [47]	A Brazilian copper-gold mine with a life of mine set at 20 years.	16	Semi - Mobile 3,805 tph to 2,718 tph	✓	-	SMIPCC CAPEX = $46.97M	-	Ore
19	Paricheh and Osanloo [49]	The constructed hypothetical instances geometrically similar to real open-pit mines	-	Semi - Mobile	-	-	-	-	Ore
20	Samavati et al. [57]	A hypothetical open pit mine with an East-West oriented main 'trunk' conveyor and includes details on the setup and operation of main, transfer, and bench conveyors.	15,000 tonne per day ore 30,000 tonne per day waste	Mobile crusher 3,000 tph	-	✓	$25 M	$5 per tonne for Crusher $1 per tonne for Conveyor	Both

21	Bernardi et al. [16]	A copper porphyry deposit, characterized by high tonnage and massive lateral and vertical extents, making it one of the largest types of open-pit mines in the world	-	Fixed Crusher Semi Mobile	✓	-	-	-	Ore
22	Shamsi and Nehring [59]	A conceptual cylinder-shaped copper deposit with an average radius and depth of 345 m and 670 m, respectively, and 20 m of overburden.	20	Semi Mobile 2690 tph	✓	✓	Crusher: $20 M Conveyor: $10.7	-	Both

23	Shamsi et al. [60]	A copper reserve with an outcrop at the surface and a uniform slope of 45 degrees. The final pit limit of this reserve is 1,000 meters deep, containing 137.5 Mt of ore, 127.5 Mt of waste, and an average Cu grade of 0.68%	20	Semi Mobile	-	-	$74 M more CAPEX for SMIPCC than the TS scenario	Average 0.0015 $/t . m	Both
24	Liu and Pourrahimian [32]	A small-scale copper mine dataset with 2006 blocks and six levels	30-25	Semi Mobile	-	-	$1million for crusher relocation	$0.3 per level·t for conveyors	Both
25	Wachira et al. [71]	A limestone quarry in Kenya	2.7	Semi Mobile	-	-	-	-	Ore
26	Gong et al. [26]	An iron mine with a block model comprising 19,561 blocks and a total of 430 million tons of material in its final pit	32	Mobile	-	-	-	$0.35 per tonne per km	Ore

27	Gong, et al. [25]	An oil sands mine case study with two working shovels and sixteen trucks was used to verify the proposed simulation and optimization model.	93.09	Semi Mobile	✓	-	-	-	Ore
28	Al Habib et al. [6]	An iron mine case study involving 16 million tonnes of ore and 35 million tonnes of waste over four benches	16 (ore) 35 (waste)	Semi Mobile 2700 tph	✓	-	-	-	Ore
29	Kamrani et al. (2024)[28]	Two pushbacks of an iron ore mine and ten benches including 9952 blocks	3.2 (ore) 7.1 (waste)	Semi Mobile -	✓	-	-	-	Ore + Ore & Waste scenarios

Samavati et al. introduced a new integer programming model to address the complexities introduced by IPCC systems in open-pit mining [57]. They aimed to maximize the NPV by optimizing block extraction schedules, conveyor placements, and integration of mining and processing capacities. They used a heuristic solution to manage the large-scale nature of the problem and the non-linear relationships between variables. Their case study featured a fully mobile IPCC system by considering the different compartments of the conveyor. The mathematical model in this study contains 16 constraints to honor block precedence based on the conveyor locations meaning that the model could grow exponentially in the real mine instances with the large number of blocks. Liu and Pourrahimian presented a methodology to optimize production scheduling and crusher location under SMIPCC systems, aiming to maximize NPV by simultaneously solving these problems [32]. They used hierarchical agglomerative clustering and an integer linear programming model to integrate material handling and crusher relocation costs into the NPV maximization process. Their case study on a small-scale copper mine indicated the importance of careful design and optimization of IPCC system layout, with substantial variations in NPV based on conveyor location.

Al Habib et al. proposed a methodology to generate monthly production schedules by optimally allocating shovels to maximize revenue while minimizing haulage costs [6]. Their case study in an iron mine demonstrated significant cost savings and increased efficiency with IPCC, reducing truck requirements by 35% and generating a higher objective function value. Gong et al. developed a MILP model to solve the long-term production scheduling problem in open-pit mines, comparing the performance of the Near Face Stockpile (NFS) mining method with traditional methods [26]. Their case study in an iron mine showed an improvement in NPV and in head grade deviation with the NFS method. Additionally, another study by Gong et al. introduced the NFS method, integrating IPCC systems with a pre-crusher stockpile to enhance stability and efficiency [25]. Their oil sands mine case study showed significant operational improvements and increased equipment utilization.

Kamrani et al. introduced a two-step methodology for optimizing in-pit crusher locations, focusing on minimizing haulage costs and maximizing the NPV [28]. Their model employs a k-medoids clustering algorithm to designate crusher panels as candidate locations for the in-pit crusher and a hierarchical clustering algorithm to create extraction units or blast polygons. The case study, involving an iron ore mine with two designed pushbacks and a road network, used the shortest path algorithm to calculate truck travel distances. Conversely, conveyor distances were calculated using the minimum distance method due to the absence of a conveyor ramp or conveyor network in the case study. The first mathematical model determines the optimal crusher panels and the best material tonnages to be processed while the crusher is in place. The second step schedules the extraction while respecting the physical precedence of the optimal crusher panels. This methodology demonstrated substantial reductions in haulage distances and a 15% improvement in cumulative discounted cash flow compared to scenarios without an in-pit crusher.

After a systematic review of artificial intelligence applications in strategic open pit min planning. Noriega and Pourrahimian stated that due to the scale of the life-of-mine plans, research solutions tend to metaheuristic algorithms which are case specific and cannot be generalized [46]. In long-term open-pit mine planning with an IPCC system, developing a practical and solvable model is essential. This model must account for additional constraints beyond those previously existing, creating a large-scale problem, and ensuring comprehensive and effective planning. According to Mariz et al. one of the dominant methods of scale reduction in the mine planning problems is block aggregation [36]. Askari-Nasab et al. proposed employing fuzzy logic clustering to generate mining cuts on a bench-by-bench basis [7, 9]. This method aims to improve the model size by aggregating blocks into meaningful clusters. Eivazy and Askari-Nasab further developed the fuzzy logic clustering algorithm into a fuzzy c-means approach for a short-term MILP model [22].

Koushavand et al. also utilized the enhanced fuzzy c-means to create mining cuts as extraction units for their stochastic strategic mine planning model [31]. Despite the limitation of not considering the spatial arrangement of mining pushbacks, fuzzy logic clustering for efficiency improvement was subsequently applied in various instances, including iron ore and oil sand mining [8, 13-14] .

To address the challenge of a mining cut encompassing blocks from adjacent pushbacks, which could result in suboptimal outcomes, Tabesh and Askari-Nasab developed a hierarchical clustering method based on an unsupervised machine learning technique [63]. This method uses a similarity index equation to group the mining blocks within each individual pushback. After its initial development, the approach was refined to enhance its functionality. Significant improvements included the automatic generation of mining polygons, a post-processing phase, and validation using a gold deposit, as detailed by Tabesh and Askari-Nasab [64]. Later, Tabesh and Askari-Nasab introduced an algorithm designed to manage geological uncertainty [65]. In this model, hierarchical clustering is applied separately to each ore-body realization, and the individual clustering are then combined to finalize the solution. These advancements highlight the methodology's robustness and adaptability in optimizing mining operations under complex geological conditions. The flexibility and reliability of this method have enabled numerous studies to apply the clustering approach, utilizing hierarchical clustering and Tabu Search, to aggregate mining blocks. This methodology has been employed in both strategic and operational mine planning contexts, transcending specific scenarios and significantly contributing to a broader understanding of optimizing mining operations efficiently [9, 11-12, 15 21, 35, 44, 58, 66-67, 68-70]. In the current study, we used the same similarity index function along with the hierarchical clustering method to create mining cuts that match the size of the blast polygons. The detailed calculations will be presented in the methodology section. This approach ensures that the mining cuts are not only consistent in size and shape with the blast polygons but also optimized for operational efficiency and resource management. We also aim to achieve a more systematic and coherent arrangement of mining cuts, which can lead to improved overall productivity and reduced operational costs.

In the latest application of mining block aggregation, Mariz et al. proposed a MILP-based mathematical model to achieve better control over the shapes of mining cuts [37]. They employed the similarity index function proposed by Tabesh and Askari-Nasab as their objective function, with the goal of maximizing it [63-63]. Also, they utilized a geometric propagation heuristic for refining the shapes of mining cut clusters. This method can modify the boundaries of the mining cuts to account for the constraints and capabilities of the mining equipment. This approach enhances the precision and efficiency of mining operations by ensuring that the cut shapes are optimized not only for geological and economic factors but also for the practical aspects of mining equipment operation.

Selecting optimal locations for crushers is crucial for the efficiency of IPCC systems, impacting both operational costs and productivity. The literature presents two categories of methods often used to select the candidate locations for the crushers which we can interpret as automated and manual. Automated methods typically follow a general principle for identifying candidate spots. Examples include dividing the deposit into slides [30], assuming a specific height or segmenting the pit circumference into different regions [2, 4, 32]. In contrast, manual selection focuses on the practicality of the location, with detailed considerations specific to each spot [48, 50-51]. For a detailed comparison of candidate locations in research studies, readers are referred to Kamrani et al. [26]. Assessments of these studies revealed that manual approaches often cannot be generalized due to their specificity. On the other hand, while less detailed, automated methods often seem impractical for many IPCC placements as they frequently overlook or excessively account for the spatial requirements necessary for effectively accommodating both in-pit crushers and conveyors.

Additionally, both approaches often ignore the distribution of nominated locations throughout the pit, making distance-based location optimization less effective.

we propose an automated method using the k-medoid clustering algorithm to select candidate locations, which we refer to as crusher panels. Each crusher panel's dimension is considered greater than or equal to the minimum mining width, providing sufficient space for the crusher and other necessary equipment, even in the narrower bottom benches of the pit. The implementation of a semi-mobile IPCC system requires establishing appropriate locations for various components, including dump points for trucks, the crusher feeder, and the conveyor belts up to the crusher discharge point. Each individual crusher panel should provide the required space for these components.

In this paper, building on the work of Kamrani et al., the optimization of IPCC systems is advanced by including a conveyor network in a real mine case study with the NPV calculation [26]. The methodology employs a two-step mathematical optimization model, modified to accommodate the new conditions and scenarios, to determine the optimal crusher panels and establish a practical long-term extraction sequence. This study includes detailed designs of the mining cuts as blast polygons or extraction units and the design of conveyor ramps and conveyor networks in a real mine-sized operation case study through which the model is verified. Additionally, a detailed cost analysis of in-pit crushing and conveying implementations is provided. The study encompasses a comprehensive case analysis involving five pushbacks, various road and conveyor ramp configurations, and multiple network scenarios. The capital and operational costs across four scenarios are evaluated: without a crusher, with an ore crusher, with a waste crusher, and with both ore and waste crushers. Because of the road distances and the possibility of calculating traveled distances, some key metrics such as total kilometers traveled, and the number of trucks required are compared. Figure 1 depicts a schematic view of five open pit mine pushbacks with road and conveyor networks, relative locations of different equipment, and crusher panels including two semi-mobile IPCC for different material types.

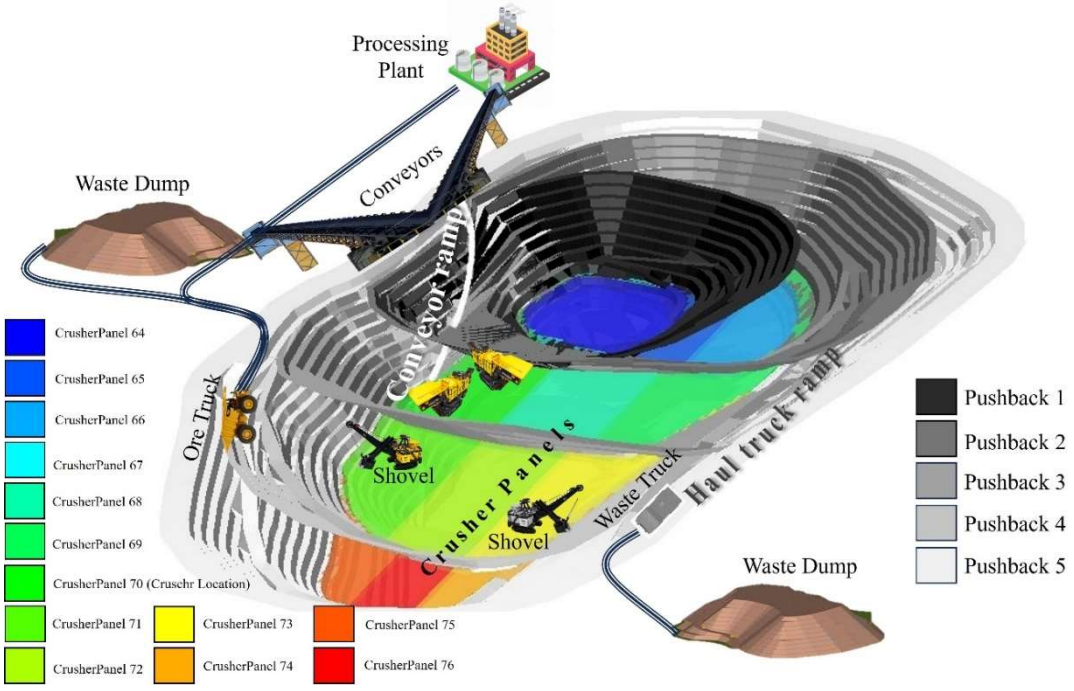

Figure 1. A schematic view of five open pit mine pushbacks with road and conveyor networks, relative locations of different equipment and crusher panels including two semi-mobile IPCC for different material types.

The significance of the current work can be summarized as proposing a comprehensive method that encompasses all four categories of previously mentioned published studies: 1) finding the optimal location, 2) addressing important industry viewpoints, 3) evaluating the IPCC option through comparative scenarios, and 4) optimizing long-term mine planning in the presence of IPCC and TS systems. This method involves designing size-managed mining cuts to represent more practical extraction units as blast polygons, ensuring these cuts are relatively rectangular in shape and contain enough blocks to feed the production until the next blasting time. It also includes proposing crusher panels as candidate locations for the crusher, which are created automatically using k-medoid clustering and provide sufficient space for the crusher placement, trucks to queue and discharge material, and conveyors to be front-fed by the crushers. In addition, the method entails designing conveyor ramps to specify material flow location and direction, thereby guiding the process of finding the optimum crusher panel(s) and designing the road network to calculate truck travel distances and determine the required number of trucks. Furthermore, the work evaluates the capital costs of the IPCC using information acquired from real manufacturers of crushers and sizers, enabling an exact trade-off cost analysis between TS and IPCC through practical scenarios. Finally, it presents a near-optimal long-term schedule that honors the precedence of the optimum crusher panels, as well as slope precedence and extraction sequence. The study assumes deterministic input parameters, serving as a strategic decision support tool without addressing variability, conveyor belt design specifics, or installation requirements for in-pit crushers, and focuses on planning for a mine with a semi-mobile IPCC system, adaptable to fixed IPCC systems with minor modifications.

2. Methodology

The methodology involves a series of preparatory steps, along with explanatory data analysis. It begins with block model optimizations and designs and concludes with the block schedule. The starting point is optimizing the blocks to find the ultimate pit boundaries and pushbacks, accompanied by a long-term schedule. This process can be executed using any mine planning software, such as GEOVIA Whittle or any related proposed mathematical model [24]. However, to the best of our knowledge, no existing mine planning software can provide a mine schedule while accounting for the in-pit crusher and conveyor system. Consequently, the output from the mine planning software must be sent to the clustering stage. Here, a two-stage clustering method is applied as part of the explanatory data analysis to identify potential crusher locations, known as crusher panels, and block aggregations called mining cuts, which create a larger extraction unit. These identified crusher panels and mining cuts form the basis for solving the first and second mathematical models, which are MILP-based models capable of handling the required constraints. Figure 2 shows the detailed breakdown of the methodology stages highlighting the process flow from start to end.

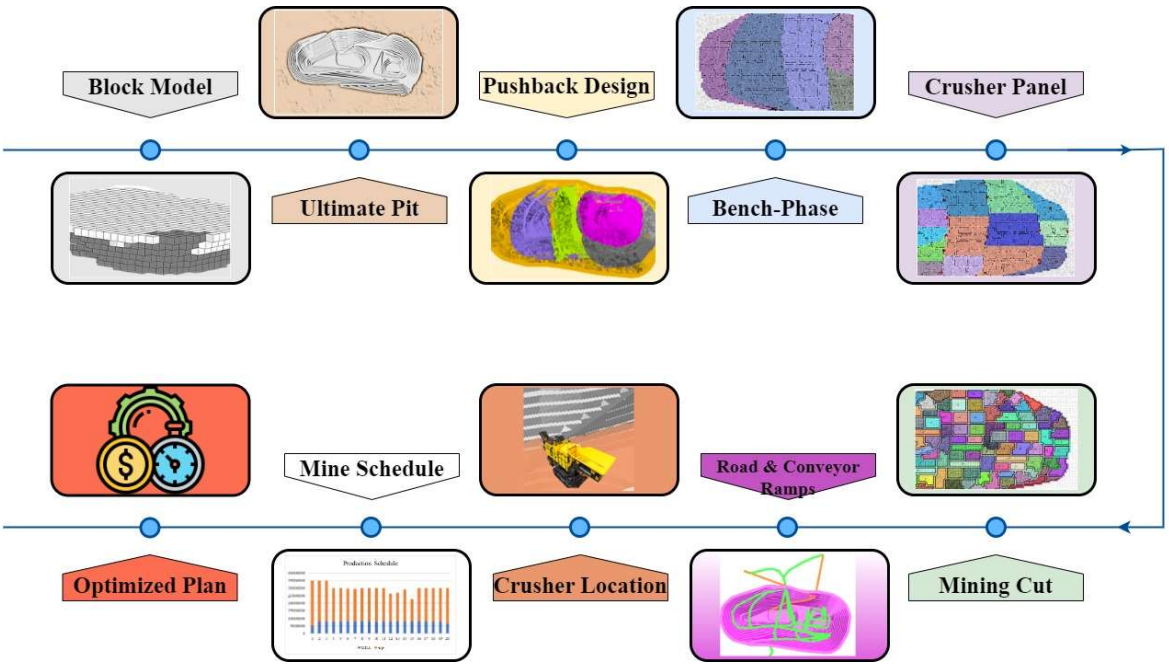

Figure 2. Detailed breakdown of the methodology stages, showcasing the process flow from start to finish.

2.1. Block Model & Design

The methodology starts with the block model optimization and design, a critical phase that lays the groundwork for all subsequent planning and scheduling. This begins with the use of advanced mine planning software, such as GEOVIA Whittle, or any appropriate mathematical modeling such as the one proposed by Tabesh et al. to optimize the block model [24, 67]. The optimization process involves identifying the ultimate pit boundaries and designing the necessary pushbacks to ensure a comprehensive long-term schedule. The optimized block model provides crucial insights into the most efficient and economical ways to extract the ore, considering various geological and operational constraints that have been suggested so far.

Once the pushbacks are designed, the block model is constrained by the pushback surfaces to create a detailed bench-by-bench model featuring the pushback boundaries, referred to as bench-phases. These bench-phases are essential for breaking down the mining process into manageable units, allowing for precise control over the extraction sequence. Each bench-phase is further partitioned into smaller extraction units, ensuring a structured mining process. This detailed block model not only aids in planning but also in visualizing the extraction process, making it easier to identify and address potential issues early on. The meticulously designed block model serves as the foundation for the subsequent clustering and scheduling stages, ensuring that the overall methodology can handle the complexities of modern mining operations.

The constrained blocks defined by the pushbacks' surfaces are categorized based on coordinates, pushback number, grade, metal content, recovery, block value, and block tonnage. Each subsequent clustering stage, whether creating crusher panels or mining cuts, maintains a record of the included ore and waste blocks. This allows for the calculation of the value, ore and waste tonnage, and metal content of the mining cuts or crusher panels. The grade and metal recovery of the mining cuts or crusher panels are averaged from the included blocks, although optimization focuses on the total value. Askari-Nasab et al. provided a detailed guidance on the parameters stored within the mining cuts [7, 9]. This same approach is used for crusher panels to record the history of the mining cuts, ensuring compliance with precedence rules defined as constraints in the mathematical model to manage the extraction process.

2.2. Crusher Panels

As discussed earlier, this study involves two separate clustering processes, each using a distinct methodology. The first stage aims to identify crusher panels for each bench-phase. Kamrani et al. proposed the concept of a “crusher panel” as a suitable location for an in-pit crusher, factoring in spatial needs for various components, and the k-medoids clustering algorithm is used to define these panels, effectively partitioning pushbacks and controlling their dimensions and orientation [28].

The k-medoids algorithm is a partitioning clustering method similar to k-means, but with a key difference: k-medoids selects medoids from the actual data points being clustered, unlike k-means, which uses the average as the cluster center. This makes k-medoids more suitable for our specific scenario involving mining cuts. The k-medoids clustering approach begins with k arbitrary clusters, each represented by a medoid (S1, S2, ..., Sk). Using these initial medoids, each cluster is updated by minimizing the distance to the performance function, resulting in new clusters (ck'). Within each cluster, the medoid is updated and the process checks for a stopping condition. If the new cluster configuration (ck') matches the previous one (ck), the process terminates. If not, the steps are repeated.

In the k-medoids clustering approach for defining crusher panels, the process begins by setting the number of clusters equal to the number of mining pushbacks in each bench-phases. Initially, k arbitrary clusters are selected, each with a representative point. For each cluster, the algorithm iteratively updates the cluster assignments, the representative point and the number of clusters until the distance between the representative becomes greater or equal to the minimum mining width, ensuring the clusters fit the spatial requirements. The algorithm continues by refining the clusters and their representatives, adjusting the cluster memberships to accurately reflect the constraints of the mining operation. Once this iterative process converges, the resulting crusher panels are determined, providing a practical configuration for the in-pit crusher that meets the spatial needs within the specified minimum mining width. Therefore, the first stage of this framework applies the k-medoids algorithm and categorizes each bench within its pushback to divide the pushbacks into crusher panels, followed by aggregating blocks within these panels while maintaining precedence relationships to create mining cuts, with the medoids optimizing the crusher's location by calculating distances and costs effectively.

2.3. Mining Cuts

As mentioned, dividing the deposit into individual blocks is a common practice. Blocks are usually rectangular in shape and uniform throughout the deposit. For decades, blocks were the extraction units of any open pit mine planning, but it was soon realized that optimizing an operation with such a large number of extraction units was impractical. To address this issue, aggregation techniques were developed to create continuous, minable plans that are practical and reduce the complexity of the problem. One approach involves using clustering algorithms to group blocks based on similarities such as rock type, ore grade, and distance or dissimilarities such as mineral composition, destination and environmental impact. In long-term open pit mine planning, block aggregation has been a common practice to reduce problem size and computational demands, and at the same time generating a practical plan in accordance with practical selective mining units. This aggregation can be simplified based on the technical attributes of the blocks, or it can be more sophisticated, using clustering methods that involve solving linear programming optimization problems. This paper discusses creating mining cuts using hierarchical clustering within crusher panels, which have already been clustered using the k-medoids algorithm.

In hierarchical block aggregation clustering for mining cut creation, the process starts with evaluating each crusher panel within the bench-phase. Initially, the number of clusters is set equal to the number of individual blocks, and both the similarity and adjacency matrices are initialized to

zero. The similarity matrix can be calculated using Equation 1 where sim_{ij} represents the similarity index between block i and j. RT_{ij} denotes the penalty assigned for different rock types between blocks i and j, with integer values starting from 1 indicating no penalty. $\widetilde{Dist}_{ij}$ and $\widetilde{Grade}_{ij}$ correspond to the normalized distance and grade difference between blocks i and j, respectively.

$$Sim_{ij} = \frac{1}{\widetilde{Dist}_{ij}} \times \frac{RT_{ij}}{\widetilde{Grade}_{ij}} \quad (1)$$

The adjacency matric estimates block distances that are smaller than the adjacency threshold and it can be calculated by Equation 2 where Adj_{ij} is the adjacency index and $Dist_{ij}$ is the Euclidean distance between centres of blocks i and j.

$$Adj_{ij} = (Dist_{ij} < Threshold) \quad (2)$$

The algorithm enters a loop that runs until the number of clusters is reduced to a specified maximum. During each iteration, the similarity and adjacency values for each block are calculated. If the combined size of two clusters is within the allowed maximum cluster size, the similarity and adjacency matrices are updated to reflect the merging of these clusters. A new cluster is then formed, and the total number of clusters is adjusted accordingly. This process of calculating values, updating matrices, and merging clusters continues iteratively until the number of clusters meets the desired maximum. The final output of this hierarchical aggregation is the creation of mining cuts, defined by the clusters formed throughout the process.

2.4. Shortes Path Algorithm

The ‘shortestpath’ function in Matlab relies on established algorithms from graph theory to determine the shortest path between two nodes in a graph [38]. Graphs consist of vertices (nodes) and edges (connections between nodes), where edges may have weights representing distances. The most common algorithms used are different variations of Dijkstra algorithm for graphs with non-negative weights. Dijkstra algorithm efficiently finds the shortest path by repeatedly selecting the node with the smallest known distance from the source, updating the distances to its neighboring nodes, and ensuring that once a node’s shortest path is found, it does not need to be revisited.

To use Dijkstra algorithm in the ‘shortestpath’ function, we need to calculate the distance matrix between all the mining cuts and crusher panels with the road network, and then from the crusher panel to the processing plant or waste dump with the conveyor network, under the following conditions. This is done after reading DXF files for both networks for each pushback and creating their appropriate graphs. For horizontal moves, i.e., from the mining cut to the road ramp entrance point and from the road ramp exit point to the crusher panel, the shortest distance will be used. For vertical moves, the shortest path will be determined by specifying the entrance point and exit point of the related elevation. Since the crusher panel assignment is automatic, any panel assigned without direct access to the conveyor ramp should be excluded from the distance matrix and the first step of the mathematical model. This condition, which occurred in our case study, led to the exclusion of nearly 43 crusher panels out of the total 215. However, to calculate the cost matrix required for both the first step and the second step of the mathematical model, as well as to handle all four scenarios of in-pit crushing, we need to find the shortest path from all mining cuts and crusher panels to the processing plant and waste dump using each of the road networks and conveyor networks, plus their horizontal shortest distance to the entrance point of road ramps and conveyor ramps at each elevation. Having these distances will also help us find important outputs needed for further analysis, such as tonne-kilometers, kilometers traveled, and the required number of trucks. Figure 3 provides the pseudocode illustration of the process of distance matrix calculations.

```
** Initialize graphs and distance matrices
FOR EACH Pushbacks
   READ DXF file for RoadNetwork
   RoadGraph{i} = create_graph_from_DXF(DXFFile)

   READ DXF file for ConveyorNetwork
   ConveyorGraph{i} = create_graph_from_DXF(DXFFile)

   ** Initialize distance matrices for road and conveyor networks
   DistanceMatrixRoad = initialize(numMiningCuts, numCrusherPanels)
   DistanceMatrixConveyor = initialize(numCrusherPanels, numProcessingPlant/s + numWasteDump/s)

   ** Function to calculate shortest path
   FUNCTION shortestpath(graph, source)
      FOR EACH vertex IN graph
         SET distance[vertex] = infinity
         SET previous[vertex] = undefined
      NEXT
      SET distance[source] = 0
      CREATE PriorityQueue
      ADD source TO PriorityQueue

      WHILE PriorityQueue is NOT empty
         CurrentVertex = vertex IN PriorityQueue WITH smallest distance
         REMOVE CurrentVertex FROM PriorityQueue

         IF distance[CurrentVertex] == infinity THEN
            BREAK
         ENDIF
         FOR EACH neighbor of CurrentVertex
            AlternativePath = distance[CurrentVertex] + EdgeWeight(CurrentVertex, neighbor)
            IF AlternativePath < distance[neighbor] THEN
               SET distance[neighbor] = AlternativePath
               SET previous[neighbor] = CurrentVertex
               ADD neighbor TO PriorityQueue
            ENDIF
         NEXT
      ENDWHILE

      RETURN distance, previous

   ** Calculate shortest path/distances for all required moves
   FOR EACH MiningCut
      FOR EACH CrusherPanel
         RoadDistance_vertical = shortestpath(RoadGraph{i}, MiningCut,CrusherPanel)
         RoadDistance_horizontal = MinimumDistance (MiningCut/CrusherPanel,RoadEntrance/RoadExit)
         RoadDistance[MiningCut][CrusherPanel] = RoadDistance_vertical + RoadDistance_horizontal

         ConveyorDistance = shortestpath(ConveyorGraph{i}, CrusherPanel,ProcessingPlant/WasteDump)
         DistanceMatrixConveyor[CrusherPanel][ProcessingPlant/s] = conveyorDistance[ProcessingPlant]
         DistanceMatrixConveyor[CrusherPanel][WasteDump/s] = ConveyorDistance[WasteDump]
      END
   END

RETURN DistanceMatrixRoad and DistanceMatrixConveyor
```

Figure 3. Pseudocode of the process of distance matrix calculations.

2.5. Crusher Locations

To determine the optimal locations for the crusher throughout the mine's life, the cost of transporting materials between different locations must be calculated. This cost is derived by multiplying each distance matrix by the cost factor according to their respective scenarios. For the first scenario, which involves only truck and shovel operations, there is no need to implement the initial step of the model. However, for the other scenarios, the formulation of the initial step varies.

The next quantitative involves creating an adapted version of the capacitated facility location model to identify the best locations for crushers. Although the model can accommodate flexible scenarios, the technical considerations for each material type and scenario, including conveyor components such as belts, rollers, frames, drives, pulleys, etc., must be carefully studied. To adapt the model to our scenarios, it is necessary to modify the equations, as each scenario requires a specific type of objective function and sets of constraints that are slightly different. The scenarios can be categorized as follows: 1) Ore IPCC scenario, where only one in-pit crusher handles ore materials, with conveyors installed on the conveyor ramp, while waste material is hauled out by trucks, 2) Waste IPCC scenario, where only a waste in-pit crusher transports waste materials with conveyors installed on the conveyor ramp on the same side of the pit, and ore materials are hauled out by trucks, 3) Ore & Waste IPCC scenario, where two in-pit crushers are placed on the same crusher panel using two different conveyors installed on an adequately spaced conveyor ramp, hauling both ore and waste materials out of the pit.

The three objective functions presented in Equations 3 to 5 correspond to the Ore IPCC, Waste IPCC, and Ore & Waste IPCC scenarios, respectively. The first component, which is shared among all three equations, accounts for the cost of installing the crusher on a specific crusher panel. This cost could be the same for all crusher panels or vary based on factors such as location, accessibility, and the physical properties of the bedrock, but it cannot be zero. In the Ore IPCC scenario, the second component calculates the cost of transporting ore tonnage from each mining cut to each crusher panel and sending the crushed material to the mill via the conveyor belt. The same applies to the second component of the Waste IPCC scenario, with the difference being that waste is crushed and hauled by the conveyor belt. In the Ore & Waste IPCC scenario, the components from the previous two scenarios are summed up. The following equations show the objective functions and constraints of the first-step model:

$$\min \sum_{p=1}^{P} (f_p \times y_p) + \sum_{k=1}^{K} \sum_{p=1}^{P} (co_{k,p} \times z_{k,p}) \rightarrow Ore\ IPCC\ Obejective\ Function \tag{3}$$

$$\min \sum_{p=1}^{P} (f_p \times y_p) + \sum_{k=1}^{K} \sum_{p=1}^{P} (cw_{k,p} \times s_{k,p}) \rightarrow Waste\ IPCC\ Objective\ Function \tag{4}$$

$$\min \sum_{p=1}^{P} (f_p \times y_p) + \sum_{k=1}^{K} \sum_{p=1}^{P} (co_{k,p} \times z_{k,p}) + \sum_{k=1}^{K} \sum_{p=1}^{P} (cw_{k,p} \times s_{k,p}) \rightarrow Ore\ \&\ Waste\ IPCC\ Objective\ Function \tag{5}$$

Subject to

$$\sum_{p=1}^{P} z_{k,p} = do_k \ \ \forall\ k \in \{1,...,K\} \tag{6}$$

$$\sum_{p=1}^{P} s_{k,p} = dw_k \ \ \forall\ k \in \{1,...,K\} \tag{7}$$

$$lMo_p \times y_p \le \sum_{k=1}^{K} z_{k,p} \le uMo_p \times y_p \quad \forall\, p \in \{1,...,P\} \tag{8}$$

$$lMw_p \times y_p \le \sum_{k=1}^{K} s_{k,p} \le uMw_p \times y_p \quad \forall\, p \in \{1,...,P\} \tag{9}$$

$$\overline{pu} \times \sum_{k=1}^{K} s_{k,p} - \overline{mu} \times \sum_{k=1}^{K} z_{k,p} \le 0 \;\forall\, p \in \{1,...,P\} \tag{10}$$

$$z_{k,p} \le do_k \times y_p \quad \forall\; k \in \{1,...,K\},\; p \in \{1,...,P\} \tag{11}$$

$$s_{k,p} \le dw_k \times y_p \quad \forall\; k \in \{1,...,K\},\; p \in \{1,...,P\} \tag{12}$$

$$z_{k,p},\; s_{k,p} \ge 0 \;\forall\; k \in \{1,...,K\},\; p \in \{1,...,P\} \tag{13}$$

$$y_p \in \{0,1\} \;\forall\; p \in \{1,...,P\} \tag{14}$$

Where:

- $p \in P$ is the index for crusher panels.
- $k \in K$ is the index for the mining cuts.
- f_p is the cost of installing crusher in the crusher panel p. It could be different for the crusher panels if they were not chosen within the same bench phase. Otherwise, it has the same value for all the crusher panels.
- y_p is a binary decision variable that is equal to one if the crusher is located in crusher panel p, otherwise zero.
- $co_{k,p}$ is the cost of transporting each tonne of the ore from mining cut k to crusher panel p and sending the crushed material to the mill via the conveyor.
- $cw_{k,p}$ is the cost of transporting each tonne of the waste in mining cut k to crusher panel p and sending the crushed material to the waste dump via the conveyor.
- $z_{k,p}$ is a continuous decision variable representing the tonnage of ore from mining cut k sent to crusher panel p.
- $s_{k,p}$ is a continuous decision variable representing the tonnage of waste from mining cut k sent to crusher panel p.
- do_k is the ore tonnage of mining cut k.
- dw_k is the waste tonnage of mining cut k.
- $\overline{pu}$ is the average of the upper bounds on the tonnage of ore processing capacity in all the periods.
- $\overline{mu}$ is the average of the upper bounds on the tonnage of mining capacity in all the periods.
- uMo_p is the upper bound on the total ore tonnage milled during the time that the ore crusher is located on the crusher panel *p*.
- uMw_p is the upper bound on the total waste tonnage dumped during the time that the waste crusher panel is located on the crusher panel *p*.

- lMo_p is the lower bound on the total ore tonnage milled during the time that the ore crusher is located on the crusher panel p.
- lMw_p is the lower bound on the total waste tonnage dumped during the time that the waste crusher is located on the crusher panel *p.*

As mentioned, Equation 3 to 5 serve as the objective functions of various scenarios which in the given formulations aimed at minimizing the cost of installing the crusher and transporting ore and waste materials. Equations 6 and 7 ensure that all ore and waste tonnages from each mining cut are extracted and assigned to a crusher panel. For the Ore IPCC scenario, only Equation 6 is implemented, and for the Waste IPCC scenario, only Equation 7 is implemented. However, for the Ore & Waste IPCC scenario, both Equations 6 and 7 are necessary. Equations 8 is for the Ore IPCC and Equation 9 is for the waste IPCC and both are required for the Ore & Waste IPCC. These Equations establish lower and upper limits for ore and waste, on the total ore tonnage milled or the total waste tonnage dumped during the time that the crusher is located on crusher panel p. Equation 10 is specific to the Ore & Waste scenario, ensuring that both crushers in the selected optimal crusher panel are fed with an equal amount of material relative to the average upper bound of mining and processing capacities across all periods. Equations 11 and 12 set an upper bound for variables *z* and *s* to ensure the feasibility of the solution. Finally, Equations 13 and 14 represent the decision variables' boundaries for *z*, *s,* and *y*, respectively. To sum up, for the Ore IPCC scenario, we use Equation 3 for the objective function and Equations 6, 8, 11, 13, and 14 as constraints. For the Waste IPCC scenario, we use Equation 4 for the objective function and Equations 7, 9, 12, 13, and 14 as constraints. For the Ore & Waste IPCC scenario, we use Equation 5 for the objective function and all remaining Equations from 6 to 14 as constraints.

2.6. Production & IPCC Schedule

The production schedule and the relocation times of the crusher(s) will be determined through a MILP formulation designed to control the optimal crusher panels from being extracted until the assumed total ore tonnage is milled or the presumed total waste tonnage is dumped. This period corresponds to the time that the crusher(s) are located on crusher panel *p*., as determined by the first step of the model. Equation 15 describes the objective function to maximize NPV, recognizing the extraction times (*T*) for both the mining cut ($x_{k,t}$) and the crusher panels ($d_{p,t}$). The decision variables identifying the extraction time and extraction portion of mining cuts and crusher panels ($x_{k,t}$ and $d_{p,t}$) are continuous variables ranging from 0 to 1. Moreover, $v_{k,t}$ and $q_{p,t}$ represent the discounted revenue minus the extra cost of mining ore in the mining cut and the discounted cost of mining, respectively. These parameters will be further analyzed to include the road and conveyor networks in the calculation. The definitions of indexes, parameters, and decision variables are as follows:

Indexes:

$t \in T$ *mining periods (year).*

$k \in K$ *mining cut.*

$p \in P$ *crusher panel or the in-pit crusher candidate location.*

$ocp \subset P$ *optimum crusher panels.*

$l \in L \subset P$ *counter for optimum crusher panels or ocp (L=Length (ocp)).*

$t' \subset t$ *starts from 1 to whatever the value of t or period is in that certain loop in the formulation.*

pl *processing plant(s)*

du *waste dump(s)*

Parameters:

$v_{k,t}$ represents the discounted revenue minus the extra cost of mining ore in the mining cut $x_{k,t}$.

$q_{p,t}$ denotes the discounted cost of mining.

o_k is the ore tonnage in the mining cut *k.*

o_p is the ore tonnage in the crusher panel *p.*

w_k is the waste tonnage in the mining cut *k.*

w_p is the waste tonnage in the crusher panel *p.*

ml_t & mu_t are the lower and the upper bounds on the tonnage of mining capacity in period *t*, respectively.

pl_t & pu_t are the lower and upper bounds on the tonnage of ore processing capacity in period *t*, respectively.

$g_{k,e}$ is the average grade of element *e* in ore portion of mining-cut *k*.

$gl_{t,e}$ & $gu_{t,e}$ are the lower and upper bounds on the percentage of the acceptable average head grade of element *e* in period *t*, respectively.

C_p is the set of the precedence panels that must be extracted prior to panel *p*.

s_p is the number of the precedence panels that must be extracted prior to panel *p*.

$Rev_{k,t}$ is the revenue because of extracting mining cut *k* in period *t*, sending it to the processing plant, smelter and refinery and selling the product considering all the recoveries and grades minus the processing, smelting and refining costs.

$TMC_{k,t}$ is the total mining cost of extracting mining cut *k* in period *t*.

$TMC_{p,t}$ is the total mining cost of extracting crusher panel *p* in period *t*.

$mc_{k,t}$ is the mining cost of extracting mining cut *k* minus the haulage cost of mining

cut *k* to its destinations (*pl* or *du*) in period *t.*

$mc_{p,t}$ is the mining cost of extracting crusher panel *p* minus the haulage cost of crusher panel *p* to the waste dump *du* in period *t.*

$RNdist$ is the shortest path calculated from the road networks. It can be the shortest path distance between either mining cut *k* or crusher panel *p* to the optimum crusher panel *ocp*, the processing plant *pl* or the waste dump *du.*

$CNdist$ is the shortest path calculated from the conveyor networks. It can be the shortest path distance between the optimum crusher panel *ocp*, the processing plant *pl* or the waste dump *du.*

r is the discount rate.

c is the dollar cost of hauling one tonne of ore or waste per one kilometre in period *t* with haul truck to its destination which is either the optimum crusher panel *ocp*, the processing plant *pl* or the waste dump *du* in period *t* ($/ton.km).

cn is the dollar cost of transferring one tonnage of ore or waste per one kilometre using the conveyor from the optimum crusher panel *ocp* to its destination which is either the processing plant *pl* or the waste dump *du* in period *t*.

pt_{ocp} is the maximum tonnage of ore milled or waste dumped while the crusher is in the optimum crusher panel *ocp.*

Decision Variables:

$x_{k,t} \in [0,1]$ is a continuous variable, representing the portion of mining-cut *k* to be extracted as ore and processed in period *t*.

$d_{p,t} \in [0,1]$ is a continuous variable, representing the portion of the crusher panel *p* to be mined in period *t*, as either ore or waste included in the panel.

$b_{p,t} \in \{0,1\}$ is a binary integer variable controlling the precedence of extraction of panels. $b_{p,t}$ is equal to one if extraction of panel *p* has started by or in period *t*, otherwise it is zero.

$y' \in \{0,1\}$ is a binary integer auxiliary variable to make the if-else possible for the MILP model. It is used to activate Equation 22 when the extraction condition of Equation 21 satisfies.

Parameters:

$$\max \sum_{t=1}^{T}\left(\sum_{k=1}^{K}(v_{k,t}\times x_{k,t})-\sum_{p=1}^{P}(q_{p,t}\times d_{p,t})\right) \tag{15}$$

Subject to

$$ml_t \le \sum_{p=1}^{p}(o_p+w_p)\times d_{p,t} \le mu_t \quad \forall t\in\{1,...,T\} \tag{16}$$

$$pl_t \le \sum_{k=1}^{K} o_k \times x_{k,t} \le pu_t \quad \forall t\in\{1,...,T\} \tag{17}$$

$$\sum_{k=1}^{K} o_k \times x_{k,t} \leq \sum_{p=1}^{p} (o_p + w_p) \times d_{p,t} \; \forall t \in \{1,...,T\} \tag{18}$$

$$0 \leq \sum_{k=1}^{K} (g_{k,e} - gl_{t,e}) \times o_k \times x_{k,t} \; \forall t \in \{1,...,T\}, e \in \{1,...,E\} \tag{19}$$

$$\sum_{k=1}^{K} (g_{k,e} - gu_{t,e}) \times o_k \times x_{k,t} \leq 0 \; \forall t \in \{1,...,T\}, e \in \{1,...,E\} \tag{20}$$

$$\sum_{t=1}^{T} d_{p,t} = 1 \; \forall p \in \{1,...,P\} \tag{21}$$

$$s_p \times b_{p,t} - \sum_{s \in C_p} \sum_{i=1}^{t} d_s^i \leq 0 \; \forall t \in \{1,...,T\}, p \in \{1,...,P\}, p \notin \{1,...,L\}, s \in C_p \tag{22}$$

$$\sum_{i=1}^{t} d_p^i - b_{p,t} \leq 0 \; \forall t \in \{1,...,T\}, p \in \{1,...,P\}, p \notin \{1,...,L\} \tag{23}$$

$$b_{p,t} - b_{p,t+1} \leq 0 \; \forall t \in \{1,...,T-1\}, p \in \{1,...,P\}, p \notin \{1,...,L\} \tag{24}$$

$$s_m \times b_{p,t+[\frac{pt_{opc}}{mu} \; or \; \frac{pt_{opc}}{pu}]} - \sum_{s \in C_p} \sum_{i=1}^{t} d_s^i \leq 0 \; \forall t \in \{1,...,T\}, p \in \{1,...,L\}, s \in C_p \tag{25}$$

$$b_{p,t+[\frac{pt_{opc}}{mu} \; or \; \frac{pt_{opc}}{pu}]} - b_{p,t+1+[\frac{pt_{opc}}{mu} \; or \; \frac{pt_{opc}}{pu}]} \leq 0 \; \forall t \in \{1,...,T-1\}, p \in \{1,...,L\} \tag{26}$$

$$\sum_{t'=1}^{t} \sum_{ocp} \left[\sum_{k=1}^{K} (o_k \times x_{k,t}) \; or \; \sum_{p=1}^{P} (w_p \times d_{p,t}) \right] + M \; y'_{t,l} \leq pt_{ocp} \forall t \in \{1,...,T\}, l \in \{1,...,L\} \tag{27}$$

$$\sum_{t'=1}^{t} \sum_{ocp} -b_{ocp} - M \; y'_{t,l} \leq -t \;\; \forall t \in \{1,...,T\}, l \in \{1,...,L\} \tag{28}$$

$$\sum_{t'=1}^{t} \left(y'_{t,l} + \sum_{i=t'+1}^{t} \left(\frac{y'_{i,l}}{t' - t} \right) \right) \leq 1 \; \forall t' \in \{1,...,T\}, l \in \{1,...,L\} \tag{29}$$

$$x_{k,t}, d_{p,t} \in [0,1] \; \forall t \in \{1,...,T\}, p \in \{1,...,P\}, k \in \{1,...,K\} \tag{30}$$

$$b_{p,t}, y'_{t,l} \in \{0,1\} \; \forall t \in \{1,...,T\}, p \in \{1,...,P\}, l \in \{1,...,L\} \tag{31}$$

In the proposed model, Equation 15 serves as the objective function to maximize the NPV. Equations 16 and 17 impose constraints on mining and processing capacities. Equation 18 adjusts the relationship between the tonnage of ore extracted and the total tonnage extracted from the corresponding cuts and panels. Equations 19 and 20 regulate the maximum and minimum grade of the material sent to either the mill or the waste dump, with these limits being freely determined within this specific model. Equation 21 ensures that all crusher panels are extracted over the mine's

lifespan. Equations 22-24 establish the extraction precedence for crusher panels that are not selected as the optimal panels in the model's initial step. These equations are formed within the mine phases and include mining cuts. Equation 22 sets a precedence constraint, preventing the extraction of crusher panel *p* until all its predecessor panels are extracted. Equation 23 ensures that extraction of crusher panel *p* does not begin until its predecessors are fully mined (i.e., its binary variable is set to one). Equation 24 sets all precedence binary variables for a crusher panel to one for all subsequent periods once its extraction begins. Equations 25 and 26 create a time delay for extracting the optimal crusher panels nearly equal to the years that the crusher(s) must be placed on these panels.

Equations 27 to 29 are executed in a loop for the number of optimal crusher panels identified in the first step, equivalent to the number of crusher relocations over the mine's life. This decision is made based on parameters uMo_p, lMo_p and uMw_p , lMw_p which define the upper and lower bounds for the total tonnage milled or dumped while the crusher is located on the panel. In these equations, *"y'$_{tloop}$"* is an auxiliary binary variable required for each loop and *"M"* is a big number exceeding the maximum upper bound of ore or waste milled or dumped. The material type tonnage decision hinges on the four considered scenarios. For the Ore & Waste IPCC scenario, since the optimal crusher panels for both crushers are identical, the relative tonnage to capacity is equalized to synchronize the relocations of both crushers. The decision variable boundaries are specified in Equations 30 and 31. As distance and transportation cost calculations differ between trucks and conveyors, adjustments to parameters $v_{k,t}$ and $q_{p,t}$ are necessary. Equations 32 to 39 detail the modified versions of these components. It is critical to note that "shortest path" references the use of a road network or conveyor network, denoted by either "*RNdist*" or "*CNdist*" parameters in the formulation.

$$v_{k,t} = \frac{\sum_{k=1}^{K}\sum_{t=1}^{T} \mathrm{Re}\, v_{k,t} - TMC_{k,t}}{(1+r)^t} \tag{32}$$

If there is an Ore Crusher in the pit (Ore IPCC):

$$TMC_{k,t} = mc_{k,t} + \left((RNdist_{k,ocp} \times o_k \times c_{k,ocp,t}) + (CNdist_{ocp,pl} \times o_k \times cn_{ocp,pl,t}) - (RNdist_{k,du} \times w_k \times c_{k,du,t})\right) \tag{33}$$

Else, if there is a Waste crusher in the pit (Waste IPCC):

$$TMC_{k,t} = mc_{k,t} + \left((RNdist_{k,pl} \times o_k \times c_{k,pl,t}) - (RNdist_{k,ocp} \times w_k \times c_{k,ocp,t}) - (CNdist_{ocp,du} \times w_k \times cn_{ocp,du,t})\right) \tag{34}$$

Else, if there is an Ore and Waste IPCC (Ore & Waste IPCC):

$$TMC_{k,t} = mc_{k,t} + \begin{pmatrix} (RNdist_{k,ocp} \times o_k \times c_{k,ocp,t}) + (CNdist_{ocp,pl} \times o_k \times cn_{ocp,pl,t}) \\ -(RNdist_{k,ocp} \times w_k \times c_{k,ocp,t}) - (CNdist_{ocp,du} \times w_k \times cn_{ocp,du,t}) \end{pmatrix} \tag{35}$$

Else, the ore material will be handled by trucks (No IPCC):

$$TMC_{k,t} = mc_{k,t} + \left((RNdist_{k,pl} \times o_k \times c_{k,pl,t}) - (RNdist_{k,du} \times w_k \times c_{k,du,t})\right) \tag{36}$$

$$q_{p,t} = \frac{\sum_{p=1}^{P}\sum_{t=1}^{T} TMC_{p,t}}{(1+r)^t} \tag{37}$$

If there is a Waste Crusher in the pit (Waste IPCC + Ore & Waste IPCC):

$$TMC_{p,t} = mc_{p,t} + \left((RNdist_{p,ocp} \times w_p \times c_{p,ocp,t}) + (CNdist_{ocp,du} \times w_p \times cn_{ocp,du,t}) \right) \quad (38)$$

Else, the waste material will be handled by trucks (No IPCC):

$$TMC_{p,t} = mc_{p,t} + (RNdist_{p,du} \times w_p \times c_{p,du,t}) \quad (39)$$

Equation 32 defines the components of the $v_{k,t}$ as the Revenue minus the Total Mining Costs (TMC) of mining cuts, discounted by the rate *r*. Equation 33 shows the Ore IPCC scenario haulage cost calculation Total Mining Costs (TMC) each mining cut in each period which is mining cost of each cut in each period ($mc_{k,t}$) plus the cost of hauling o_k tonnages of ore to the optimum crusher panel (*ocp*) by truck with the road network plus cost of conveying it to the processing plant (*pl*) taking the conveyor network minus hauling the waste portion of the mining cut if any to the waste dump (*du*) by truck with the road network. Similarly, Equation 34 shows the Waste IPCC scenario haulage cost calculation in which the waste portion of the mining cut will be carried away using the conveyor belts requiring the use of conveyor network, while the ore is hauled by trucks all the way to the processing plant. Equation 35 presents the haulage calculation for the Ore & Waste IPCC scenario, where there are two crushers. In this scenario, both the ore and waste portions of a mining cut are conveyed by their respective conveyors. However, initially, both materials need to be transported to the optimum crusher panel by trucks in period *t*. In Equation 36, the haulage system of the mine is dominated by the conventional TS method, with distances calculated using road networks, as there is no IPCC.

Equation 37 represents the components of the discounted Total Mining Costs (*TMC*) of crusher panels shown by $q_{p,t}$. Equation 38 can calculate the mining cost for the Waste IPCC and Ore & Waste IPCC scenarios at the same time. It takes the waste material from a crusher panel, hauling it to the optimum crusher panel at time *t* using trucks, and then conveying it to the waste dump (*du*). The distances are estimated using both the road network and the conveyor network. Equation 39 is for the truck and shovel haulage option when there is no IPCC. It calculates the Total Mining Costs (*TMC*) solely based on the road network distances to handle waste material. Since there is not any ore component in Equation 37, the Ore IPCC scenario will not be affected by it.

3. Case Study

To verify the mathematical model, an iron ore deposit case study is selected, which is designed for five pushbacks. The case study includes 19 benches with the primary element of magnetite, containing approximately 440 million tonnes of waste and 160 million tonnes of ore, 85,856 blocks, 20 years of operation with a scheduled mining capacity of 30 million tonnes (MT) and a processing capacity of 8 MT per year. It was decided to hire a contractor for the first three years of mining to increase the capacity from 30 MT to 35 MT to compensate for the plant shortage due to the pre-stripping stage. The first to fifth pushbacks contain 13,541, 13,064, 20,362, 11,328, and 14,561 blocks measuring 20m × 10m × 15m in X, Y, and Z dimensions, respectively. The total tonnages for each of the pushbacks from the first to the last one are approximately 90 MT, 73 MT, 147 MT, 214 MT, and 74 MT. These blocks are fed to one mill and dumped into two waste dumps located on the northern and southern sides of the pit. The waste dump selection happens based on the shorter distance, meaning each waste dump that has a shorter distance from a working panel will be chosen as the waste dump destination of that panel.

Both mathematical models ran on a machine equipped with an Intel® CPU featuring seven cores operating at 2.10 GHz speed and 64 GB of RAM, and both mathematical models were solved using the CPLEX solver (IBM ILOG CPLEX Optimization Studio., 2011). The runtime of the first step of the proposed model, when applied to the described case study, ranged from 25 to 30 minutes,

while the runtime for the second step to get to the 5% gap tolerance is around 3 to 4 hours, depending on the scenario. Figure 4 provides an illustration of the layout of the last pushback of the iron ore mine, with two waste dumps on both sides of the pit, and crusher panels of the 9th bench accompanied by the road and conveyor network.

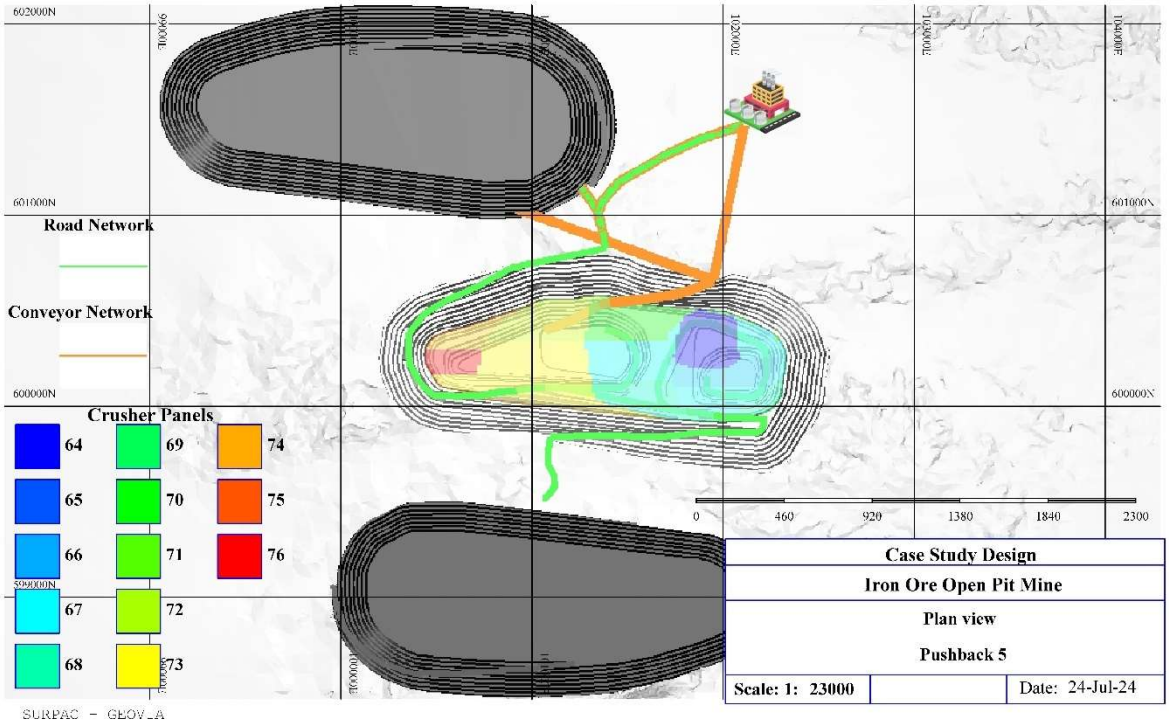

Figure 4. Last pushback and waste dumps layout and crusher panels of the 9th bench with their relative road and conveyor networks.

The coordinate extension of each pushback from the first to the fifth in the X direction is 860 m, 1100 m, 1460 m, 2040 m, and 2360 m, and in the Y direction is 710 m, 980 m, 1140 m, 1150 m, and 1150 m, respectively. Pushbacks one to three contain 12 benches each, pushback four has 18 benches, and pushback five has 19 benches. This arrangement results in crusher panels with a diagonal distance of 400m to 450m, based on the minimum mining width considered for the creation of the crusher panels. The algorithm chosen to find medoids is "partitioning around medoids," and the method for distance minimization in cluster creation is "Euclidean".

Considering 52 weeks of operation in this iron ore open pit case study, and knowing that the yearly production is 30 MT, we require around 580,000 tonnes of blasted material every week if it is decided one blast per week. With an average density of 4.31 tonnes/m³ (for both ore and waste) and the volume of each block being 10×20×15, totaling 3,000 m³, we can assume a total of 45 blocks for each blast polygon or mining cut. Therefore, setting the blocks per cluster range equal to 45 will create a base for the second stage of our clustering, which is aggregating blocks into mining cuts. The rest of the parameters in the hierarchical clustering method, according to Equations 1 and 2, are 0.1 for distance weight, 1 for rock type difference penalty, and close to zero (e.g. 0.01) for grade difference penalty. Figure 5 illustrates the schematic view of the crusher panels and the mining cuts' boundaries within each crusher panel on the 9th bench-phase.

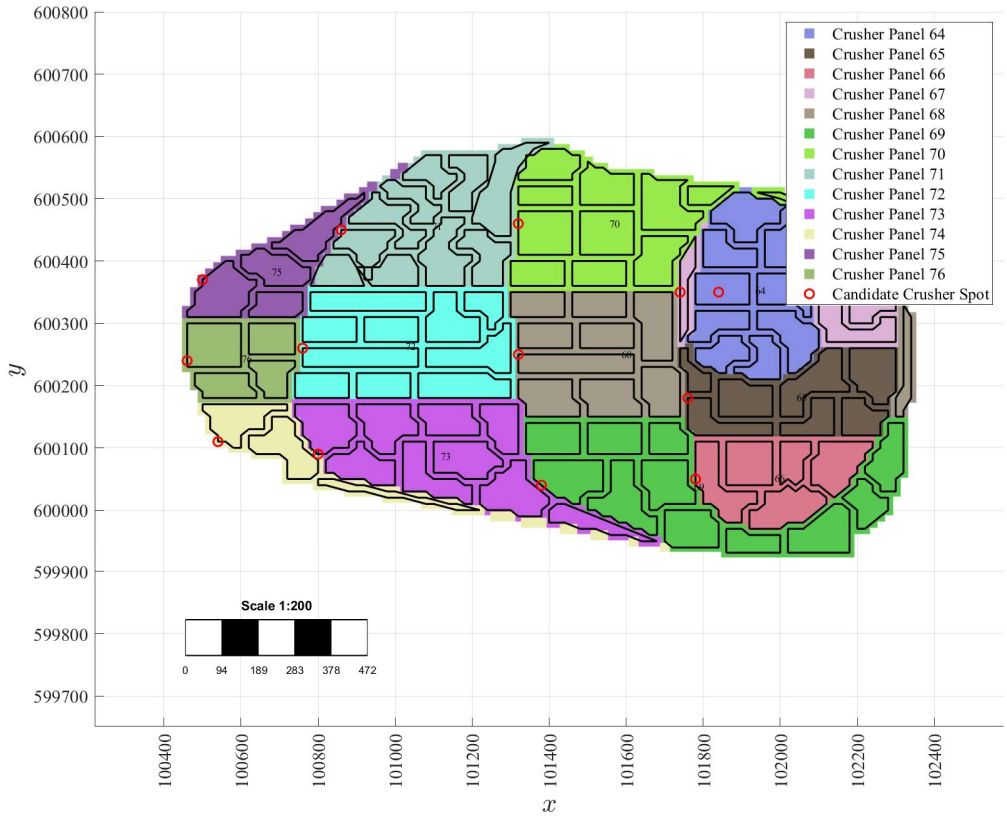

Figure 5. The schematic view of the 9th bench-phase crusher panels and mining cuts.

For the case study, the selected fleet comprises two types of shovels and three types of trucks, each chosen for their specific capacities and roles. The shovels include the Hitachi EX2500 for ore, with a bucket capacity of 12 m³, and the Hitachi EX5500 for waste, with a bucket capacity of 22 m³. Correspondingly, the primary trucks in use are the Caterpillar 785C, which has a 140-tonne nominal capacity and an overall width of 6.64 meters for ore, and the Caterpillar 793C, with a 178-tonne nominal capacity and an overall width of 7.44 meters for waste. Additionally, the Caterpillar 797B with a substantial 350-tonne capacity and an overall width of 9.15 meters, was included as a potential upgrade to the fleet to ensure meeting the operations' targets. Therefore, the main ramp width was designed based on the dimensions of the largest truck, ensuring a two-way traffic capacity of 32 meters. For smaller, right-side bottom benches, a narrower ramp was calculated at 16 meters. All ramps feature a consistent gradient of 10%, ensuring safe and efficient ascent and descent. The curvature for the switchbacks is designed with a radius of 40 meters, accommodating the turning radius of the largest trucks and ensuring smooth navigation through the pit.

4. Results and Discussion

In this study, we explore the semi-mobile IPCC option through four distinct scenarios: 1) No IPCC, 2) Ore IPCC, 3) Waste IPCC, and 4) Ore & Waste IPCC. The initial step of the model, designed to identify optimal crusher locations, is not applied to the first scenario, as traditional truck and shovel (TS) methods are used for material hauling. Nonetheless, crusher panels remain the primary extraction units for determining the waste material. For the other scenarios, the ore crusher's upper and lower limits (*uMo* & *lMo*) are set at 28 MT and 16 MT, respectively, while the waste crusher's upper and lower limits (*uMw* & *lMw*) are set at 105 MT and 60 MT. Adjusting these limits would yield varying relocation counts, though determining the optimal number of relocations lies beyond

this study's scope. Table 2 presents the results from both steps of the model, showcasing the optimum crusher panels and their relative tonnages from the first step, as well as the relocation year or extraction sequence of the optimum crusher panels from the second step for scenarios 2-4. This indicates the extraction of 159.5 MT of ore and 439.9 MT of waste material.

Table 2. The results of the first and second steps for the optimum crusher panels.

Bench No.	Crusher Panel No. (CP)	Ore Crusher (MT)	Ore Crusher Relocation Year	Waste Crusher (MT)	Waste Crusher Relocation Year	Ore Crusher (MT)	Ore & Waste Crusher Relocation Year	Waste Crusher (MT)
Bench 4	**CP 154**	-	-	60	1	24	2	60
Bench 5	**CP 139**	27.7	2	60	2	-	-	-
Bench 6	**CP 124**	16	4	61.6	5	24	5	60
Bench 7	**CP 114**	16	7	-	-	-	-	-
Bench 8	**CP 99**	16	9	68.8	9	24	9	60
Bench 10	**CP 70**	19.8	12	-	-	24	12	60
Bench 11	**CP 57**	16	14	60	12	24	15	60
Bench 12	**CP 47**	16	16	-	-	-	-	-
Bench 13	**CP 31**	16	18	60	18	23.5	19	79.9
Bench 17 (Pit bottom)	**CP 4**	16	20	69.5	20	16	20	60
Total Tonnage		159.5		439.9		159.5	-	439.9

As illustrated in Table 1, the number of relocations varies across the scenarios. Notably, scenario 2 experiences two more relocations than scenarios 3 and 4. The model identifies the pit bottom as the final location for the crusher(s) across all scenarios, underscoring the efficiency of the conveyor networks. The crusher panel numbers, shown in the second column of the table, will be utilized as input parameters for the second step of the mathematical model within the *ocp* subset. Additionally, the tonnages in each scenario will be used to ensure that the *ocp* crusher panels remain unextracted.

Given the existing ore and waste amounting to approximately 600 MT of mineable material, the optimal operational setup to sustain mill throughput over the mine's lifespan includes a mill with an 8 MT annual capacity and a mining capacity of 30 MT annually. During the initial three-year pre-strip period, a contractor will be engaged to boost the mining capacity by an additional 5 MT per year, resulting in a total mining operation span of 20 years. The long-term production rates, determined by the model's second step, produce four distinct outcomes for each scenario. Figure 6 Figure 7, Figure 8, and Figure 9 display the yearly production charts over the long term, as derived from the model's second step for scenario 1 to 4, respectively.

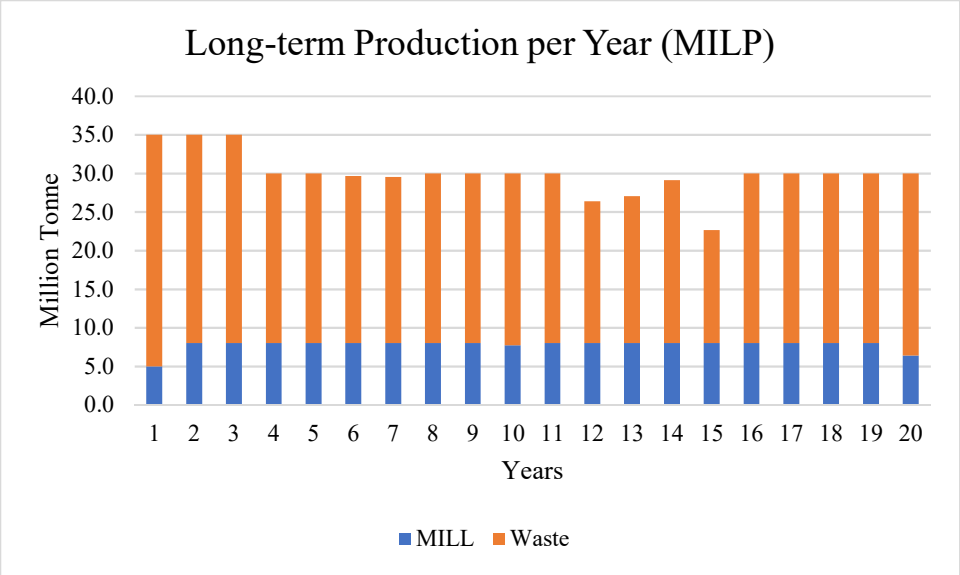

Figure 6. Long-term schedule for No IPCC scenario.

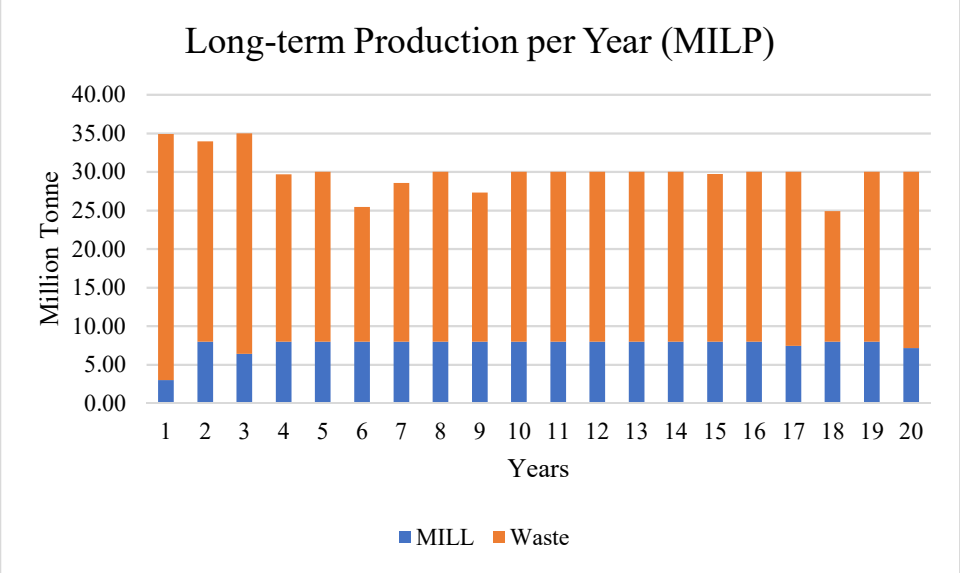

Figure 7. Long-term schedule for Ore IPCC scenario.

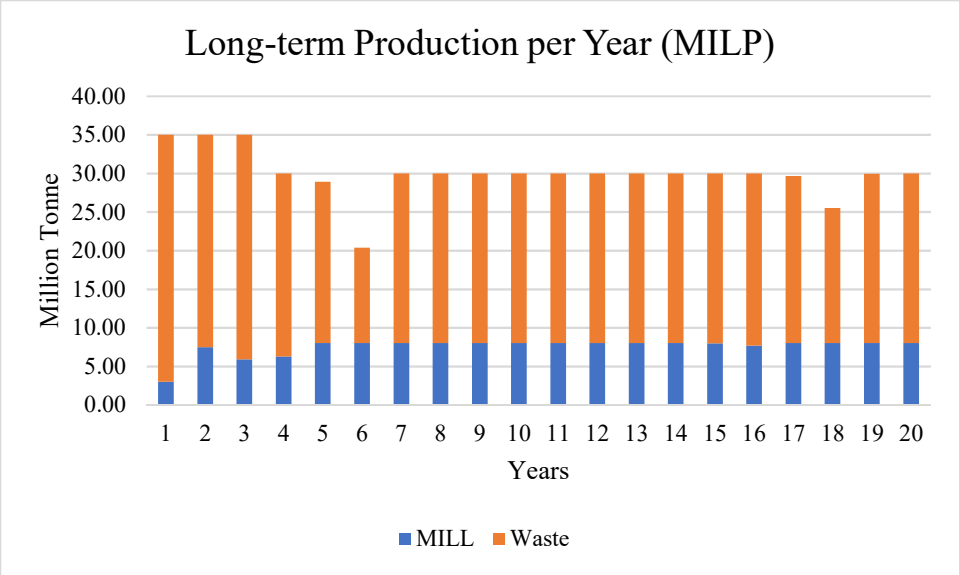

Figure 8. Long-term schedule for Waste IPCC scenario.

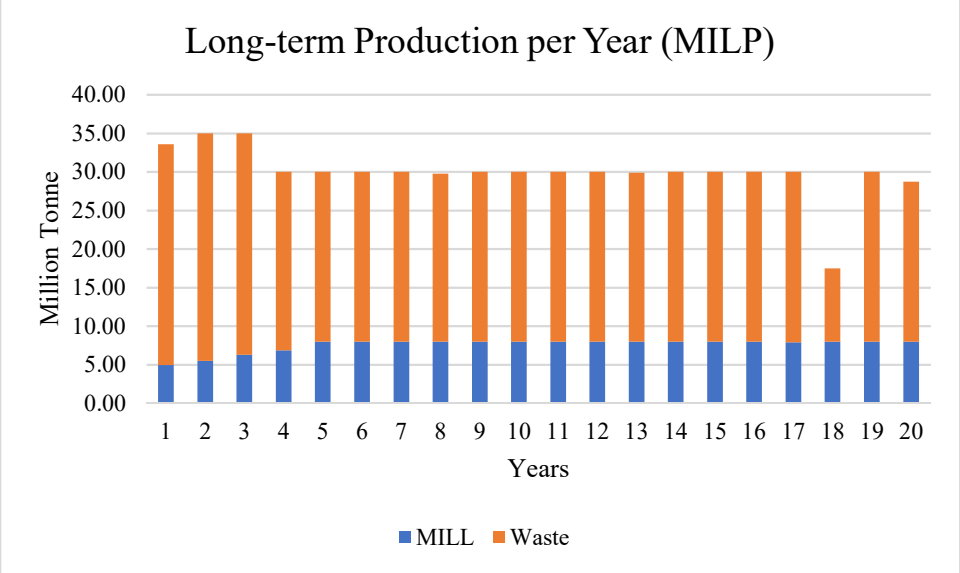

Figure 9. Long-term schedule for Ore & Waste IPCC scenario.

The operation is constrained by the capacity of the mill, meaning the primary objective of the model is to consistently reach the target for feeding the mill. This goal is achieved in scenarios 1 and 4. In scenarios 2 and 3, however, there are noticeable, albeit acceptable, fluctuations in feeding the mill to its maximum capacity due to delays in extraction from the optimum crusher panels. Despite these variations, all scenarios remain profitable, as the discounted cash flow values for the scenario 1 to 4 are $2042M, $2130M, $2119M, and $2350M showing 4.22% improvement by only implementing ore crusher, 3.70% improvement by only implementing waste crusher and 14.02% improvement by implementing both ore and waste crusher.

The subsequent figures demonstrate the sequence of extraction of the crusher panels in the cross-sectional view of northing direction with the plan view strip on the top of the plot. The Y coordinates for the cross-sectional view remains 600400 the same for all the plots. Figure 10 shows

the schedule for all the crusher panels in the mentioned section for the No IPCC scenario. However, Figure 11, Figure 12, and Figure 13 show the schedule of the optimum crusher panels demonstrating the capability of the model to account for not extracting the crusher panels for as long as the crusher must be placed on them for Ore IPCC, Waste IPCC and Ore & Waste IPCC scenarios, respectively. The scale, the schedule coloring legend and the Y coordinate kept similar to make the plots comparable. For the sake of better visualization of the pit and the crusher panels, the "to" and "away" distance of 150 m is selected which makes the strips of the cross-section thicker than they should be.

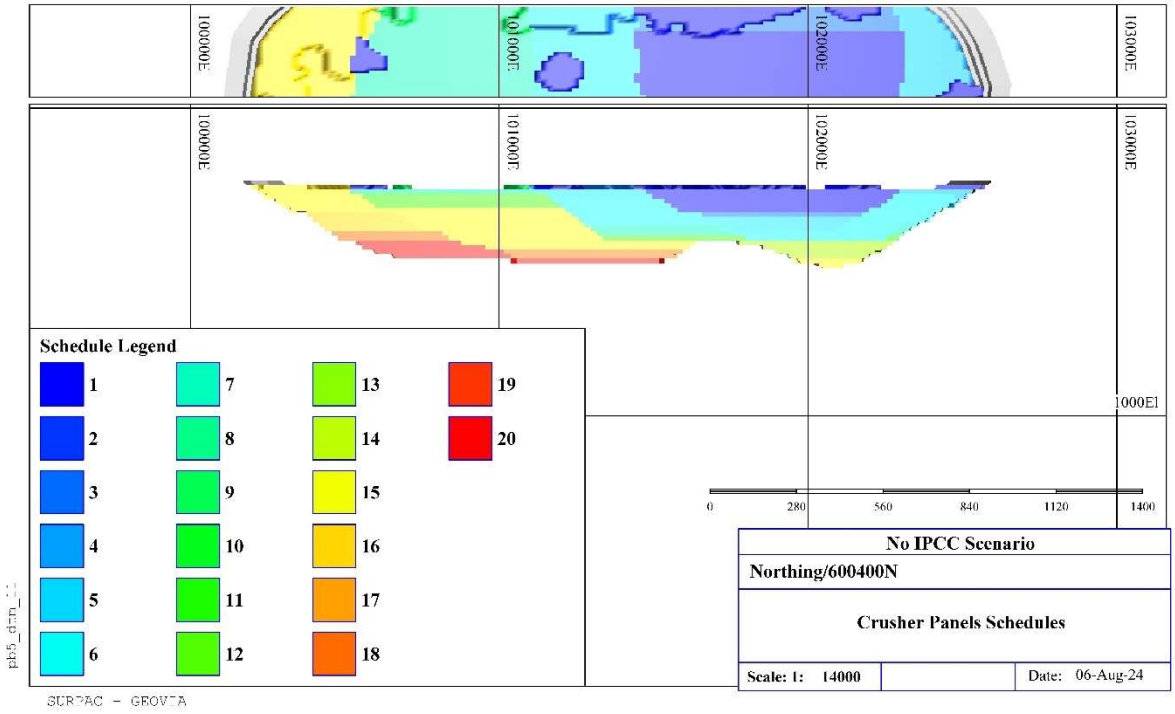

Figure 10. Crusher panels sequence of extraction, No IPCC Scenario.

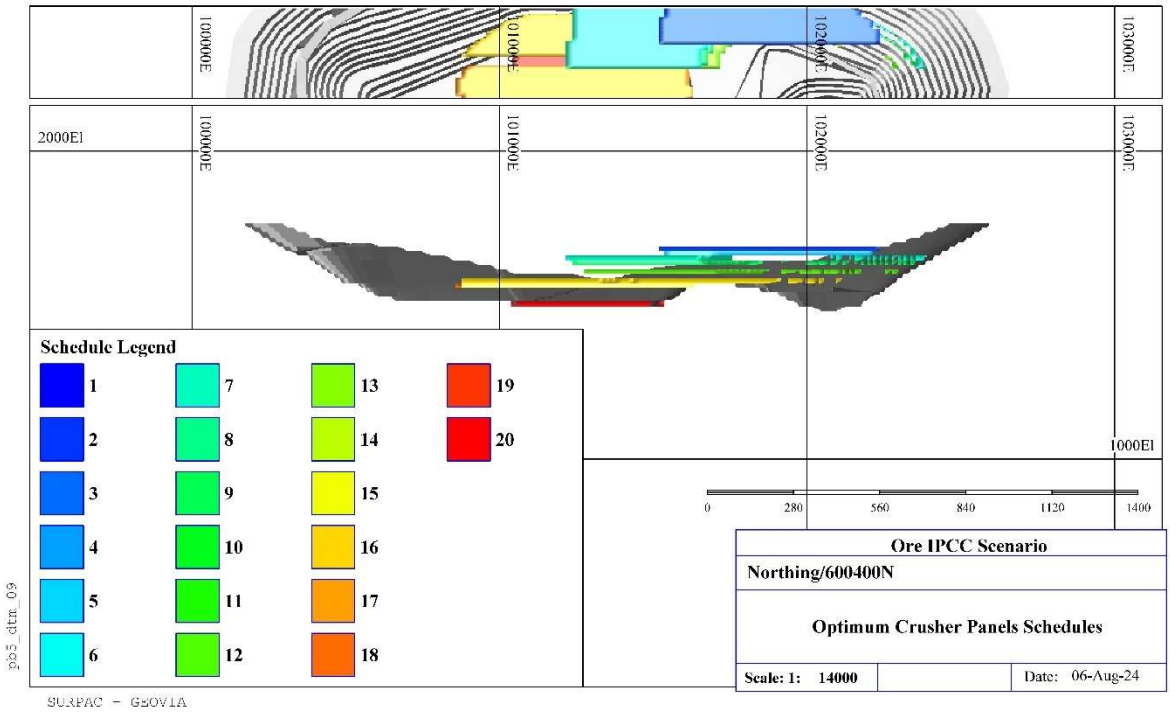

Figure 11. Optimum Crusher Panels sequence of extractions, Ore IPCC Scenario.

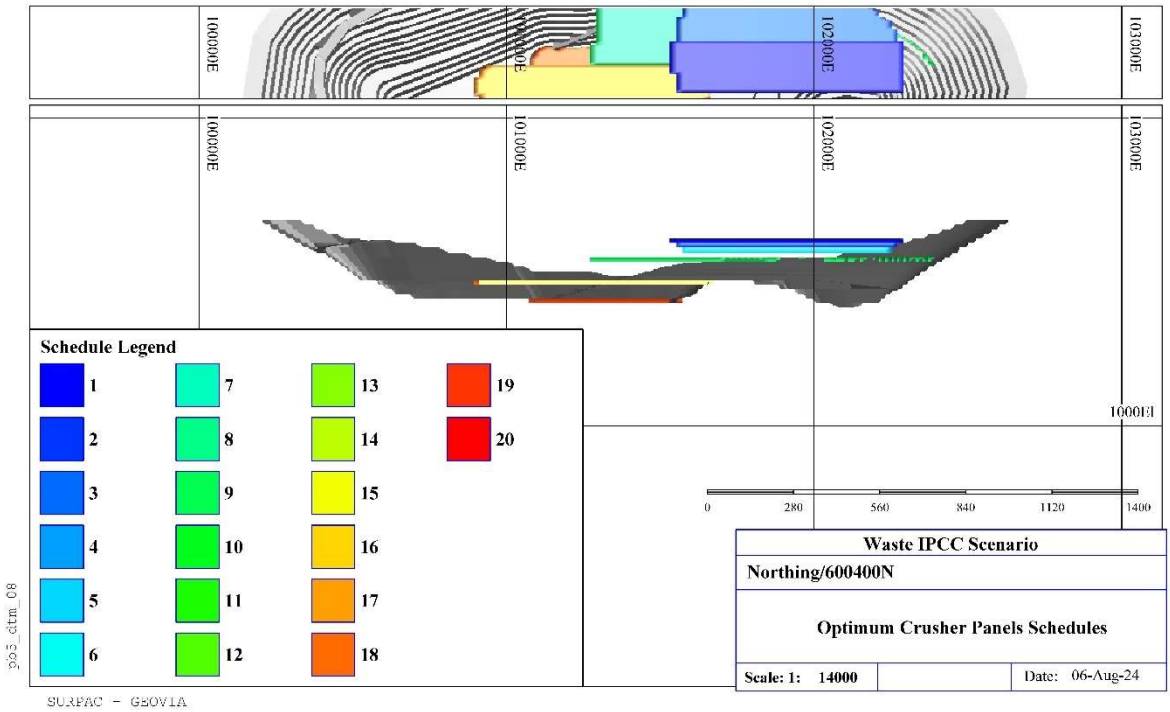

Figure 12. Optimum Crusher Panels sequence of extractions, Waste IPCC Scenario.

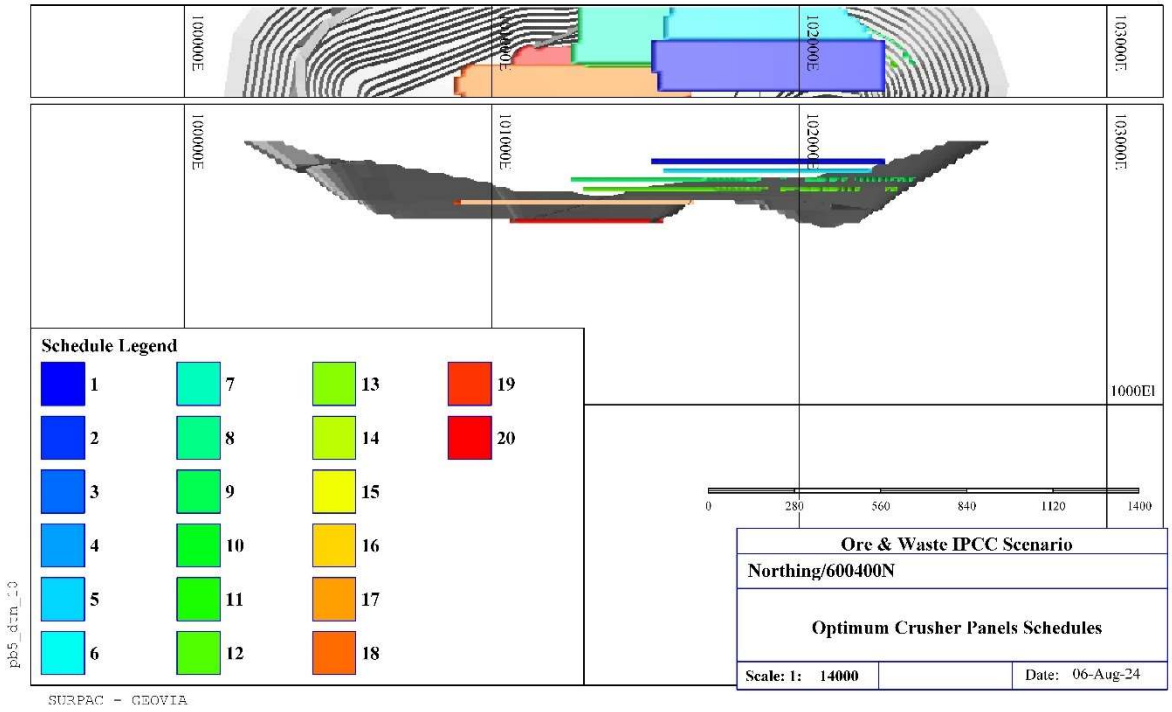

Figure 13. Optimum Crusher Panels sequence of extractions, Ore & Waste IPCC Scenario.

The tonne × kilometre (TKM) is a vital metric used to quantify the transportation of material specifically measures the movement of one tonne of material over one kilometre. TKM is also essential for assessing the efficiency and effectiveness of material handling systems when comparing different configurations, such as IPCC systems versus traditional truck-based methods. By analyzing TKM data, operators can gain insights into the operational performance, energy consumption, and cost implications associated with moving ore and waste across a mine site. To ensure an accurate comparison between scenarios with and without IPCC, it is necessary to focus on the truck-related TKM and truck kilometers traveled, excluding the distances covered by conveyors in IPCC scenarios. This adjustment allows for a direct comparison of the transportation efficiency of trucks in each scenario. Figure 14 shows the TKM cumulative and values for ore, categorized by year, across the four evaluated scenarios: No IPCC, Ore IPCC, Waste IPCC, and Ore & Waste IPCC. Figure 15 presents the TKM values for waste under the same four scenarios, illustrating the annual transportation demands for waste management.

For ore, in the No IPCC scenario, the TKM is 512 million with a total distance of 2,271 km. In the Ore IPCC scenario, after deducting the conveyor contribution, the TKM reduces to 175 million, with trucks covering 801 km. In the Waste IPCC scenario, the TKM is 497 million with a distance of 2,240 km, showing the continued reliance on trucks despite the presence of waste IPCC. In the Ore & Waste IPCC scenario, the TKM for trucks is 174 million with 855 km traveled, indicating the most efficient truck usage when both ore and waste are managed through IPCC.

For waste, the No IPCC scenario shows a TKM of 1,339 million and a distance of 9,283 km, reflecting the extensive truck usage required without IPCC. In the Ore IPCC scenario, the TKM remains high at 1,346 million, with trucks covering 9,300 km, as the waste is still primarily handled by trucks. In the Waste IPCC scenario, after accounting for conveyor contributions, the TKM decreases to 709 million with a travel distance of 5,162 km, illustrating a significant reduction in truck usage. Finally, in the Ore & Waste IPCC scenario, the TKM for trucks further drops to 619 million, with 4,663 km traveled, highlighting the efficiency gains when both ore and waste are managed by conveyors, reducing the reliance on trucks.

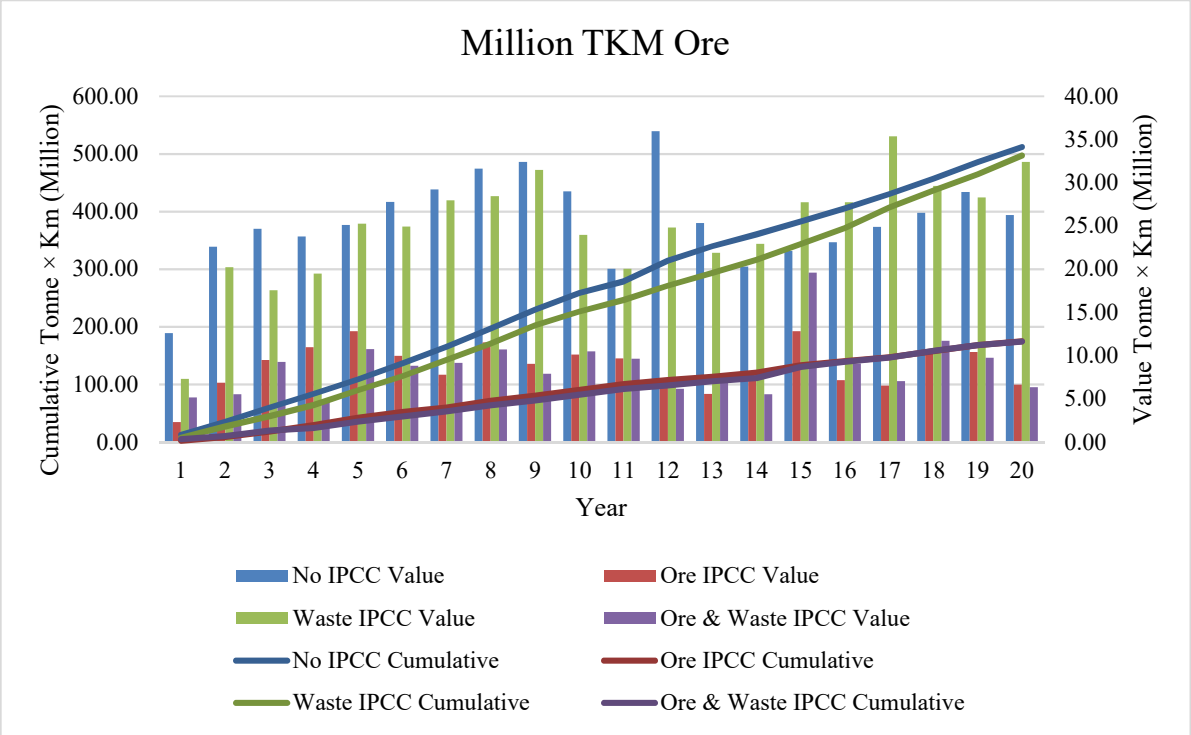

Figure 14. Yearly ore TKM cumulative and values.

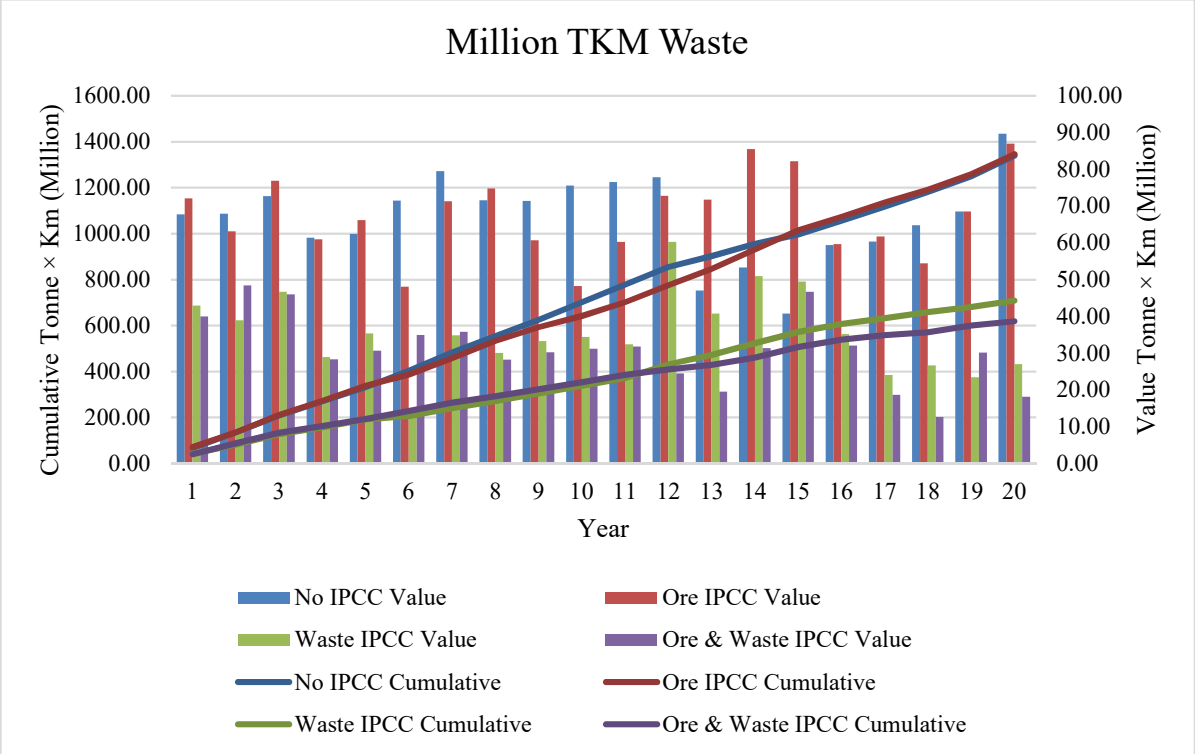

Figure 15. Yearly waste TKM cumulative and values.

To calculate the present value for each year and finally the NPV for better evaluation, we need to determine the number of trucks required for each scenario annually. Additionally, the length of the conveyor system, including the conveyor ramp, must be calculated. This length comprises the distance from the crusher in the crusher panel to the conveyor ramp, conveyer ramp, and from the ramp's exit on the topographic surface to the processing plant and waste dump. For shovel calculations, we have already established a fixed number of ore and waste shovels along with their associated costs. Regarding the conveyor system, we assume that the full length of the ore and waste conveyor costs will be incurred in the first year. This is based on the premise that the addition of a few hundred meters each year will not significantly alter the overall cost. The number of trucks required will be determined based on the total travel distance and the ore and waste tonnage of each mining cut. This calculation, in conjunction with the extraction time for each cut, will establish the necessary number of trucks for ore and waste transport annually. However, this number will vary from year to year due to the differing distances of the mining cuts from the optimal crusher panel, the processing plant, and the waste dump. Hence, it is assumed that once the number of trucks is increased for a specific year, it cannot be decreased in subsequent years. Figures 17 and 18 illustrate the required number of trucks for ore and waste in each scenario, respectively. Figure 19 shows the total kilometers of conveyor required for the ore conveyor in the Ore IPCC and Ore & Waste IPCC scenarios. Similarly, Figure 20 depicts the total kilometers needed for the waste conveyor in the Waste IPCC and Ore & Waste IPCC scenarios.

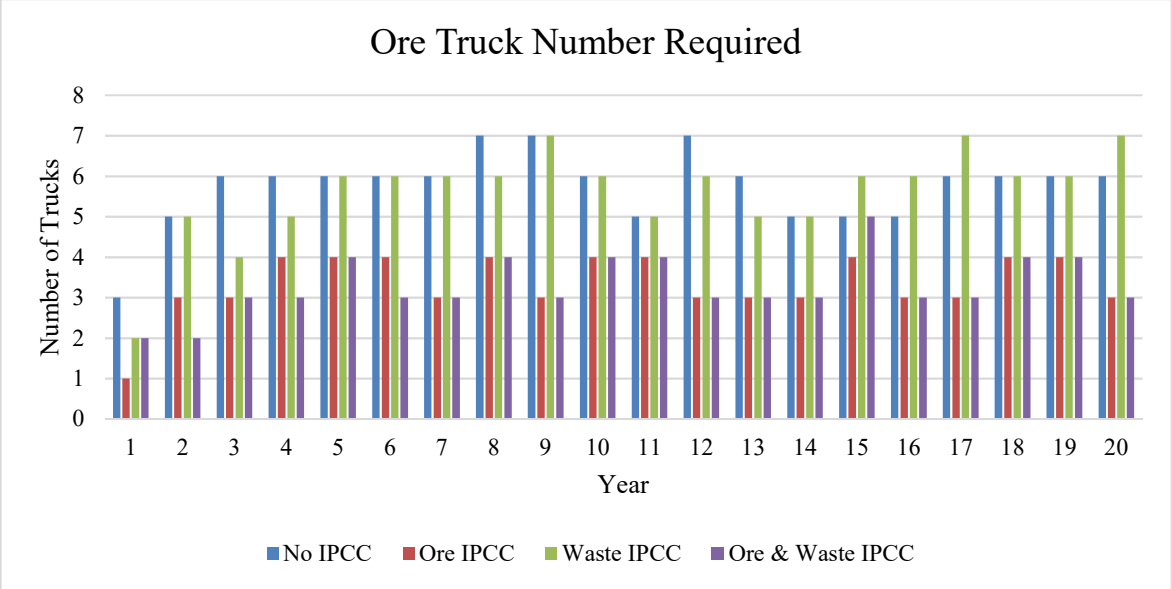

Figure 16. The required numbers of trucks for Ore in each scenario.

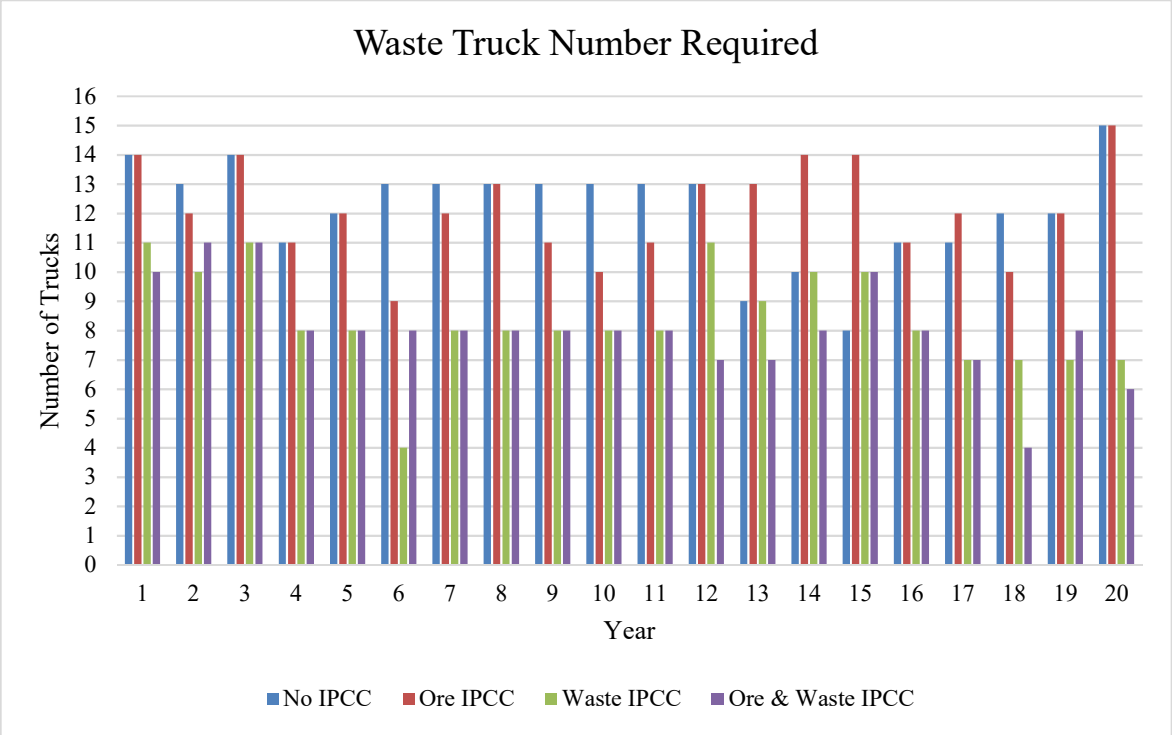

Figure 17. The required numbers of trucks for Waste in each scenario.

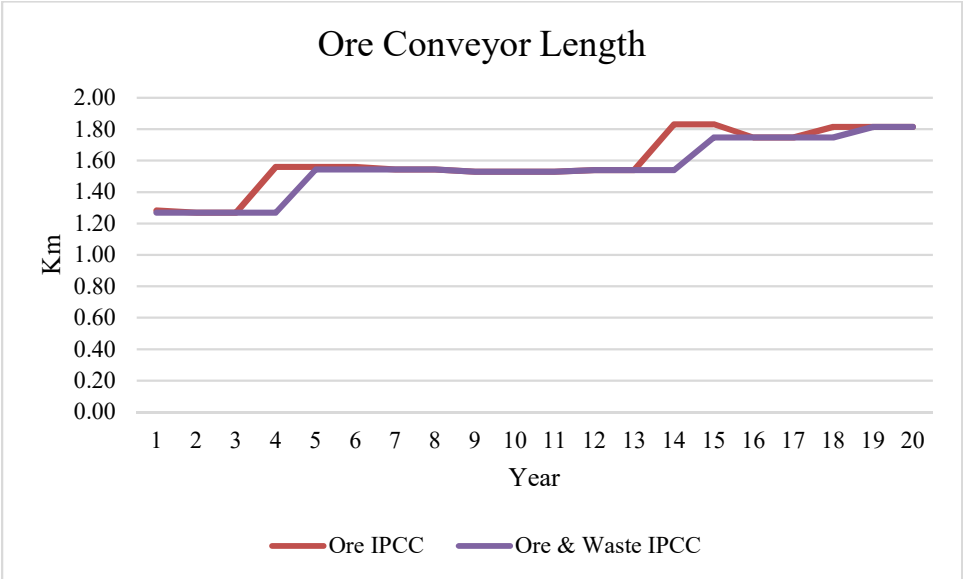

Figure 18. Ore conveyor length through the mine life.

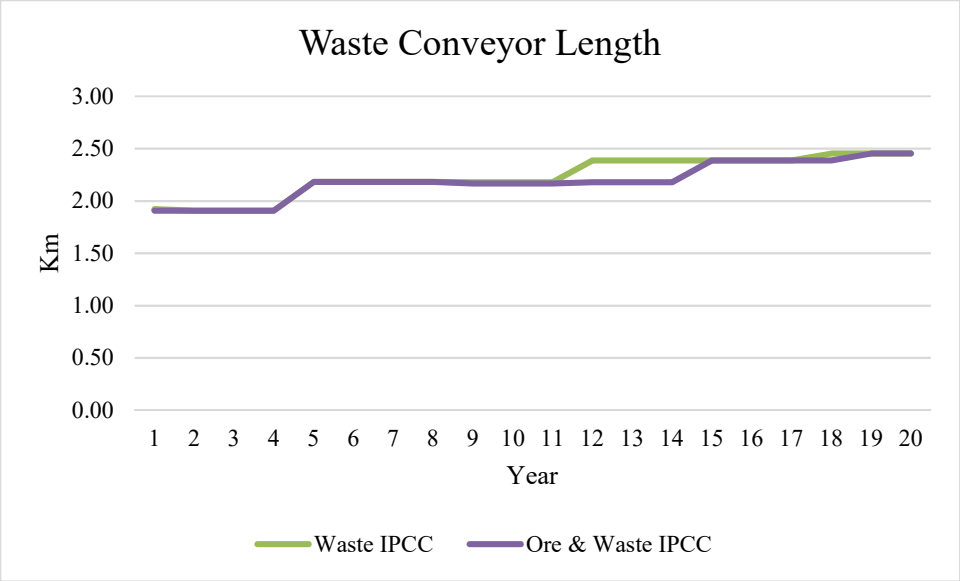

Figure 19. Waste conveyor length through the mine life.

The yearly present value graph is estimated based on the capital investments required for this case study, which includes several key components. Firstly, the investment encompasses a dry separation magnetic processing plant for iron ore with an 8 million tonne per year capacity, presumed to require U$600 million. Additionally, the capital required for drilling and blasting equipment, as well as other road, ramp, and building construction equipment such as dozers, rollers, graders, and sprinkler tankers, totals U$50 million. Furthermore, an additional U$100 million is necessary for other critical items, including an electrical substation, diesel-electric plant, surface electrical distribution system, administrative offices, maintenance shops, change houses, warehouses, and miscellaneous facilities. Altogether, these investments amount to a total capital expenditure of U$750 million.

The subsequent analysis focuses on the costs associated with trucks, shovels, crushers, and conveyors, leading to the net costs for the first scenario (No IPCC) being approximately U$865 million, for Ore IPCC U$884 million, for Waste IPCC U$881 million, and for Ore & Waste IPCC U$900 million. There is also a sizer option for waste, mentioned earlier, which is relatively cheaper compared to crushers. This will be evaluated in the Waste IPSC and Ore IPCC & Waste IPSC scenarios with the net costs of U$ 875 million and U$ 895 million, respectively. Figure 18 shows the present value yearly analysis of four scenarios to determine the economic viability of the in-pit crusher.

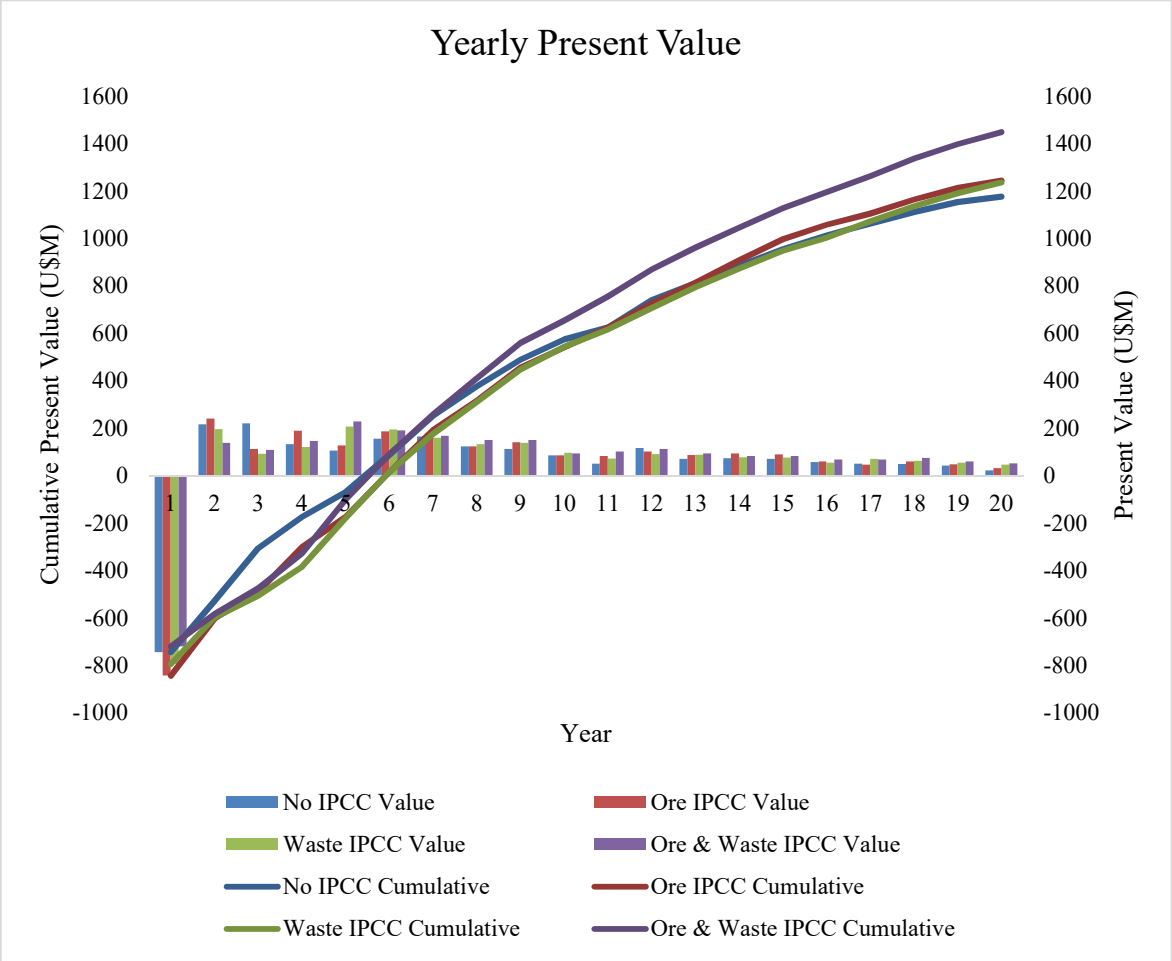

Figure 20. Present value yearly analysis of four scenarios.

The comparison of NPVs for different scenarios of IPCC and IPSC systems reveals interesting insights into their economic impacts. As it can be observed from Figure 18 the payback period is 6 years nearly for all scenarios. The "No IPCC" scenario, serving as the baseline, has the lowest NPV at U$1177 million. Introducing an IPCC system for ore increases the NPV to U$1245 million, representing a 5.76% improvement. Similarly, using an IPCC system for waste results in an NPV of U$1238 million, a 5.16% increase. Combining IPCC for both ore and waste in the Ore & Waste IPCC scenario significantly boosts the NPV to U$1450 million, a substantial 23.17% rise from the baseline. This scenario highlights the potential economic benefits of a comprehensive IPCC system in handling both ore and waste materials.

Switching to a Waste IPSC system yields an NPV of $1244 million, reflecting a 5.68% improvement over the "No IPCC" scenario. However, the most notable increase is observed when combining Ore IPCC with Waste IPSC, achieving the highest NPV of $1455 million, which is 23.66% higher than the baseline. This suggests that integrating both technologies for specific material handling tasks can optimize economic outcomes significantly. The analysis demonstrates that while each individual system (Ore IPCC or Waste IPCC/IPSC) provides moderate economic benefits, integrating IPCC and IPSC for ore and waste handling respectively delivers the most substantial improvement in NPV underscoring the value of adopting a hybrid approach to material handling in open pit mining operations to maximize economic returns.

5. Conclusion and Future Work

In this study, we conducted a comprehensive investigation into the implementation of IPCC across four distinct scenarios using a two-step mathematical model. The first step of the model determines the relocation times and the upper and lower capacities, while the second step provides the long-term schedule and the timing of relocations. This study includes key features such as two stages of clustering, the design of road and conveyor ramps and networks, and a detailed cost analysis.

Initially, the study employs a two-stage clustering approach—first using k-medoid clustering, followed by hierarchical clustering. These techniques are applied to the block model to partition the blocks into rationally sized areas for designated crusher locations, known as crusher panels, and then aggregate the blocks into practical mining units, or blast polygons, referred to as mining cuts. Both can be used as extraction units in the second step of the model. In the first step, based on the distances obtained from the road and conveyor network, we calculate the shortest path from each mining cut to each crusher panel (if all panels are practical options for crusher placement) and then from each crusher panel to either the processing plant or waste dump. The costs are calculated based on the distance for both the truck-shovel (TS) system and the IPCC system. The model then determines the optimal crusher panels based on the lower and upper capacity of material processed or dumped while the crusher operates on each panel. The optimal crusher panels and their corresponding tonnages are input into the second step of the model, which then determines the sequence of material extraction, crusher relocation times, and feeding schedule to the processing plant, aiming to maximize discounted cash flow (DCF). Considering the capital expenditure of the equipment and facilities allows for the calculation of net present value (NPV). Prior to these stages, pushbacks are designed with road and conveyor ramps, considering safety and ramp design considerations.

This proposed two-step model, incorporating two stages of clustering, has been validated with a real-sized iron ore mine, designed with five pushbacks and corresponding road and conveyor networks for IPCC implementation. Four scenarios are investigated, each requiring specific formulation or adjustment to the model: No IPCC, Ore IPCC, Waste IPCC, and Ore & Waste IPCC. These result in four different schedules and outcomes for both steps. Based on technical insights from in-pit crusher manufacturers, sizers can also be applied to waste. Consequently, two additional cost analysis scenarios are introduced: Waste IPSC and Ore IPCC & Waste IPSC. The operation size is set at 30 MT over a 20-year mine life, except for the first three years, during which a contractor increases the capacity by 5 MT. The mill is designed to process 8 MT of iron ore annually.

The results of the first step, after solving it for three scenarios involving IPCC, reveal different optimal crusher panels for each scenario, depending on the concentration of ore and waste and their distances from road and conveyor ramps. However, in all scenarios, the final crusher location is positioned at the bottom of the pit, demonstrating the model's capability to account for the conveyor ramp. After introducing the optimal crusher panels of each scenario into the second step of the model and making necessary adjustments, the results show different extraction sequences for each scenario as expected. Notably, the No IPCC scenario consistently meets mill capacity throughout the 20-year mine life, while the other scenarios exhibit slight fluctuations due to extraction disturbances caused by crushers at the optimal panels.

The Ore & Waste IPCC scenario shows significant advantages, with over a 23% increase in the NPV of the mine, despite an initial capital cost that is over US$36 million higher than the No IPCC base scenario. The impact of the sizer option is minimal (0.5% increase), so it may not be a viable option if it introduces technical complexity from using two different machines. The total kilometers traveled in the Ore & Waste IPCC scenario are reduced by more than 1,400 km for ore and over 4,600 km for waste, indicating significant savings in truck travel.

The major contributions of this study include the development of a two-step mathematical model for determining optimal crusher locations and scheduling open-pit mining in the presence of IPCC, with the goals of minimizing transportation costs in the first step and maximizing NPV within a reasonable timeframe. The model also provides the sequence of extraction while respecting both crusher and slope precedence. Additionally, the study integrates pit design with road and conveyor networks, calculates the shortest path instead of the minimum distance, creates practical blast polygons based on weekly tonnage requirements, introduces an automatic method for selecting crusher panel locations, incorporates technical insights from crusher manufacturers, and calculates NPV for a real-size mine case study under four practical scenarios. The research establishes a workflow for future in-pit crusher studies.

For future research, several areas warrant exploration, particularly those addressing the limitations of the current study. One key area is the development of a simultaneous optimization model that integrates the determination of crusher locations and the scheduling of operations into a single stage. This could enhance the efficiency and accuracy of decision-making by considering both aspects concurrently.

Additionally, future studies should incorporate the environmental impact of both IPCC and truck-shovel (TS) systems into the NPV calculation by including the costs associated with gas emissions from both electrical and diesel-powered equipment. This would provide a more comprehensive assessment of the economic and environmental trade-offs between the two systems, offering a broader perspective on their long-term viability.

Another important consideration is the inherent uncertainty in material handling systems, such as variations in equipment availability, the likelihood of failures, and fluctuations in operational efficiency. These uncertainties can significantly impact the outcomes of different scenarios. Future research should develop a dedicated model designed to handle such uncertainties, possibly through stochastic modeling or reliability analysis, to better capture the real-world variability in mining operations.

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Evaluating Truck-Shovel and IPCC Scenarios through Discrete Event Simulation: An Iron Ore Mine Case

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ABSTRACT

In-Pit Crushing and Conveying (IPCC) systems represent a revolutionary approach to mineral extraction in open-pit mining. By integrating the crushing process with a conveyor system within the pit, these systems replace part of the haulage cycle that is done conventionally through the Truck-Shovel (TS) system, resulting in significant savings in haulage cost. This not only enhances operational efficiency and reduces costs significantly, but also streamlines material handling, reduces energy consumption, and minimizes environmental impact. In this study, a robust methodology is employed to analyze the cost-effectiveness and production efficiency of IPCC systems in a mature open-pit mine. First, statistical analysis and data wrangling are conducted to achieve valid operational data as input to distribution function fitting. Next, a full-scale Discrete Event Simulation (DES) model is developed using Simpy, an open-source Pythonic library for implementing DES. The model accounts for all in-pit operations, such as loading, haulage and dumping, refueling, shift changes, dispatching modes, equipment failures, and routine maintenance. The simulation model is validated by comparing its results against actual operational data. The model will be used as a decision support system for comprehensive scenario analysis to evaluate various scenarios of pure TS, IPCC, and Out-Pit Crushing and Conveying (OPCC) systems through a detailed assessment of the impact on operational costs, production rates, and overall timeline efficiency. The findings of this study offer valuable insights into the practical aspects of transitioning to IPCC systems in mature open-pit mines.

Keywords: *IPCC, Truck-Shovel system, Discrete Event Simulation, Mining Optimization, Continuous Haulage.*

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1. Introduction

In open-pit mining, the choice of mining method significantly influences production efficiency and schedule adherence. Continuous methods, such as In-Pit Crushing and Conveying (IPCC) and Out-pit Crushing and Conveying (OPCC), offer notable advantages over traditional Truck-Shovel (TS) systems. Continuous methods streamline the material handling process by integrating the extraction, crushing, and conveying stages into a seamless operation. This integration reduces the reliance on heavy truck fleets, which are prone to mechanical failures, high fuel consumption [1], and logistical bottlenecks.

While semi-mobile crushers in continuous methods applications still require trucks for feeding, this approach significantly reduces the distance trucks need to travel, thereby decreasing fuel consumption and maintenance requirements. This ensures a steadier flow of minerals from the pit to the processing plant, leading to consistent throughput and improved overall efficiency. Additionally, continuous systems are less susceptible to weather-related disruptions and provide greater operational predictability, aiding in more accurate schedule achievement.

On the other hand, traditional TS operations have their own set of advantages. They tend to be more cost-effective initially, requiring less capital investment compared to the extensive infrastructure needed for continuous methods. Additionally, TS systems offer greater flexibility and adaptability to varying mining conditions and ore body shapes. This flexibility allows for rapid adjustments in operations and is often more accessible worldwide due to the widespread availability of trucks and shovels. Thus, while continuous methods can markedly enhance production rates and ensure more reliable adherence to planned schedules, TS methods remain a viable and often preferable option in terms of initial investment cost and operational flexibility.

Due to the advantages of continuous mining methods, it is pretty common for large-scale open-pit mines to switch to continuous methods from the traditional TS approach. The decision to apply IPCC in a mature open-pit mine that has been under extraction using TS methods is more complex than implementing it in a new open-pit mine due to several factors inherent in the transition from an established system to a fresh one. These complexities arise from both operational and financial considerations, as well as the integration of new technologies into an existing workflow.

In a mature open-pit mine, significant investments have already been made in the TS infrastructure. This includes not only the purchase of trucks and shovels but also the establishment of maintenance facilities, fuel storage, and road networks optimized for truck movement. Switching to an IPCC system requires a reevaluation of these sunk costs and the potential for asset redundancy, leading to financial complexities that do not exist in a fresh mine where infrastructure is yet to be built.

Operationally, a mature mine has well-established workflows and production schedules that are finely tuned to the TS method. Introducing IPCC necessitates substantial changes to these workflows, which can disrupt production during the transition period. For instance, integrating semi-mobile crushers and conveyors requires redesigning parts of the pit, altering the haulage routes, and possibly reconfiguring processing plants and stockpiling areas. These changes can lead to temporary inefficiencies and potential production losses, making the transition more challenging compared to a fresh mine where systems can be designed around IPCC from the outset.

Another significant factor is the remaining life of the mature mine. The decision to invest in IPCC must consider the remaining mineral reserves and the expected operational lifespan. The financial justification for the high initial capital investment in IPCC infrastructure is more straightforward in a mine with a longer life. In contrast, for a mature mine with a limited remaining lifespan, the payback period might be insufficient to justify the switch unless there are substantial operational savings or productivity gains.

Additionally, mature mines often face spatial constraints that fresh mines do not. The layout of the pit, the location of waste dumps, and the proximity of infrastructure are already established, potentially limiting the optimal placement of IPCC components. This can lead to suboptimal system performance and increased operational costs, further complicating the decision. In contrast, fresh open-pit mines can be planned and developed with IPCC in mind from the early stages of mine design. This allows for the design of the entire operation around the strengths of the IPCC system, such as minimized truck haulage distances and optimized crusher and conveyor locations. The absence of legacy infrastructure and established workflows allows for a smoother and more efficient implementation, with fewer disruptions and a more transparent financial justification.

In evaluating whether to switch from a TS system to an IPCC system in a mature open-pit mine, modeling and analysis of operations are critical. Such a study must provide a detailed understanding of both current and potential future operations, enabling informed decision-making that balances operational efficiencies, costs, and strategic objectives. These include a detailed comparison of operational efficiencies, cost implications, financial viability, risk assessment, and environmental impact, enabling a comprehensive evaluation of the potential benefits and challenges associated with the transition. To achieve a comprehensive understanding of haulage methods, the literature offers diverse methods, including linear programming, queue theory, metaheuristic algorithms, and simulation modeling, among which the Discrete Event Simulation (DES) modeling has proven particularly effective. DES modeling allows for the creation of detailed dynamic models that simulate the sequence of operations and interactions within the mining process. By representing the mining system as a series of sequential discrete events, DES captures the complexities and variabilities inherent in mining operations, such as equipment breakdowns, maintenance schedules, and varying haulage velocities and distances. DES provides a robust and detailed approach for evaluating the feasibility and cost-effectiveness of adopting the IPCC method in a mature open-pit mine currently using the truck-shovel method. By capturing the complexities and variabilities of mining operations, DES enables informed decision-making, ensuring that the transition, if pursued, yields optimal operational and financial outcomes.

In the existing literature, much of the focus on the implementation of IPCC has been centered around new mine developments. This body of work predominantly assumes that IPCC systems are integrated from the onset of mining operations, overlooking the unique challenges and complexities associated with transitioning from established TS methods in mature open-pit mines. Consequently, there is a significant gap in the literature addressing the practical and operational difficulties inherent in such transitions.

This study aims to bridge this gap by leveraging the analytical power of DES to rigorously compare two primary scenarios: (1) transitioning to an IPCC system, including the optimization of the mine layout to minimize the distances trucks must travel to semi-mobile crushers, and (2) continuing with the TS system. By examining these scenarios through the lenses of economic viability and productivity metrics, this research provides a comprehensive analysis that enhances our understanding of the practical implications and potential benefits of IPCC implementation in mature mining operations. This study's contributions will offer valuable insights for decision-makers considering similar transitions in their mining practices, thereby addressing an important but often overlooked aspect of mining operations.

This study is organized as follows: Section 1 presents a brief introduction to the research problem. In the Background section, relevant literature is reviewed, and existing gaps in knowledge are elaborated. Section 3 explains the applied methodology, covering everything from data acquisition to DES modeling. Subsequently, Section 4 illustrates the obtained results and offers a detailed discussion of the insights retrieved. Finally, the manuscript concludes by highlighting key results and study limitations and suggesting avenues for future research.

2. Background and Literature Review

This section aims to review the relevant background and the available literature on IPCC and TS material haulage in open-pit mines and applications of DES in modeling and analyzing such systems to provide context, demonstrate the relevance of the research, identify gaps, and establish a foundation for the study's objectives.

2.1. Background

IPCC systems, first introduced in Germany at the Werk Hover mine in 1956 [2], have significantly innovated open-pit mining operations by relocating the primary crusher into the pit and extending the conveyor system deeper into the site. This method eliminates the need for many haul trucks, reducing extensive costs associated with truck haulage, which constitutes nearly half of mining operational expenses. Conveyors, compared to trucks, offer substantially lower operating costs over long distances [3], enhanced operational efficiency, and reduced environmental impact due to lower emissions and energy consumption. While IPCC systems require a high initial capital investment, they provide significant long-term savings through reduced truck usage, lower fuel consumption, and minimal maintenance, making them ideal for high-production, long-term projects.

In contrast, the TS system, predominant in over 80% of Greenfield mining operations, is favored for its flexibility and adaptability, particularly in the early stages of mining where haulage distances are short and fewer trucks are needed [2]. Trucks in the TS system can easily adjust to varying production rates by changing the number of trucks in operation. However, as mining operations progress and pits deepen, the efficiency of trucks diminishes due to increased travel distances, leading to higher fuel consumption, frequent maintenance, and a greater need for trucks, driving up operational costs. The TS system also generates higher emissions and causes more significant environmental impacts due to extensive fuel consumption and the requirement for larger road networks. Despite lower initial costs, the TS system's long-term sustainability decreases, making IPCC systems a more economically and environmentally viable option for long-term, stable mining operations.

2.2. Relevant Literature

2.2.1. TS Haulage System

This section reviews the most recent advancements in haulage systems. A thorough examination of the literature reveals a substantial body of work focused on enhancing dispatching and fleet management in TS haulage systems. Some of the notable studies are reviewed below. For instance, Moradi-Afrapoli et al. [4] applied Fuzzy Linear Programming (FLP) to achieve an interaction-aware dispatching plan. Their framework could address the significant operational cost associated with material handling in surface mines, which accounts for around 50% of the total cost. Traditional truck dispatching models in surface mining often overlook crucial interactions between truck fleets, shovel fleets, and processing plants, fail to incorporate strategic-level goals and disregard the uncertainty of input parameters. They introduced a new truck dispatching model that aims to overcome these limitations by employing FLP to handle the inherent uncertainty in mining operations. The proposed model was implemented in a surface mining operation, where it demonstrated a significant improvement in production and fleet utilization. Specifically, the FLP model increased the hourly ore delivery to processing plants by 21% and 15% for the two plants in the study and optimized shovel utilization by prioritizing ore shovels over waste shovels. Additionally, the truck fleet efficiency was enhanced, reducing the average queue time per truck by 15%.

While the majority of research initiatives have been focused on the operational dimensions of mining to utilize the available fleet efficiently, it is noteworthy that enhancing fleet performance can also be realized with respect to the strategic plan. Moradi-Afrapoli et al. [5] highlighted this point and developed a Nested Fleet Management System (NFMS) that bridges the gap between operational execution and strategic planning by integrating shovel allocation with plant feed optimization. Such

an integration is crucial for ensuring that operational decisions are closely aligned with strategic production goals, thereby enhancing overall efficiency. By employing two nested multiple-objective Mixed-Integer Linear Goal Programming (MILGP) models, the NFMS can make more holistic and informed decisions. The developed framework led to a 14.6% enhancement in its required truck fleet capacity to meet the production target, compared to a traditional locked-in operation. This improvement underscores the potential of the NFMS to boost operational efficiency and resource utilization in open-pit mining.

Similarly, Mohtasham et al. [6] developed a framework to optimize truck and shovel scheduling in open-pit mines. This research addressed four main objectives: maximizing production, minimizing deviations in head grade, minimizing deviations in tonnage to ore destinations, and minimizing fuel consumption of mining trucks. The study utilized a MILGP to achieve these goals while examining how the prioritization of objectives affects the efficiency of the mining operation. Their approach involves the development of a mathematical optimization model that schedules the allocation of trucks and shovels, considering operational constraints such as equipment compatibility, ore quality, and stripping ratios. The model used Sequential Linear Goal Programming (SLGP), an interactive approach that optimizes goals in a sequence based on their priority levels. Their results underscore that different priorities can lead to vastly different operational outcomes, emphasizing the need for a flexible and adaptive approach to mine planning.

Mohtasham et al. [7] employed Mixed-Integer NonLinear Programming (MINLP) models to estimate the optimal number of trucks based on the match factor, with two distinct strategies: one addressing each loader type individually and the other considering all types of loaders simultaneously. The novelty of this research lies in the dual-strategy approach to optimizing truck fleet size, which includes both individual loader-focused optimization and a comprehensive model that addresses all loaders together. Additionally, the study integrated short-term production scheduling and traffic conditions into the match factor calculation. The study revealed that both MINLP models effectively improve fleet efficiency and productivity compared to the truck fleet size used in the case study.

Time complexity is one of the limitations in optimized dispatching, particularly in large-scale problems. This issue hinders their real-time applications. In this context, Noreiga et al. [8] harnessed Artificial Intelligence (AI) capabilities to achieve real-time dispatching systems. They developed a truck dispatching system based on deep reinforcement learning that optimizes the real-time assignment of trucks in open-pit mines, aiming to enhance the efficiency and utilization of mine equipment and achieve production and processing targets. They leveraged a Double Deep Q-Learning (DDQN) algorithm to handle the dynamic and uncertain environment of open-pit mining operations. Their methodology involved developing a DES model that replicates the TS environment in an open-pit mine. The DES model incorporates various uncertainties, such as equipment cycle times and road conditions, to create a stochastic training environment for the deep reinforcement learning agent. The DDQN algorithm is employed to train a centralized dispatching agent that makes real-time dispatch decisions based on the current state of the mining system.

Fuel consumption is one of the critical factors in the TS haulage system as it directly influences both the operational costs and environmental impact of mining operations. High fuel consumption not only increases the expenditure on diesel, which constitutes a significant portion of the overall mining costs, but also leads to higher emissions of greenhouse gases. Efficient fuel consumption can be achieved by optimizing truck sizes, load capacities, and haul road conditions, ultimately enhancing the cost-effectiveness and sustainability of mining operations. Therefore, minimizing fuel consumption not only aligns with economic objectives by lowering operating costs but also supports environmental goals by reducing emissions, making it a vital aspect of the haulage method decision in mining. In this regard, Vera-Burau et al. [9] aimed to analyze the impact of different production scenarios on fuel consumption and truck model performance in open-pit mining operations. Utilizing

a comprehensive methodology that included Vulcan-Maptek tools for mine planning and design, the researchers developed a block model of a real uranium deposit to evaluate the economic feasibility, operational efficiency, and environmental implications of various production rates and equipment configurations. Critical parameters such as NPV, ramp widths, and slope gradients were assessed to determine their influence on mine design and profitability. The findings revealed that higher production scenarios significantly increased NPV and reduced the life of the mine, emphasizing the importance of optimizing production rates for economic viability. Additionally, while variations in ramp width affected waste removal and final slope angles, the overall pit geometry remained stable. The study highlighted the critical role of equipment selection in minimizing fuel consumption and CO_2 emissions, aligning with sustainable mining practices. However, the research was limited to the parameters and conditions of the specific case study, suggesting a need for further exploration across different mining contexts and the integration of advanced technologies to enhance environmental performance.

2.2.2. IPCC material handling system

Recently, literature has witnessed massive efforts on different aspects of continuous haulage, particularly the IPCC method. IPCC affects pit-design requirements to accommodate semi-mobile crushers compared to traditional pit-shape constraints. In this regard, Hay et al. [3] investigated how to integrate the additional requirements of Semi-Mobile In-Pit Crushing and Conveying (SMIPCC) systems into the Ultimate Pit Limit (UPL) determination process, thereby altering the traditional pit shape requirements to accommodate the unique constraints of SMIPCC operations. By leveraging the mathematical principles of convex hulls, bounding boxes, and future value discounting, the study introduces a novel algorithm that extends the existing network flow method, ensuring both mathematical rigor and practical applicability. The developed algorithm efficiently incorporates the need for a straight conveyor wall, a constraint previously unaccounted for in traditional UPL determination methods, thus optimizing pit limits for metalliferous mining operations.

Key insights from the study reveal that despite SMIPCC pits being smaller than traditional TS pits, they can achieve higher Net Present Values (NPVs) due to reduced mining costs, underscoring their economic viability. The algorithm's efficiency, demonstrated through a detailed case study, highlights its applicability to a range of mining operations, proving its practicality for real-world implementation. However, One significant limitation is the complexity and computational intensity associated with accurately modeling the optimal pit limit in three dimensions. While the algorithm is designed to be mathematically rigorous and efficient for small case study block models, its performance and scalability for larger, more complex models remain uncertain. Additionally, the study highlights that the scheduling of SMIPCC systems is more constrained compared to traditional TS systems, which can negatively impact the NPV of mining operations. The economic viability of SMIPCC systems, despite higher upfront capital costs, depends heavily on accurate scheduling and operational consistency. Lastly, the developed algorithm assumes the final position of the crusher without accounting for progressive relocations over the mine's life, potentially limiting its adaptability to dynamic operational conditions.

Likewise, Al Habib et al. [10] delved into short-term mine plan updating under the IPCC system due to the semi-mobile crusher relocations. They focused on optimizing short-term production plans for open-pit mines utilizing SMIPCC systems. The primary objective is to generate an annual production schedule that minimizes material handling costs and maximizes revenue while meeting plant requirements and adhering to IPCC location constraints. The study proposes a mixed integer programming (MIP) model to achieve these goals, contrasting scenarios with and without IPCC systems. They revealed that incorporating SMIPCC can generate 0.66% higher profit compared to traditional TS systems, with a notable 30% reduction in truck requirements. The model effectively allocates shovels to mining faces, ensuring production targets align with long-term plans. However, the study's deterministic nature is a limitation, as it does not account for operational uncertainties

such as equipment failures or maintenance. Additionally, the model does not consider ore blending requirements or the costs associated with shovel movements between benches, which could impact the realism and applicability of the results.

In a similar vein, Kamrani et al. [11] evaluated the long-term planning of open-pit mining operations in the presence of IPCC. The paper developed a two-step mathematical model that first determines optimal crusher locations and relocation times and then sequences the extraction process over the mine's operational lifespan. The study investigated three distinct scenarios: no IPCC, IPCC for ore, and IPCC for both ore and waste. Their findings demonstrated that the third scenario, incorporating crushers for both ore and waste, significantly reduces ore and waste travel distances by 110 km and 395 km, respectively, compared to traditional truck haulage. Furthermore, the discounted cash flow analysis reveals a 15% improvement in the scenario with dual in-pit crushers, underscoring the cost-saving potential. While the study offers valuable insights, it has several limitations. Firstly, the model does not account for real-time operational uncertainties such as equipment failures and maintenance, which can impact overall efficiency. Additionally, the economic analysis does not fully consider capital investment variations under different scenarios.

As outlined in [12], choosing IPCC over TS is not a straightforward decision and can be a controversial issue. Consequently, a number of studies have focused on cross-comparisoning these two methods. Abbaspour and Drebenstedt [13] evaluated the effectiveness of various transportation systems in open-pit mining through the development and application of a technical index based on system dynamics modeling. The research addresses the need for a comprehensive assessment of the TS and IPCC systems, which include Fixed In-Pit Crushing and Conveying (FIPCC), Semi-Fixed In-Pit Crushing and Conveying (SFIPCC), SMIPCC, and Fully Mobile In-Pit Crushing and Conveying (FMIPCC). They developed a decision-making framework that incorporates system availability, utilization, and power consumption, thereby identifying the most effective transportation system at any point during the mine's operational lifespan.

Their findings indicate that the TS system generally emerges as the most preferred transportation method, except for two specific periods during the mine's operation. The results demonstrate the highest availability for the TS system (99.45% to 99.73%) and the highest utilization for FMIPCC (86.6%). One notable limitation of this study is its deterministic approach, which may not fully capture the stochastic nature of real-world mining operations. The research acknowledges that factors such as equipment failures, maintenance schedules, and operational delays can introduce significant variability. Future research should consider incorporating stochastic elements to enhance the model's robustness and reliability.

While the available literature mainly offers research initiatives aimed at enhancing the IPCC haulage system, a few studies focus on IPCC-driven novel extraction methods. In this regard, Gong et al. [14] proposed a new conceptual mining method known as the Near-Face Stockpile (NFS), combining IPCC systems with a pre-crusher stockpile. The primary objective of the study was to quantitatively evaluate the performance of the NFS method, which theoretically offers enhanced production efficiency, stability, and equipment utilization over traditional TS and IPCC methods. A MILP model was developed for short-term production scheduling, which optimized the mining schedule and integrated it into the simulation framework for comprehensive performance evaluation. A case study conducted on an oil sands mine validated the framework. Key insights from the study reveal that the NFS method increased overall production by 5.06%, reduced the transporting distance of minerals by 17.87%, and improved the utilization rates of shovels and crushers by 4.96% and 4.85%, respectively. The research confirmed that the NFS method effectively reduces truck cycle times and

enhances operational stability by minimizing the impact of subsystem failures. However, the initial investment required for the NFS method is higher than that for traditional IPCC methods.

Additionally, while the operating cost of conveyors is relatively low, any damage to the conveyor system can have severe consequences. The NFS method also imposes higher requirements on the bottom size of the open pit and is more suitable for ore bodies with lower strip ratios. Furthermore, the added reclaim shovel introduces potential bottlenecks and additional risks.

From the economic perspective, Gong et al. [15] evaluated the NSF method's impact on plant throughput quality and NPV of the mining project. They introduced a novel approach by incorporating a stockpile near the mining face, which serves as a buffer to enhance the stability and efficiency of the mining operation. They employed a MILP model to optimize the short-term production schedule, ensuring an optimal mining sequence that maximizes NPV. The results indicated a 5.06% increase in overall production, a 17.87% reduction in truck transportation distance, and improvements in shovel and crusher utilization by 4.96% and 4.85%, respectively. However, the study also acknowledged certain limitations, such as the higher initial investment costs and the need for precise management of the stockpile to ensure consistent feed quality. Additionally, the study did not address the verification of quality blending and the impact of stockpile capacity and zoning on overall performance, which are areas suggested for further research.

2.2.3. DES applications in material haulage

DES can be highly effective in analyzing TS and IPCC scenarios by providing a detailed and dynamic representation of the mining operations. For TS scenarios, DES allows for the modeling of complex interactions between trucks, shovels, and other auxiliary equipment, capturing the variability in cycle times, travel distances, and operational delays. This level of detail enables the identification of bottlenecks and inefficiencies within the haulage system, facilitating the evaluation of different operational strategies and their impacts on productivity. By simulating various scenarios, DES can help optimize fleet size [16], equipment allocation [17], and scheduling [18], thereby improving the overall efficiency and cost-effectiveness of TS operations.

Fleet dispatching is one of the highly regarded use cases of DES in haulage systems. Empowering DES with the optimization algorithm makes a robust framework for finding optimal working scenarios. In this regard, Mohtasham et al. [17] presented an optimization framework that includes three sequential stages: fleet size selection, fleet allocation, and real-time truck dispatching. They integrated simulation and optimization to determine the optimal fleet size, which is coupled with a heuristic algorithm for operational decisions. This combination could address the stochastic nature of mining operations and incorporate real-time decision-making processes. The results demonstrated that the proposed framework significantly improves operational efficiency. This optimal sizing led to a balanced truck-shovel system with improved equipment utilization and a higher match factor.

In the DES-based dispatching context, Mirzaei-Nasirabad et al. [19] developed a DES-based truck dispatching framework that addresses the real-time truck dispatching problem in open-pit mining operations. Their approach was built on a multi-stage dispatching approach to optimize TS material handling systems. This research is significant due to the critical role of efficient truck dispatching in enhancing operational efficiency and productivity in mining. The proposed methodology consists of two primary stages: allocation planning and dynamic allocation. Initially, a scenario-based method was employed to estimate the optimal number of trucks required for the mining operation, ensuring that the fleet size is well-suited to meet production demands. This model aimed to minimize fleet waiting times and deviations from the production paths established during the allocation planning

stage. By incorporating multiple objectives, the model provides a comprehensive solution that balances various operational priorities, such as reducing idle times and ensuring consistent material flow. The results demonstrated that the model can achieve a better balance between minimizing waiting times and maintaining adherence to the planned production paths, thereby enhancing overall operational efficiency.

DES can also serve as a reliable tool for fleet estimation. Huayanca et al. [20] focused on estimating the required truck fleet size for an expanding open-pit copper mine in Peru using DES modeling. The DES model incorporated random variables such as fixed times and tonnages loaded to hauling equipment, allowing for a more realistic replication of the mine's yearly production plan. The study's methodology involved the development of a calibrated model that simulated daily operations, followed by the application of this model to a yearly plan under both stochastic and deterministic scenarios. The results demonstrated that the stochastic model required additional trucks and resulted in longer cycle times compared to the deterministic model. This finding indicates that the deterministic approach may underestimate the variability and operational challenges faced in real-world scenarios. The study provides valuable insights into the benefits of using DES for truck fleet estimation, highlighting its ability to anticipate potential issues such as longer queues and increased cycle times. However, the research is limited by its focus on a specific case study, suggesting that further studies are needed to generalize these findings to other mining operations.

In IPCC scenarios, DES offers a valuable tool for assessing the integration and performance of conveyor systems alongside traditional haulage methods. The simulation can model the continuous flow of material through crushers and conveyors, accounting for variations in material properties, equipment capacities, and maintenance schedules. This holistic view allows for the examination of how IPCC systems interact with and potentially enhance or disrupt existing TS operations. By analyzing different configurations and operational strategies, DES can help determine the optimal balance between truck haulage and conveyor transport, leading to more sustainable and efficient mining practices.

2.3. Gaps in Knowledge

Existing literature has extensively examined the implementation of various forms of IPCC systems, predominantly focusing on their integration into new mining operations. These studies typically assume the incorporation of IPCC systems from the initiation of mining activities, thus neglecting the unique challenges and complexities involved in transitioning from traditional TS methods to IPCC systems in mature open-pit mines. This oversight presents a substantial gap in current research, as the operational difficulties and practical implications of such transitions remain inadequately addressed.

This study seeks to address this critical gap by employing DES to conduct a rigorous comparative analysis of two primary scenarios: (1) the transition to an IPCC system, with an emphasis on optimizing the mine layout to minimize truck travel distances to semi-mobile crushers, and (2) the continuation of the conventional TS method. By focusing on the practical aspects of transitioning in established mines, this research aims to provide a comprehensive evaluation of the operational and economic impacts, thereby offering valuable insights for decision-makers in the mining industry.

3. Methodology

To evaluate the cost-effectiveness and production efficiency of transitioning to the IPCC/OPCC system in a mature open-pit mine, it is essential to develop a viable and accurate DES model that

reflects the actual haulage operations. This section details the efforts undertaken to create and validate a comprehensive DES model replicating the activities of the open-pit ore mine used as a case study. The methodology applied encompasses several critical stages: data collection, data wrangling, DES model development, and model verification. Each of these stages is elaborated upon in the following sub-sections.

3.1. Data Collection

The initial phase of the study involved site visits and the collection of diverse input data essential for simulation input modeling. This data encompasses the following aspects:

- Pit design: The pit design data was used to extract road networks and understand the pit's shape at specific time sections, providing crucial information about the mine's layout and transportation routes. This detailed layout helps in creating an accurate representation of the operational environment within the simulation model.

- Short-term mine plan and production schedule: The production schedule was employed to determine mining polygons, blast patterns, and extraction sequences, offering insights into the mine's operational flow. This data, derived from the mine's short-term (monthly) plans, specifies the quantity of material to be displaced from various benches by each contractor. Such information is vital for simulating the dynamic and sequential nature of mining operations.

- Operational data: Historical data regarding mining operations, such as load times, dump times, and full-haul and empty-haul velocities, are critical for understanding the efficiency of mining operations. These data points were collected using equipment-mounted GPS over the preceding year. This historical operational data provides a basis for modeling realistic operational behaviors and performance metrics.

- Available fleets and their maintenance Data: Given the fluctuating number of pieces of equipment employed throughout the project, accessing the exact number of equipment is essential for achieving dependable results. This includes information on the available equipment at any given time, as well as their associated downtimes and intervals. The study leverages Mean Time to Repair (MTTR) and Mean Time Between Failure (MTBF) data as the primary available data for modeling resource downtimes.

- Dispatching rules: This includes the criteria for allocating shovels to mining faces and assigning trucks to shovels. The pit design, mine topology, equipment functionality and capacity, and access restrictions influence these considerations. Understanding these dispatching rules is crucial for accurately modeling the decision-making processes involved in mine operations.

By analyzing this comprehensive set of data, the study aims to develop a robust DES model that accurately reflects the real-world operations of the open-pit ore mine.

3.2. Data analysis

Following data collection, rigorous data analysis was applied. This step is crucial in achieving valid operational data suitable for data preprocessing and input modeling. Since data analysis was conducted on different data types, a concise description for each data type is provided as follows.

3.2.1. Road Network

To begin with, it is crucial to establish a comprehensive road network to determine the distances between various dig and dump locations. This road network is derived based on the periodic pit profiles generated from aerial survey of the pit. By utilizing these pit designs and leveraging a semi-automated algorithm, an accurate representation of the mine's road profile is generated, ensuring that all routes between key points are accounted for. Furthermore, this road network undergoes validation through site visits, confirming that the extracted routes are aligned with actual road conditions and accessibility. This validation step is essential as it ensures the reliability and accuracy of the data, forming a solid foundation for further calculations and optimizations in the mining process.

3.2.2. Schedule

The short-term monthly plan serves as the cornerstone of the mine schedule. This plan delineates the areas (referred to as polygons) to be extracted, along with their corresponding priorities. The subsequent step involves extracting the mining schedule using polygon maps from these monthly plans. This schedule is vital for outlining the entire mining operation, detailing the locations of loading faces that represent different extraction points within each polygon. Each face includes specific information, such as the tonnage of material to be extracted and the load types involved. By meticulously mapping out these details, a structured and efficient schedule is developed to manage the mining process, ensuring that all necessary faces are mined out during the planned periods.

3.2.3. Distance Matrix

Following the analysis of the road network and mine schedule, Dijkstra's algorithm is employed to compute the matrix distances between various nodes on the road network. These nodes encompass dig points, dump points, crushers, fuel stations, maintenance shops, and parking areas. Dijkstra's algorithm is particularly effective for this purpose as it identifies the shortest paths between nodes in a graph, ensuring that the distance matrix is both accurate and optimized. This matrix serves as a critical tool for planning and logistics, allowing for precise calculation of travel times and routes.

3.2.4. Operational Data

Operational data encompasses several key metrics, including loading time, dumping time, full-haul, and empty-haul velocities. Each of these metrics is categorized based on influential factors such as equipment capacities, load types, and seasonal variations. It is noteworthy that these factors are not uniformly applicable across all metrics. For example, loading time is influenced by the capacity of the trucks and shovels, the type of load, and the season. In contrast, empty-haul velocity depends on the type of truck, load types, and the season.

The initial preprocessing of this operational data involves omitting null values and corrupt data entries, such as zero logging or aggregated time records, to ensure the integrity of the dataset.

Following this, an outlier-dropping procedure is conducted to remove data points that deviate significantly from the norm, further refining the dataset for analysis.

Subsequently, various statistical measures are calculated to gain a comprehensive understanding of the dataset. These measures include the count, mean, standard deviation, mode, median, percentiles (25th and 75th), and minimum and maximum values. This statistical analysis provides valuable insights into the distribution and variability of the data.

Multiple methods are employed to model the data distribution accurately, including Maximum Likelihood Estimation (MLE), moment matching, and least square methods. Additionally, empirical distribution fitting is conducted to capture the underlying patterns in the data. The goodness of fit for standard distributions is then evaluated using a combination of visual assessments, Kolmogorov-Smirnov (k-s) tests, and chi-square tests. These evaluations ensure that the chosen distributions accurately represent the operational data, providing a robust foundation for further analysis and decision-making in the mining process.

3.2.5. Dispatch Rules

By analyzing database records and multiple site visits, the general rules for fleet dispatching and shovel-to-face assignment have been extracted. Some of the paramount rules to be applied while dispatching in the DES model are cited in this section for the sake of brevity. This section explains the rules for allocating shovels to working faces and trucks to shovels, ensuring optimal resource utilization and operational efficiency.

Allocating shovels to workfaces involves several key factors: working face priority, shovel mobility, and load compatibility. In terms of workface priority, it should be noted that not all faces have the same priority. Larger shovels are assigned to higher-priority workfaces. For example, a workface with waste material above ore has a higher priority, necessitating the allocation of larger, more efficient shovels to expedite the removal process. Moreover, shovels move very slowly, which restricts their ability to be relocated frequently. To optimize operational efficiency, shovels are moved between nearby working faces, minimizing downtime and maximizing productive time at each face. Likewise, the efficiency of a shovel is significantly influenced by the load density it handles. Shovels with smaller buckets are more efficient with higher-density loads, such as ore, whereas larger shovels are better suited for lower-density loads, such as waste material. This compatibility ensures that each shovel operates at its optimal capacity, ensuring that equipment is working within its limits.

Similarly, allocating trucks to shovels involves several essential factors: workface priority, truck and shovel compatibility, and truck mobility. Due to resource constraints (i.e., the system works in under-truck conditions), it is essential to prioritize their allocation. Shovels operating at higher priority working faces, particularly those working on ore extraction, are given precedence for truck allocation. This prioritization ensures that critical material is transported efficiently, maintaining the continuity of mining operations. Furthermore, **t**he fleet's heterogeneity necessitates careful matching of trucks and shovels. Larger trucks are assigned to shovels with larger buckets, ensuring that the loading process is efficient and that each truck can carry its maximum load capacity.

Conversely, smaller trucks are paired with excavators that have smaller buckets, maintaining operational harmony and preventing mismatched resource allocation. Lastly, it is noteworthy that larger trucks require wider paths for travel, influencing their allocation. These trucks must be assigned to shovels at working faces with adequate access and sufficient maneuvering space. This

rule ensures that larger trucks can operate without hindrance, reducing the risk of delays and enhancing the overall safety and efficiency of material transport.

3.3. DES Model Development

A core component of the methodology is the development of a full-scale DES model. The DES model of an open-pit mine is structured around three primary components: resources (trucks, shovels, and crushers), locations (dig points and dump sites), and operational processes. According to the reality of the case study, the model employs a fixed allocation strategy, where resources are pre-assigned to specific locations based on a predetermined plan. This approach allows for the evaluation of different resource allocation strategies and their impact on overall mining efficiency. It is developed using the Simpy package in Python, creating a specialized module to simulate the entire process from extraction to material transportation. The model focuses on moving waste, ore, and tailing material to designated dump sites, utilizing essential resources such as trucks, shovels, and crushers. The developed model simulates real-world scenarios of open-pit mining operations, enabling the evaluation of different strategies for resource allocation and process optimization. Figure 1 visualizes different components of the developed DES model, which are described below.

A. Modeling and dig point schedule

The process begins with modeling objects and relationships, followed by running the simulation. The initiation of dig points is prioritized, and once ready, the dig point process is initiated. Trucks and shovels are requested to facilitate the excavation. A prerequisite waiting period occurs until the necessary dig points are prepared. If required, trucks are requested to support the operation. The sequence completes with trucks and shovels moving to their respective locations.

B. Shovel process

The shovel process is closely tied to the dig point schedule. After releasing the shovel from maintenance or failure checks, shovels proceed to serve trucks at the dig points. If a dig point is finished, the shovel is moved to a new dig point. In case of maintenance failure, the shovel undergoes necessary repairs before resuming operation. This process ensures that shovels continuously serve trucks until the extraction task is complete, after which they are released from the site.

C. Truck cycle

The truck cycle begins with trucks being dispatched to dig points where they request shovels for loading. Post-loading, trucks move to dump points. Depending on the presence of crushers at the dump point, trucks either dump material directly or queue for the crusher. After dumping, trucks determine if the previous mining face is finished, whether trucks require maintenance, refueling, or if the shift has ended. If the mining face is fully extracted, trucks follow alternative plans if available or are released from duty. Trucks needing maintenance or refueling are directed to maintenance shops or fuel stations. At the end of a shift, trucks are parked to await the next shift.

D. Truck decision-making

Decision-making for trucks is dynamic. Post dumping, trucks assess if the assigned dig point is completely mined out. If not, they check for maintenance needs, shift end conditions, and fuel status. Based on these checks, trucks either move to parking lots, fuel stations, or maintenance shops or return to the previous dig location to continue operations. This decision-making process ensures that trucks are always ready to serve the excavation needs efficiently.

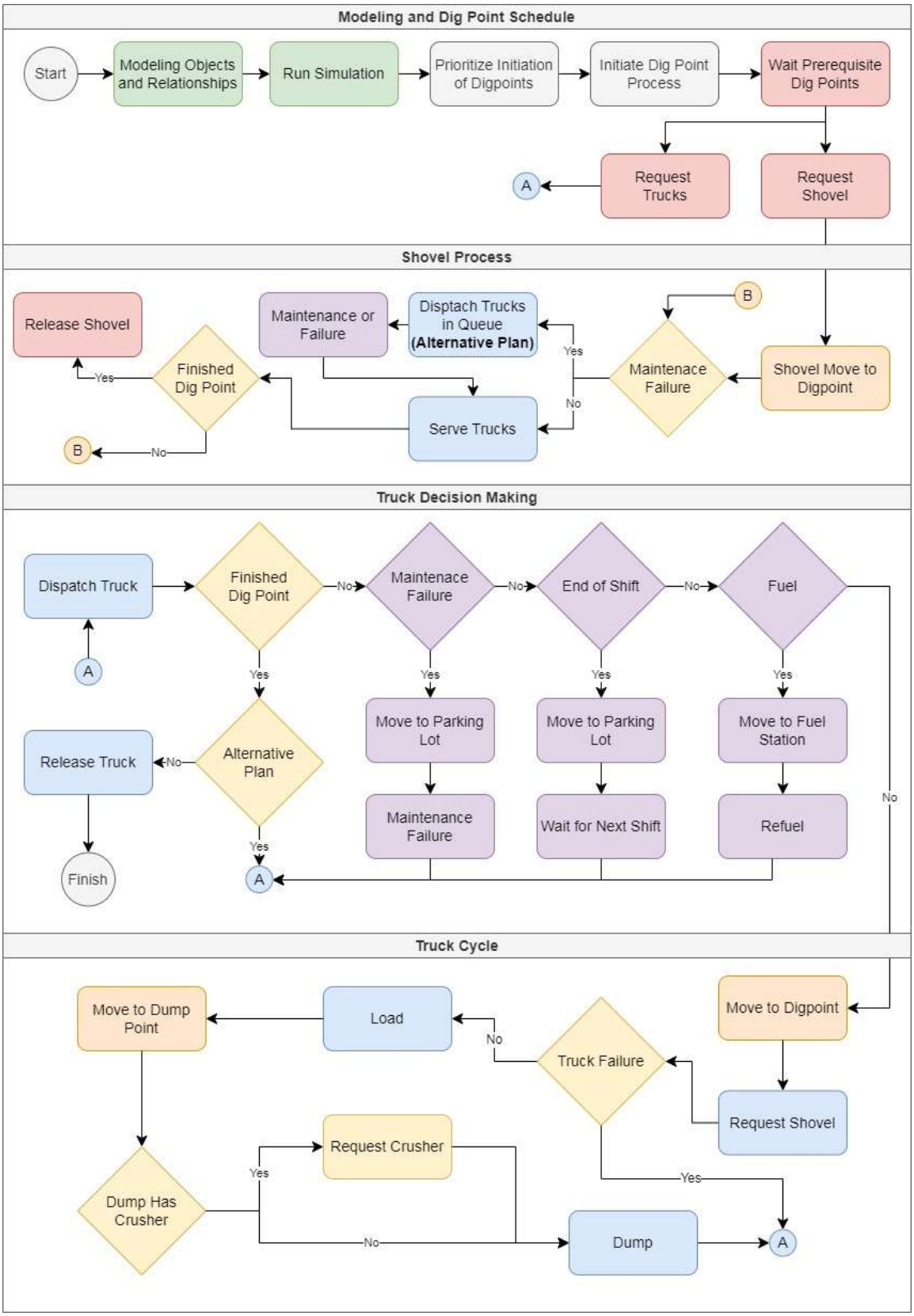


Figure 1. Overview of the developed DES model.

4. Case Study

This study focuses on an open-pit iron ore mine, being actively under extraction using a truck-shovel system for over two decades, facilitating continuous haulage operations 24/7 throughout the year. The mining operation employs a diverse fleet of trucks and shovels with varying capacities sourced from different manufacturers, reflecting a complex logistical and operational framework. The mine extracts three primary material types: ore, waste, and overburden. The ore reserve at this site is substantial and is projected to be sufficient for the next ten to twelve years, ensuring the mine's operational continuity and economic viability.

In addition to the current truck-shovel system, this study explores IPCC as an alternative scenario for the remaining work packages. The analysis will provide insights into the potential efficiency gains and operational benefits of IPCC compared to the traditional truck-shovel system, offering a comprehensive evaluation of both methodologies in the context of this specific open-pit mining operation.

4.1. Simulation Experiment Setup

The developed model is designed to interface seamlessly with a configuration file in Excel™ format, allowing for the manipulation of the majority of simulation behaviors. This approach provides extensive parameterization capabilities, enabling the adjustment of various operational aspects based on the configuration file. Key configurable parameters include allocation mode (fixed and floating), truck dispatch method (fixed and floating), simulation types (deterministic and stochastic), operational considerations (e.g., maintenance, failures, and refueling), general simulation settings (e.g., shift duration, daily shift count, and pit evacuation period), and replication length. Table 1 indicates the applied experiment setting in the configuration file.

Table 1. Simulation setup.

Item	Value
Allocation mode	Fixed
Dispatch method	Post-loading/post-dumping
Simulation type	Stochastic based on empirical distributions
Maintenance, Failure, Refueling	True
(# of shifts per day, shift duration)	(3, 480 minutes)
Evacuation period	30 minutes
Replication length	90 shifts

4.2. Input Data

The developed DES model can process both deterministic and stochastic data, as indicated in Table 1. With the exception of the distance matrix and schedule, the model primarily utilizes stochastic inputs to ensure more reliable results. By categorizing influential factors on operational data, multiple combinations were generated, some of which were deemed invalid. Categories with marginal data counts were considered invalid combinations, as they are unlikely to occur in reality. Table 2 presents the influential factors for each data set, along with the corresponding total and valid number of combinations.

Table 2, Operational data classification.

Data	Influential factors (# of instances)	Total combinations	Valid combinations
Loading	Truck capacity (4), Shovel capacity (3), Load types (3), Season (2)	72	40
Dumping	Truck capacity (4), Dumpsites (9), Load types (3), Season (2)	216	37
Full-haul velocity	Truck capacity (4), Load types (3), Season (2)	24	17
Full-haul velocity	Truck capacity (4), Load types (3), Season (2)	24	17

[1]:Truck capacities ranges from 35 to 135 tones.
[2]: Shovel capacity includes small, medium, and large (bucket capacities range from less than 5 m^3 to over 14 m^3).

Due to the high number of combinations, and for the sake of brevity, only a subset of the valid combinations is described statistically in Table 3.

Table 3, Combination data statistics (values are modified for the sake of confidentiality).

Data	Combo	Mean	Std	Fitted distribution	Fitting error
Loading (sec.)	100-Small-Waste-Wet	0.61	0.14	NORM(0.61, 0.15)	0.05%
Dumping (Sec.)	60-Waste-DWST2-Wet	0.5	0.17	0.12 + GAMM(0.08, 0.02)	0.2%
Full-haul velocity (Km/h)	35-Waste-Wet	0.66	0.14	0.28 + 0.75 * BETA(0.12, 0.11)	0.09%
Empty-haul velocity (Km/h)	35-Waste-Wet	0.69	0.12	TRIA(0.28, 0.77, 1)	0.46%

As shown in Table 3, distribution fitting was conducted rigorously, resulting in negligible fitting error. Moreover, all the analyzed data were subjected to empirical distribution fitting. Using an empirical distribution fitted on data in simulation modeling may be preferable to a standard distribution because it captures the actual observed behavior and nuances of the data, leading to more accurate and realistic simulation results. Empirical distributions do not assume a predefined shape, allowing them to better reflect the inherent variability and specific characteristics of the data set. This

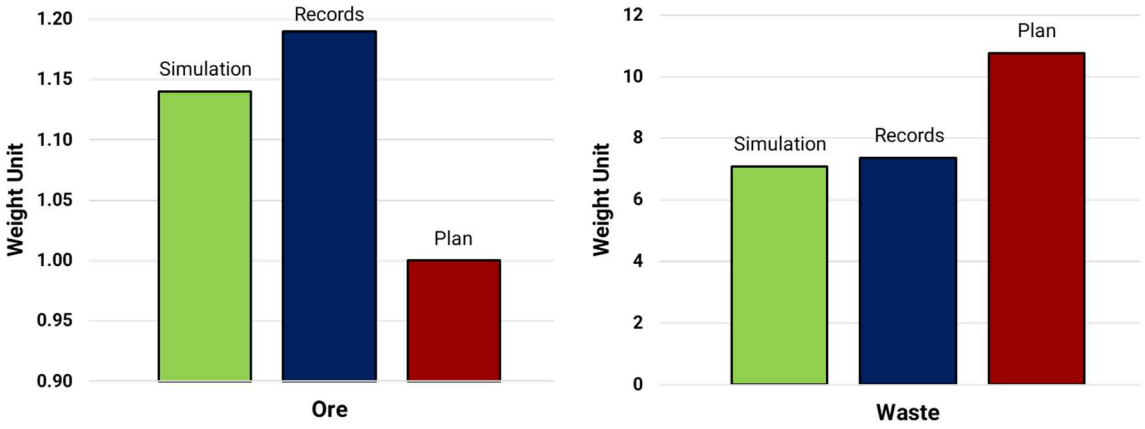
approach enhances the reliability of the simulation results by directly utilizing the empirical data's frequency and pattern, thereby improving decision-making and predictive accuracy in complex systems.

4.3. Results and Validation

Utilizing the adjustments detailed in Section 4.1, the simulation model was executed for a period equivalent to 90 working shifts, simulating one month of operations. In this section, the results retrieved from the simulation are validated against the actual data recorded in the database. Among the various simulation outputs, hauled tonnage is of paramount importance. Table 4 and Figure 2 compare the performance of the DES model against the actual operational data.

Table 4. Hauled tonnage comparison (values are modified for the sake of confidentiality).

Ore Monthly plan: 1 unit			**Waste** Monthly plan: 10.77 unit		
Simulation	**Record**	**Difference**	**Simulation**	**Record**	**Difference**
1.14	1.19	-4.27%	7.09	7.37	-3.67%



a. hauled ore tonnage b. hauled waste tonnage

Figure 2. Hauled tonnage in plan, simulation, and reality.

Figure 2 demonstrates that the DES model can accurately replicate real-world conditions. The difference between the simulation results and actual data is less than five percent for both ore and waste, which is considered highly acceptable. Since the validation process was completed for all input parameters, this minor difference can be attributed to discrepancies between the actual fixed assignments and the simulated assignments. Although the applied assignments adhered to the established dispatching rules, they may not precisely replicate the exact conditions and decisions made in reality.

To better understand the hauled tonnage breakdown structure, a Sankey diagram is plotted in Figure 3 to visually illustrate the portion of extracted material from each bench and their corresponding dump destination.

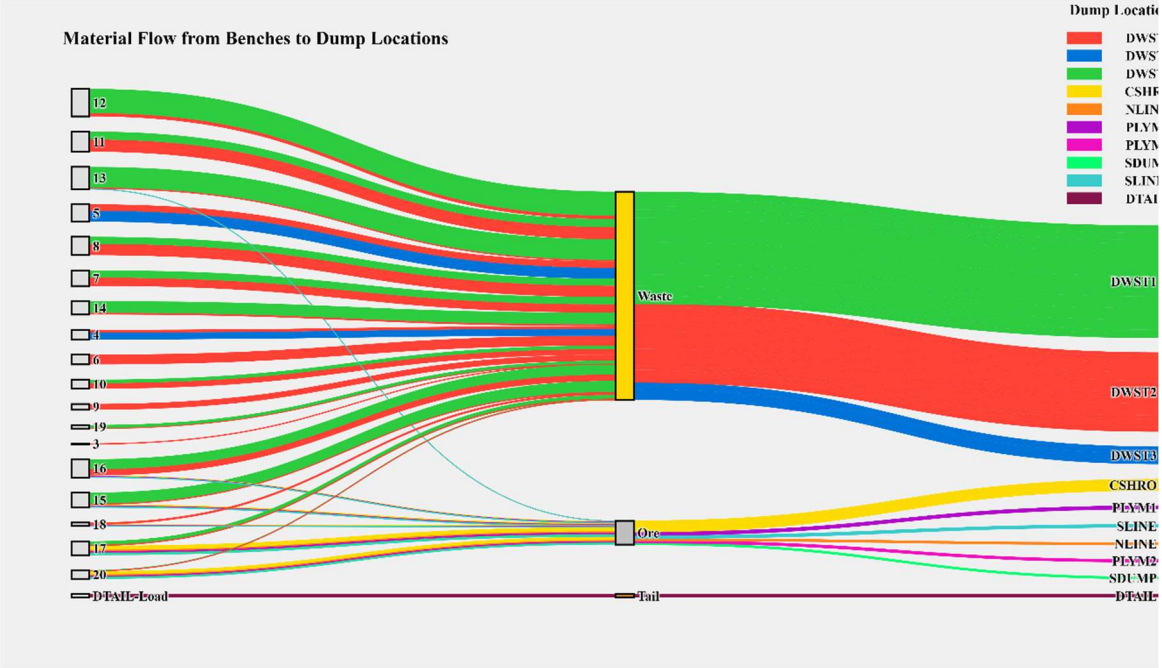
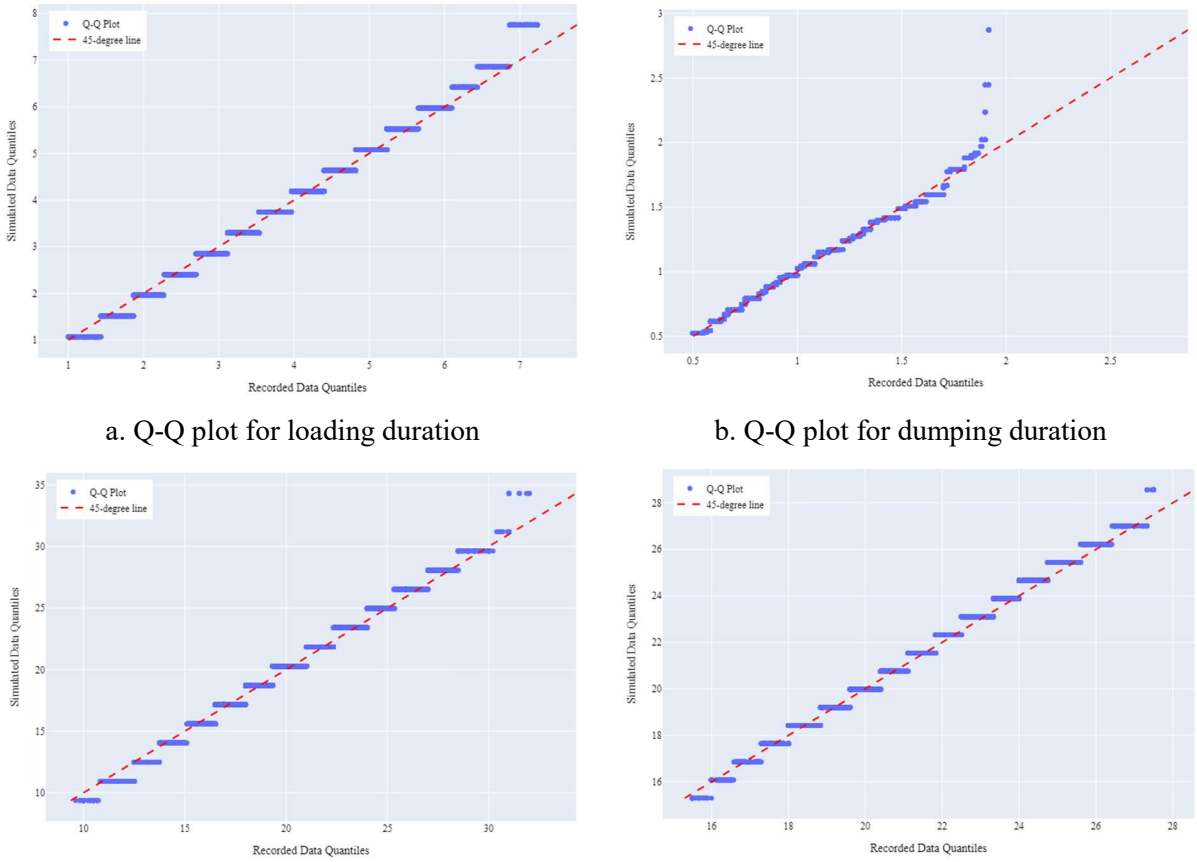


Figure 3. Hauled tonnage from each bench to dump locations.

The Sankey diagram presented shows the flow of material from various benches to their respective dump locations. Each bench is represented on the left side of the diagram, with lines extending to the right, indicating the destination of the material. The width of each line corresponds to the volume of material being hauled, providing a clear visual representation of the haulage pattern. Figure 3 indicates that the majority of waste from the upper benches is directed to DWST2, while DWST1 primarily receives waste from the lower benches. Similarly, most benches produce a single load type, which is then transported to various dump locations.

In addition to cumulative material tonnage, Quantile-Quantile (Q-Q) plots were employed to illustrate the alignment between the simulation input data and the actual data distributions. These plots provide a visual representation of how well the sampled simulation data matches the statistical properties of the actual data. Specifically, Figure 4 presents Q-Q plots for selected combinations of input data, demonstrating the degree of conformity between the empirical and theoretical distributions. This analysis further validates the robustness of the simulation model in replicating real-world conditions by ensuring that the input data used in the model closely mirrors the actual operational data.



a. Q-Q plot for loading duration

b. Q-Q plot for dumping duration

c. Q-Q plot for empty-haul velocity

d. Q-Q plot for full-haul velocity

Figure 4. Q-Q plots for a sample of loading, dumping, full/empty-haul velocities.

The Q-Q plots presented in Figure 4 provide a visual comparison between the simulated data and the recorded data for various input data. The usage of empirical distribution in the depicted Q-Q plots is evident from the alignment of the data points. The diagonal form of the plot, represented by the close alignment of the data points along the 45-degree reference line, confirms that the simulated data and recorded data are drawn from similar distributions. This alignment indicates a substantial similarity between the quantiles of the two data sets, further validating the accuracy and reliability of the simulation model in replicating real-world conditions. The close fit along the diagonal suggests that the simulation model effectively captures the statistical properties of the actual data, ensuring that the empirical distribution used in the model accurately represents the recorded data distributions.

5. Conclusion and Future Works

This study presents a comprehensive analysis of the idea of In-Pit Crushing and Conveying (IPCC) systems as a transformative alternative to the conventional Truck-Shovel (TS) system in mature open-pit mining operations. By integrating a conveyor system with the crushing process within the pit, IPCC systems offer a significant reduction in haulage costs, enhance operational efficiency, streamline material handling, reduce energy consumption, and minimize environmental impact.

Utilizing a robust methodology, the research involved statistical analysis and data wrangling to generate valid operational data for distribution function fitting. A full-scale Discrete Event Simulation (DES) model was developed using Simpy, an open-source Python library, to accurately

represent all in-pit operations. The developed model was validated against actual operational data, ensuring its reliability and accuracy.

This model accurately simulates in-pit operations, providing insights into resource allocation, equipment maintenance, shift management, and haulage efficiency under the TS system. The findings from this analysis serve as a crucial baseline for future comparisons with the IPCC system. Although a conveyor simulation model has been developed, it has not yet been integrated with the TS model. Consequently, the analysis of the IPCC scenario, including the site layout optimization and the comparison of economic consequences between IPCC and TS systems, remains under development.

Future work by the authors will integrate the conveyor simulation model with the existing TS model to enable a comprehensive analysis of the IPCC scenario. This integration will facilitate a detailed evaluation of site layout optimizations aimed at minimizing truck travel distances to semi-mobile crushers and assessing the economic viability and productivity benefits of transitioning to an IPCC system. The forthcoming research will thus provide a holistic comparison of the two systems, offering robust recommendations for mining operations considering a transition from TS to IPCC.

The contributions of this study address a significant gap in the literature by focusing on the practical and operational challenges associated with transitioning from established TS methods to IPCC systems in mature mining operations. By leveraging the analytical power of DES, this research provides valuable insights into the economic viability and productivity metrics of IPCC implementation, offering a practical framework for decision-makers considering similar transitions in their mining practices.

In conclusion, while this study lays the groundwork by thoroughly analyzing the TS system, the full potential of IPCC systems and their comparative benefits are subjects of ongoing research. The insights gained from this study will inform future efforts, ultimately contributing to more efficient and cost-effective mining operations.

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Towards Sustainable Mining: GHG Considerate Open Pit Long-Term Planning Using Adaptive Large Neighborhood Search Algorithm[1]

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ABSTRACT

Mine planning involves the systematic design and coordination of mineral extraction, integrating exploration, production, and engineering considerations. The mining industry is under increasing pressure to incorporate environmental responsibility into these processes. This paper addresses the precedence-constrained production scheduling problem (PCPSP) within the context of green long-term mining planning, aiming to optimize extraction processes while restricting carbon emission. Given the NP-hard nature of the PCPSP, this study introduces an adaptive large neighborhood search (ALNS) algorithm tailored specifically for long- term mine planning. A range of computational experiments have been carried out, including parameter tuning for the ALNS algorithm, comparisons against an exact solver, and analysis of our destroy- repair operators to determine their key elements. The efficacy of developed ALNS, evaluated using various benchmarks, reveals optimality gaps around 0.08. These results highlight the effectiveness of the proposed approach in addressing the PCPSP within mine planning and production scheduling, providing insights into improving mining operations while considering environmental concerns.

1. Introduction

Mine planning is the strategic process of designing and coordinating the extraction of minerals from the earth's crust, encompassing stages from exploration to production. This involves meticulous analysis of geological data, resource estimation, and engineering considerations to optimize extraction while minimizing environmental impact and ensuring safety [20]. Effective mine planning maximizes the recovery of valuable minerals, reduces operational costs, significantly contributing to national economies and global resource supply chains. Moreover, it ensures the responsible utilization of finite natural resources, aligning with sustainability objectives and environmental regulations.

The mining industry is experiencing a significant effect from growing environmental concerns and the drive toward achieving net-zero carbon emissions, given its vast scale of processing and

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operations. Thus, the pursuit of sustainable mining practices has become imperative, which necessitates a delicate balance between economic viability, environmental stewardship, and societal benefits [28]. Addressing ecological issues through reclamation plans and environmental impact assessments (EIAs), both of which need to be submitted to regulatory agencies. The mining plan, EIA, and reclamation plan are revised and progressively become more detailed as mining proceeds [7].

The tactical and operational aspects of mine planning are subject to periodic updates, presenting opportunities to integrate environmental considerations. Strategic planning, which spans the entire lifespan of a mine, often struggles with the precedence-constrained production scheduling problem (PCPSP), recognized for its NP-hard complexity [42]. The PCPSP is crucial for balancing operational efficiency, economic viability, and environmental sustainability within the dynamic landscape of modern mining operations.

Despite significant advancements in modeling and solution methodologies, the optimization of mineral value chains still requires the development of improved algorithms to overcome challenges related to scale, complexity, and uncertainty [24]. This challenge motivates the current study, which aims to pioneer the development of an adaptive large neighborhood search (ALNS) algorithm specifically tailored to address PCPSP within mine planning. Although the ALNS has demonstrated superior performance on various routing and scheduling problems [27], its application in production scheduling remains relatively rare [15-16].

This research addresses the PCPSP in the context of mine planning to maximize the net present value (NPV) while adhering to multiple constraints. These constraints include upper limits for environmental costs, grade blending limitations, equipment availability, and processing plant capacity. To tackle this complex optimization task, we introduce a novel solution approach based on the ALNS algorithm.

This paper is structured as follows: Section 2 provides a literature review of the most relevant studies on PCPSP in mine planning. Section 3 defines the proposed problem, presents the mathematical formulation, then Section 4 details the development of the ALNS algorithm to address the PCPSP with a focus on environmentally responsible mine planning. Section 5 presents the experimental setup and the results of testing the proposed algorithm and optimization model. Finally, Section 6 offers conclusions, discusses potential findings, highlights limitations, and proposes directions for future research.

2. Literature Review

Significant advancements have been made in the development of mathematical and computational approaches for optimizing open-pit mine planning. These strategies, whether exact or heuristic, focus on optimizing the NPV. Johnson (1968) identified the need of optimizing NPV by considering constraints such as mining and processing capacity, ore grades, and pit slopes, among other essential input considerations. Several studies written by Askari Nasab et al., Fathollahzadeh et al., Lambert and Newman, Lamghari, Newman et al., Osanloo et al., and Zeng et al. reviewed long-term optimization models for open-pit scheduling [4, 17, 22-23, 32-33, 45]. Tabesh et al. introduced a two-stage simultaneous optimization approach for long-term production planning in open-pit mines, incorporating multi-range stockpiling, which resulted in significantly improved NPV and throughout quality control [41].

Alipour et al., Busnach et al., Chicoisne et al., Cullenbine et al., and Lamghari et al. have employed heuristic strategies to discover integer viable solutions that roughly match the optimal linear programming solution [3, 9-10, 12, 25]. Ali et al. introduced an efficient Lagrangian relaxation reformulation using a neighborhood-based algorithm to solve the proposed model [2].

Furthermore, GU et al., and Moradi and Osanloo argued the importance of incorporating environmental considerations into optimizing mine design [19, 29]. Efforts have been made to integrate sustainable development concepts into mine design procedures, such as cut-off grade optimization [1, 11, 35-37]. Xu et al. developed a method for planning the production schedule of open pit mining operations, including ecological costs as part of the internal costs [44]. Building upon this, Xu et al. added an insightful layer by incorporating ecological costs, NPV, and social benefits into a multi-objective formulation confined to the pit limit [43]. However, the lack of integration with block extraction and sequencing decisions remained. Gong et al. explored integrating near-face stockpile mining methods with IPCC systems, showing demonstrating significant improvements in efficiency and output rates for open-pit operations [18].

Attari and Torkayesh developed an optimal approach using multi-objective mixed integer programming to minimize costs and CO_2 emissions associated with transportation [5]. Pell et al., presented a novel life cycle assessment (LCA) methodology to quantify the environmental costs of mining projects [34]. For sustainable long-term production planning in open-pit mines, Mirzehi and Moradi Afrapoli developed an integrated LCA-MILP framework, balancing economic and environmental performance and ensuring optimal extraction schedules that adhere to both profitability and environmental responsibility [28].

Recent research has investigated sophisticated optimization methods for complex optimization contexts, such as long-term open-pit mining planning using large neighborhood search (LNS), mineral value chain optimization through ALNS [8, 24], and product disassembly algorithms employing a tailored ALNS approach [15-16].

While significant advancements have been made in the development of mathematical and computational approaches for optimizing open-pit mine planning, the incorporation of sustainability factors has not been thoroughly investigated. In 2022, Azhar et al. advanced the PCPSP by incorporating carbon emission costs as a constraint [6]. Subsequently, in 2023, they developed a multi-objective framework to balance profit maximization with environmental costs [7]. Despite a growing interest in sustainable mining planning, quantitative studies utilizing operations research, artificial intelligence, and machine learning are still scarce compared to qualitative techniques [7]. Additionally, the application of advanced optimization methods like ALNS within open-pit mine planning has been limited, despite their development for various other purposes.

This research addresses PCPSP to maximize NPV while adhering to constraints such as environmental costs, grade blending, equipment availability, and processing plant capacity. To address these complexities and achieve optimal results, we introduce an ALNS algorithm tailored for open-pit mine planning.

3. Methodological Framework

Methodology In the following, we begin by delineating the optimization problem in Section 3.1, followed by introducing the carbon cost formulation aimed at enhancing the environmental sustainability of mine planning in Section 3.2. We then establish the notations pertinent to the optimization problem and present the mathematical optimization model in Section 3.3. After that we present the data by the benchmark's definition in Section 3.4.

3.1. PCPSP Problem

The PCPSP is a pivotal challenge within the mining industry, shaping critical decisions in both the extraction and processing phases of valuable mineral ores. Beyond its operational significance, the PCPSP is crucial for providing investors with a detailed comprehension of a mine's potential value. A typical mining operation includes key elements like the pit, dump, stockpiles, processing plants, and a fleet of heavy machinery. The mineral ore deposits within the pit are divided into uniform

blocks for modeling, each having its own value and adhering to specific precedence constraints linked to geological features. These constraints determine the sequence of block extraction over time, influencing the entire ore processing workflow.

Once extracted, the blocks are transported to processing facilities for treatments, including crushing, grinding, and screening to meet stringent quality specifications. The material then undergoes further refinement to enhance its quality and transform it into desired end products. However, the intricate value chain of mining operations is not without its challenges. Mining activities are resource-intensive, consuming significant amounts of energy, water, and gases. Additionally, the mining process generates harmful by-products, ranging from water and air pollution to chemical waste, which present significant environmental and social challenges that necessitate careful management and mitigation strategies.

In essence, the PCPSP is crucial for balancing operational efficiency, economic viability, and environmental sustainability in modern mining operations.

3.2. Environmental Costs of Open Pit Mining

Our primary goal is to enrich the formulation of the PCPSP by integrating carbon costing within predefined constraints. To quantify carbon emissions, we use the following formula proposed by Xu et al. [43]:

$$C_{i,e} = \frac{(Q_{i,o} + Q_{i,w})e_m + Q_{i,o}e_p}{1000} f_c f_a C_c \quad (1)$$

In this formulation, the quantity of excavated and processed ore is denoted by $Q_{(i,o)}$, while $Q_{(i,w)}$ represents the volume of waste material handled. The energy required to extract a single ton of material, regardless of whether it's ore or waste, from the pit is symbolized by e_m. Processing energy consumption per ton of ore is indicated by e_p. The coefficient f_c represents the carbon content of coal, f_a indicated the conversion coefficient from carbon-to-carbon dioxide, and C_c denotes the expense linked to carbon dioxide absorption.

3.3. Problem Formulation

Based on the problem definition, our notations, encompassing sets, parameters, and decision variables, are defined as follows:

- Sets
  - $m \in M$ Set of machines,
  - $b \in B$ Set of blocks,
  - $t \in T$ Set of periods,
  - $l \in L_b$ Set of blocks that must be extracted prior to block $b \in B$
- Parameters
  - s_{bt} NPV from mining block $b \in B$ in the period $t \in T$
  - α Discount factor
  - n_t Number of available machines for mining in each period $t \in T$
  - c_m Capacity of mining from machine $m \in M$
  - f_b Cost of mining block $b \in B$
  - G Total budget for carbon cost of mining
  - f_{mb} Carbon emission generated by machine $m \in M$ from mining each unit of block $b \in B$
  - r_b Amount of effortneeded for mining block $b \in B$

g_b The average grade of block $b \in B$
Max The maximum grade value for blocks mining
Min The minimum grade value for blocks mining

- Variables

x_{mbt} 1, If machine $m \in M$ is used on mining on block $b \in B$ during period $t \in T$, otherwise, 0.

Using above notations, we build the following integer programming model:

- Objective function

$$Z = \max\left(\sum_{m\in\mathcal{M}}\sum_{b\in\mathcal{B}}\sum_{t\in\mathcal{T}}\frac{s_{bt}}{(1+\propto)^t}\times x_{mbt}\right) \quad (2)$$

$s.t.$

$$x_{mlt'} \geq x_{mbt} \qquad \forall m \in \mathcal{M}, l \in \mathcal{L}_b, b \in \mathcal{B}, t, t' \in \mathcal{T}, t' < t \quad (3)$$

$$\sum_{b\in\mathcal{B}} r_b \times x_{mbt} \leq c_m \qquad \forall m \in \mathcal{M}, t \in \mathcal{T} \quad (4)$$

$$\sum_{t\in\mathcal{T}}\sum_{m\in\mathcal{M}}\sum_{b\in\mathcal{B}} f_{mb} \times x_{mbt} \leq G \quad (5)$$

$$\sum_{m\in\mathcal{M}}\sum_{b\in\mathcal{B}} x_{mbt} \leq n_t \qquad \forall t \in \mathcal{T} \quad (6)$$

$$\sum_{m\in\mathcal{M}}\sum_{b\in\mathcal{B}} (g_b - Max)x_{mbt} \leq 0 \qquad \forall t \in \mathcal{T} \quad (7)$$

$$\sum_{m\in\mathcal{M}}\sum_{b\in\mathcal{B}} (g_b - Min)x_{mbt} \geq 0 \qquad \forall t \in \mathcal{T} \quad (8)$$

$$x_{mbt} \in \{0, 1\} \quad (9)$$

The proposed integer programming model addresses the PCPSP for challenge of green mine planning. The objective function is given in Eq. (2) and its associated constraints are outlined in Eq. (3) to Eq. (8). The goal, as represented by Eq. (2), is to maximize the NPV. The value of each block is estimated by geologists based on its ore composition and grade. Summing up the NPV over the entire duration of the mine highlights the significance of prioritizing the extraction of higher-value blocks at earlier stages. Constraint set Eq. (3) specifies that a block can only be extracted after the extraction of other linked blocks, establishing the sequence that must be followed within a given time frame. Eq. (4) defines the machinery capacity for mining blocks in each time period, highlighting the limits of mineral processing capacity. Meanwhile, Eq. (5) introduces financial restrictions, including carbon expenses incurred during mining operations. The constraint set Eq. (6) represents the availability of machinery in each time period, which restricts the mining capacity accordingly. Also, the grade blending constraint sets, Eq. (7) and Eq. (8), enforce a specific grade threshold when material is dispatched to a mill in each period. Finally, Equation Eq. (9) defines the allowable range for the variables, establishing feasibility criteria.

3.4. Benchmark Cases for Model

To evaluate the efficacy of our mine planning model, we conducted rigorous assessments using three diverse real-world benchmarks. Firstly, we leveraged a modified version of the Wilma1 dataset, extracted from an active copper and gold mine, meticulously tailored to align with our overarching optimization framework. This dataset, originally studied by Azhar et al. offers a nuanced representation of operational intricacies [6]. Expanding our evaluation, we enriched our dataset with benchmark cases drawn from MineLib [13], a renowned repository of mining case studies. Among these, Newman1 and Kd emerged as pivotal benchmarks for their distinct characteristics. Newman1 encapsulates a compact dataset, serving as an ideal yardstick for evaluating algorithmic efficiency in smaller-scale scenarios. Conversely, Kd embodies a medium-scale dataset sourced from a copper mine in North America, reflecting the complexities inherent in larger operational settings. These benchmark instances, originally cataloged by Muñoz et al. provide a comprehensive spectrum of challenges for robust algorithmic evaluation [30].

Finally, Table 1 provides details regarding the number of blocks ($|B|$), precedence ($|L_b|$), time periods ($|T|$), and machines or resources ($|M|$). All the parameters linked with the traditional PCPSP are taken from MineLib. The remaining parameters specific to our green mine planning optimization model are the total budget for our carbon cost of mining (G) is 100, 000, 000, the average grade value of each block (g_b), the maximum grade value of each block (Max) is 1, and the minimum grade value of each block (Min) is 0.

Table 1. Size of our test instances.

Name of instances	$\|\boldsymbol{B}\|$	$\sum_{\boldsymbol{b}\in\boldsymbol{B}} \|\boldsymbol{\mathcal{L}_b}\|$	$\|\boldsymbol{T}\|$	$\|\boldsymbol{M}\|$
Newman1	1060	3922	6	2
Wilma1	1960	7112	4	3
Kd	14153	219778	12	2

4. ALNS Framework

The adaptive large neighborhood search (ALNS) is a heuristic approach derived from Shaw's large neighborhood search (LNS), introduced by Røpke and Pisinger [38, 40]. The underlying principle of this method is to iteratively deconstruct and rebuild solutions to enhance variety and escape local optima [39]. This method is distinguished by considering a set of destroy and repair operators, while its predecessor uses only a single destroy and repair operator [27].

The ALNS search space is a set of feasible solutions, which include diverse options regarding the assignment of machines to blocks across different time periods [15-16]. The algorithm effectively explores the search space by applying decision rules within the destroy and repair operators, aiming to identify high-quality solutions.

This paper adopts the ALNS strategy with a combination of three destroy operators, three repair operators, alongside a local search-based algorithm, and the Simulated Annealing (SA) metaheuristic algorithm to solve the optimization problem. The ALNS algorithm is adapted from Fathollahi-Fard et al. [15-16]. The process begins with the construction of an initial solution set up using repair operators.

The algorithm explores new solutions in each iteration by using operators for destroying and repairing the current best-known solution. Each new solution is evaluated, and if it improves, it replaces the existing best solution. Otherwise, the SA decision rule is applied to determine its retention. Subsequently, a local search method is employed to refine the solution. Then, the algorithm

updates its parameters to guide the following iterations. The algorithm presents the optimal solution identified after completing a predetermined number of iterations.

4.1. Algorithm Components

4.1.1. Operator Selection

Operator selection is one of the activities that ALNS requires. The primary reason for this is that different operators are more useful at different stages of the search process than others. The selection among the destroy and repair operators is based on the roulette wheel selection principle, prioritizing those who have historically proven to be more effective. The probability of selecting each destroy operator, denoted as P_r^-, and each repair operator, denoted as P_c^+, is calculated as follows:

$$P_d^- = \frac{w_d^-}{\sum_{r\in R} w_d^-}, \qquad \forall r \in R \tag{10}$$

$$P_r^+ = \frac{w_r^+}{\sum_{c\in C} w_r^+}, \qquad \forall c \in C \tag{11}$$

where w_r^- and w_c^+, reflect the historical performance of the respective destroy and repair operators. Initially, these weights are assigned a value of one and then modified in each iteration as shown in Eq. (12) and Eq. (13).

$$w_d^- = \vartheta \times w_d^- + (1-\vartheta)\Omega \qquad \forall r \in R \tag{12}$$

$$w_r^+ = \vartheta \times w_r^+ + (1-\vartheta)\Omega \qquad \forall c \in C \tag{13}$$

A forgetting factor, denoted by $\theta \in [0, 1]$, and a performance score, Ω, are assigned to each operator based on its effectiveness in identifying superior solutions during the most recent iteration, determined as follows:

$$\Omega = \begin{cases} \omega_1 & \text{If the new solution is the new global best.} \\ \omega_2 & \text{If the new solution is accepted.} \\ \omega_3 & \text{If the new solution is rejected.} \end{cases} \tag{14}$$

A method is considered effective when it has a high value of Ω, with the parameters arranged as $\omega_1 \geq \omega_2 \geq \omega_3$.

4.1.2. Acceptance Criteria

As previously described, each iteration involves applying a pair of destroy and repair operators to the current solution to generate a new one (S^n). If the new solution, New_S^n, does not improve upon the best-known solution (S^*), the SA algorithm determines whether to accept it for the next iteration. This decision is made by comparing a randomly generated value in the range [0, 1] ($rand_1$) with a probability of $e^{-|Z(New_S^n)-Z(S^*)|/Tem}$, where Tem is the temperature parameter. It steadily decreases by being multiplied by a cooling rate of α during each iteration, leading to a lower acceptance rate for worse solutions over time. (15)

4.1.3. Solution Refinement

In the proposed ALNS algorithm, the best solution obtained thus far is refined by conducting a local search at each iteration, using a combination of destroy-repair operators. It begins by randomly choosing one or two blocks from the current best solution, which were initially assigned to specific time periods. Initially, one of three repair operators is

chosen at random to rebuild the partially feasible solutions. Additionally, a new solution is generated by randomly assigning blocks to time periods. Among these new solutions, the best one is compared with S^*. Thus, the local search algorithm follows these steps:

Step 0: Initiate the local search algorithm with the current best solution (S^*).

Step 1: Randomly select one or two blocks from S^* and remove the associated machines and time periods.

Step 2: Utilize one of the repair operators to repair the partial feasible solution obtained in Step 1.

Step 3: In addition to the repaired solution, generate a random solution from the search space and select the best solution among the two alternatives.

Step 4: If the newly identified best solution (S^n) surpasses the S^*, update S^* accordingly.

Step 5: If the maximum number of sub-iterations (*Sub_n*) has not been reached, return to **Step 1**. Otherwise, display the current best solution (S^*).

4.2. Destroy and Repair Operators

This study focuses primarily on three repair operators, extending those introduced by Naderi and Ruiz (2010), but also introduces and applies novel destroy operators, enriching the landscape of research in this domain.

In crafting the initial solution (S^0), we have utilized the power of three distinct repair operators, each contributing to the formation of an optimal starting point for the optimization process. This initial solution serves as our baseline representation of the best-known solution (S^*), setting the stage for subsequent iterations to refine and improve upon it.

R1: This operator prioritizes assigning blocks from first to the last block to time periods based on the highest available NPV before the assignment. By selecting the most economically beneficial blocks first, we aim to maximize the overall profitability of the solution. When multiple blocks have the maximum NPV, the operator selects the first encountered block for assignment. Following block allocation, an idle machine is chosen for processing to ensure efficient resource utilization. To prevent the re-selection of blocks in subsequent assignments, the NPV of each assigned block is set to negative infinity, effectively removing it from consideration. The details of this repair operator are given in Figure 1.

Algorithm 1 R1 greedy repair

1: **Data:** Destroyed assignment variables: x_{mbt}, NPV: s_{bt}
2: **Result:** Repaired assignment variables: x_{mbt}
3: **while** b less than B **do**
4: $m \leftarrow$ randomly if this machine is not busy $x_{mbt} = 0$
5: $x_{mbt} = 1 \leftarrow$ Select a period t with maximum s_{bt} if only if $x_{mbt} = 0$
6: $s_{bt} = 0 \leftarrow$ The selected period for is equal to zero.
7: $b \leftarrow b + 1$
8: **end while**

Figure 1. R1 greedy repair.

R2: In contrast to R1, this operator allocates blocks to time periods based on the highest available NPV after the assignment. By prioritizing immediate gains, we aim to maximize the potential profitability of recently allocated blocks. Similar to R1, if multiple blocks have the maximum NPV, the first encountered block is prioritized for assignment. Following block allocation, an available machine not currently engaged in processing is selected to perform the assigned task.

As with R1, the NPV of each assigned block is set to negative infinity to prevent its re-selection in subsequent assignments, maintaining solution integrity. The pseudo-code provided in Figure 3 demonstrates this greedy repair.

Algorithm 2 R2 greedy repair

Data: Destroyed assignment variables: x_{mbt}, NPV: s_{bt}
Result: Repaired assignment variables: x_{mbt}
while p less than B **do**
    $m \leftarrow$ randomly if this machine is not busy $x_{mbt} = 0$
    $b \leftarrow$ randomly if this block is not extracted before $x_{mbt} = 0$
    $x_{mbt} = 1 \leftarrow$ Select a period t with maximum s_{bt} if only if $x_{mbt} = 0$
    $s_{bt} = 0 \leftarrow$ The selected period for is equal to zero.
    $p \leftarrow p + 1$
end while

Figure 3. R2 greedy repair.

R3: This operator introduces randomness into the allocation process by randomly assigning blocks to time periods based on the availability of machines. While less deterministic than R1 and R2, this approach offers flexibility and exploration potential within the solution space. Unlike R1 and R2, the allocation of blocks in this operator is not influenced by NPV concerns. Instead, blocks are assigned purely based on machine availability, providing a different perspective on solution generation. Similar to the other operators, an infinite negative value is assigned to infeasible allocations that violate capacity or grade constraints. This ensures compliance with the problem constraints and solution feasibility. This random repair is shown in Figure 2.

Algorithm 3 R3 random repair

Data: Destroyed assignment variables: x_{mbt}
Result: Repaired assignment variables: x_{mbt}
while p less than B **do**
    $m \leftarrow$ randomly if this machine is not busy $x_{mbt} = 0$
    $b \leftarrow$ randomly if this block is not extracted before $x_{mbt} = 0$
    $x_{mbt} = 1 \leftarrow$ Select a period t randomly if only if $x_{mbt} = 0$
    $s_{bt} = 0 \leftarrow$ The selected period for is equal to zero.
    $p \leftarrow p + 1$
end while

Figure 2 R3. random repair.

By employing these diverse operators, our goal is to generate initial solutions that are both feasible and strategically advantageous, establishing a solid foundation for subsequent optimization iterations. Each operator brings its unique perspective and methodology to the solution generation process, enriching the exploration of the solution space and contributing to the overall effectiveness of the optimization algorithm.

Destroy operators differ from repair operators in that they prioritize exploration of the search space by discovering unexplored areas, rather than just focusing on exploitation [27]. Let n represent the iteration index of the ALNS algorithm, ranging from 1 to *Max_N*. At the first iteration (n = 1), the algorithm uses the solution produced by the repair operators as its initial optimal solution, denoted as S^*, which is equal to S^0. As the algorithm progresses through iterations, it systematically applies various destroy operators to eliminate elements from the existing solution structure. This process involves modifying certain values of the decision variables x_{mbt}^{n} to yield a provisional solution for the next iteration, represented as x_{mbt}^{n+1}. The destroy operators involve a parameter Q that defines

the proportion of components to be removed from the solution in each iteration n, represented as S^n. The value of Q ranges from 0 to 1. Each destroy operator employs a distinct approach to obtaining partial feasible solutions:

1. Random-block-based destroy operator (D1): Randomly selects a maximum percentage Q of blocks from the set B. Removes the time periods assigned to the selected blocks, resulting in a modification of the solution. This destroy operator is shown in Figure 4.

Algorithm 4 Random-block-based destroy operator (D1)

Data: Percentage of removal: Q, Assignment variables: x_{mbt}
Result: Destroyed assignment variables: x_{mbt}
$p \leftarrow 0$
while p less than $Q \times |B|$ **do**
    $x_{mbt} = 0 \leftarrow$ Select a random block p if only if x_{mbt}=1
    $p \leftarrow p + 1$
end while

Figure 4. Random-block-based destroy heuristic (D1).

2. Random-machine-based destroy operator (D2): Randomly selects a maximum percentage Q of machines from the set M. Removes the blocks assigned to these selected machines, facilitating solution modification. This destroy operator is coded in Figure 5.

Algorithm 5 Random-machine-based destroy operator (D2)

Data: Percentage of removal: Q, Assignment variables: x_{mbt}
Result: Destroyed assignment variables: x_{mbt}
$p \leftarrow 0$
$t \leftarrow 0$
while t less than $Q \times |T|$ **do**
    while p less than $Q \times |M|$ **do**
        $x_{mbt} = 0 \leftarrow$ Select a random machine p if only if x_{mbt}=1
        $p \leftarrow p + 1$
    end while
    $p \leftarrow 0$
    $t \leftarrow t + 1$
end while

Figure 5. Random-machine-based destroy heuristic (D2).

3. Random-time-period-based destroy operator (D3): Randomly selects a percentage Q of time periods from set T. Removes these time periods from the sequence of blocks assigned to machines, affecting solution adjustment. This destroy operator is coded in Figure 6.

Algorithm 6 Random-time-period-based destroy operator (D3)

Data: Percentage of removal: Q, Assignment variables: x_{mbt}
Result: Destroyed assignment variables: x_{mbt}
$p \leftarrow 0$
$b \leftarrow 0$
while b less than $Q \times |B|$ **do**
    while p less than $Q \times |T|$ **do**
        $x_{mbt} = 0 \leftarrow$ Select a random time period p if only if x_{mbt}=1
        $p \leftarrow p + 1$
    end while
    $p \leftarrow 0$
    $b \leftarrow b + 1$
end while

Figure 6. Random-time-period-based destroy heuristic (D3).

By employing these diverse destroy operators, our ALNS algorithm navigates through the solution space. It strategically modifies solutions to explore new possibilities while maintaining feasibility and meeting optimization objectives.

5. Result and Discussion

5.1. Calibration of Our ALNS

The algorithm consists of several key parameters, as defined in Table 2 and discussed earlier. Given their significance in determining the algorithm's performance, it is imperative to fine-tune them before proceeding with experiments and comparisons. Various methods exist for parameter calibration, including the Response Surface Method, the Taguchi Method, and the Design of Experiments (DoE) approach [15-16]. For this study, we opt for the widely recognized DoE approach. The DoE approach initiates by providing a comprehensive factorial set encompassing all potential parameter configurations, which are then evaluated on test instances. Following this assessment, the configuration striking a balance between solution quality and computational time is selected [14].

Key parameters within the proposed ALNS, including those of the ALNS and SA, were identified through preliminary experiments. Notably, four parameters significantly influence both algorithmic speed and efficiency. During calibration, we set forth three candidate values for each parameter, resulting in a total of 81 parameter combinations ($3^4 = 81$). Moreover, the values of other parameters, such as those governing the destroy procedure and adaptive mechanism, are derived from insights gleaned from the classical ALNS algorithm [38]. Finally, Table 2 illustrates the candidate values and tuning configurations for the ALNS parameters, facilitating a systematic approach to parameter optimization.

Table 2. The tuning results for the ALNS.

Symbol and explanation	Range of parameter's value	Selected value
q: The percentage of removals	{[0.1, 0.15], [0.15,0.25], [0.25,0.35]}	[0.15, 0.25]
T_0: Initial temperature	[5, 10, 20] $\times\|B\|$	$\|B\| \times 10$
T_f: Terminal temperature	[0.01, 0.05, 0.1] $\times\|B\|$	$\|B\| \times 0.01$
β: Cooling rate	[0.99, 0.995, 0.999]	0.999

$|B|$ represents the number of blocks in the corresponding instance.

5.2. Comparisons and Evaluations of Our ALNS

Once the input parameters of proposed ALNS algorithm have been fine-tuned, we proceed to execute the ALNS for a designated time frame of one hour per test instance. Recognizing the stochastic nature of our ALNS approach, we iterate the algorithm 10 times for each test instance to capture variability. The choice of 10 iterations is based on established practices in similar studies, which often use a comparable number of iterations to balance computational effort and result reliability [15-16, 26]. Subsequently, we aggregated the results, comprising the best, worst and average solutions derived from these 10 runs, along with their corresponding standard deviations.

To assess the effectiveness of our approach, we compute the optimality gap by comparing the best solution attained through ALNS with an exact solution benchmark. Detailed results are presented in Table 3, providing insight into the performance characteristics of the proposed algorithm in diverse test instances.

Table 3. The results of our ALNS.

Name of instances	Exact solution from benchmarks	ALNS				
		Best	Worst	Average	Standard deviation	Optimality gap
Newman1	23658230	21765572	20241982	21037105	482454	0.08
Wilma1	67826631	59687435	56106189	57975152	1134024	0.12
Kd	406871207	313290829	297626289	305801221	4960277	0.23

The results presented in Table 3 underscore the efficacy of our ALNS approach, particularly evident in the Newman1 and Wilma1 test instances, characterized as smaller-scale scenarios. Here, the optimality gaps of 0.08 and 0.12, respectively, signify the remarkable proximity of our ALNS solutions to optimality. Even in the more complex operational setting represented by the Kd instance, classified as a large-scale scenario, the optimality gap of 0.23 showcases the ability of our ALNS to produce solutions of substantial quality.

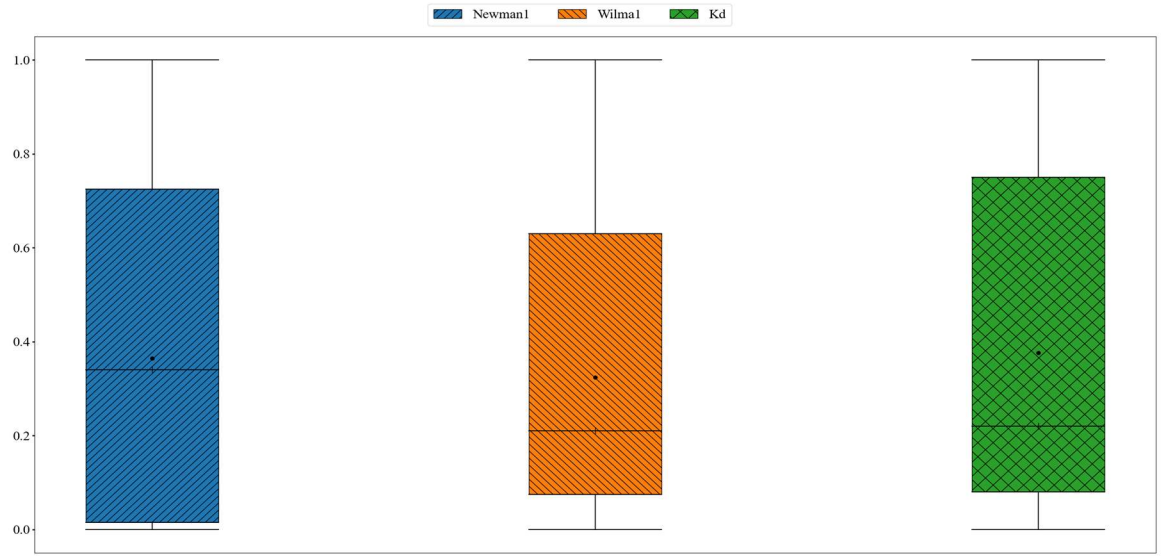

Figure 7. Box plot for solving test instances by the ALNS.

Figure 7 provides valuable insights into the performance characteristics of our ALNS algorithm across the various test instances. Through normalization of 10 algorithm runs for each instance, the box plot offers a comprehensive view of the distribution and consistency of the solutions obtained. The analysis reveals a consistent performance of the ALNS across all test instances, indicating the

algorithm's reliability and stability in diverse operational settings. However, noteworthy distinctions emerge, particularly in the case of the Wilma1 instance. This heightened accuracy and robustness in the Wilma1 test instance suggests that our ALNS approach is exceptionally well-suited to addressing the specific challenges and intricacies inherent in this operational context. Such findings underscore the adaptability and effectiveness of our algorithm in achieving superior performance, particularly in scenarios resembling the Wilma1 dataset.

To get a more comprehensive understanding of the performance dynamics of the ALNS algorithm, we performed a thorough analysis of the destroy-repair pairs. Our objective is to determine which combination yields optimal outcomes compared to others within the context of a specific test instance, namely Wilma1. To identify the optimal combination of operators for the Wilma1 test instance, we systematically evaluate the average performance of each destroy-repair operator pair by conducting multiple runs of our ALNS algorithm. These findings are presented in Table 4, which shows the percentage of changes observed relative to the original scenario where all destroy-repair operator pairs are available.

Table 4. Analyzing the destroy-repair operators.

Destroy operators	Repair operators	Percentage of average changes on the solution quality
D1	R1	37.28%
	R2	24.55%
	R3	35.26%
D2	R1	14.25%
	R2	19.47%
	R3	18.84%
D3	R1	13.47%
	R2	15.13%
	R3	16.64%

The analysis presented in Table 4 underscores the pivotal role of the destroy-repair operator pair comprising the D1 and R1 repair in augmenting solution quality within the context of our ALNS algorithm.

Figure 8 provides a visual representation of the average changes in solution quality attributed to each destruction and repair operator.

Notably, D1 emerges as the standout performer among the destroy operators, exerting a pronounced influence on enhancing solution quality. Conversely, among the repair operators, R3 demonstrates the highest average performance, consistently contributing to superior solutions.

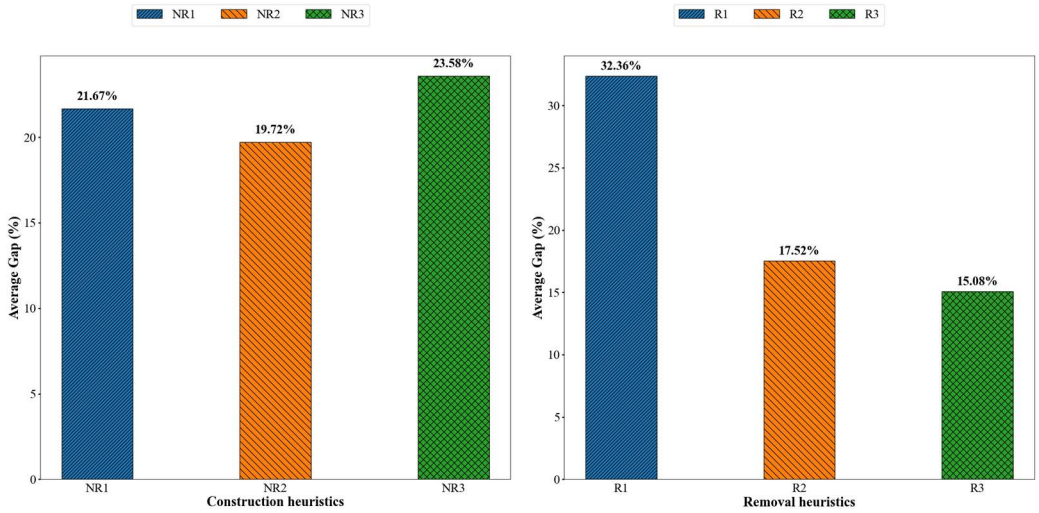

Figure 8. Evaluation of the destroy-repair operators.

5.3. Sensitivity Analysis

This sensitivity analysis aims to clarify how changes in key factors affect the overall outcomes, offering insights into the model's response to variations in carbon emissions constraints, NPV, average grade values, and carbon emissions generated in each period.

During these analyses, the ALNS algorithm is executed 10 times, and the best solution found across these runs is considered for evaluation. Regarding the initial sensitivity analysis on carbon emissions constraints, we partition our optimization model into two scenarios. In the first scenario, we maintain the carbon emissions constraint set defined by constraint set Eq. (5), while in the second scenario, we remove this constraint set.

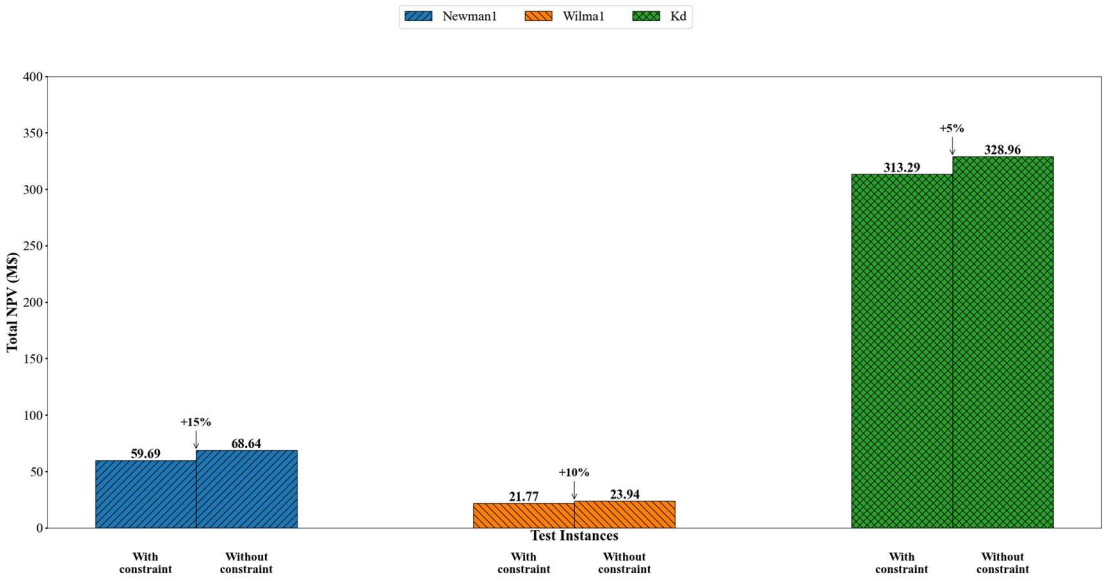

Figure 9. Sensitivity analysis on the carbon emissions constraints.

Error! Reference source not found. illustrates that relaxing the model by excluding carbon emission constraints leads to an increase in total NPV derived from our objective function. Consequently, the absence of these constraints allows an enhancement in overall profitability.

Following, we examine the NPV values obtained from the objective function per time period, as shown in Figure 10.

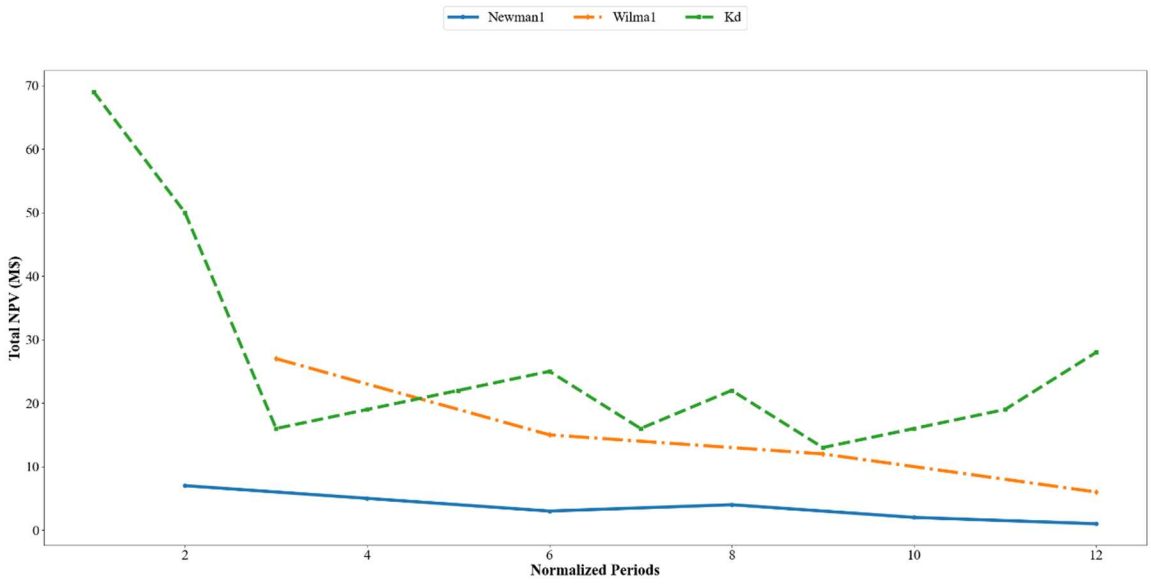

Figure 10. Sensitivity analyses on the NPV for each period.

The NPV values exhibit a downward trend across periods due to the increasing impact of precedence constraints on block extraction. This limitation results in a reduction in NPV values as each period progresses.

The grade blending constraints, Eq. (7) and Eq. (8) aim to ascertain the maximum and minimum values of grade allowed. In our scenario, we assume the minimum grade value to be zero and the maximum grade value to be one. We compute the average grade values from all extracted blocks

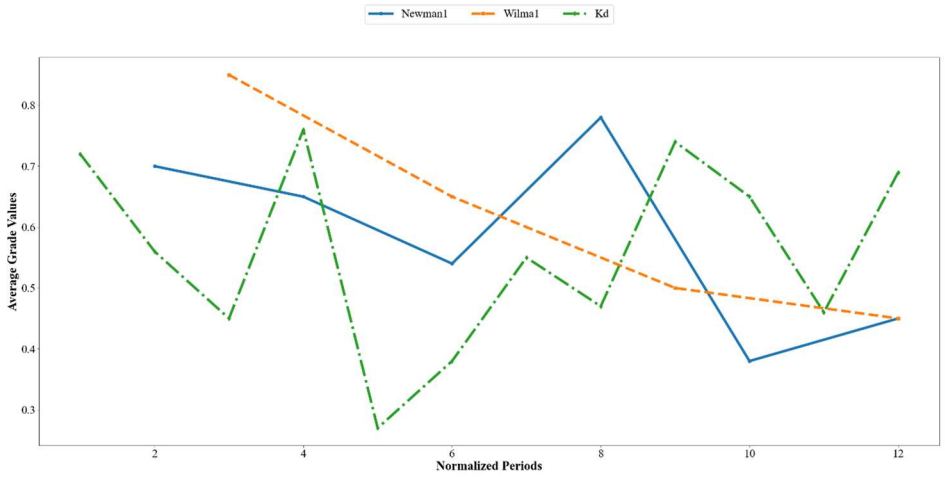

Figure 11. Sensitivity analyses on the grade values for each period.

within each period and present these analyses in Figure 11. As can be seen in, the behavior of the average grade values mirrors that of NPV per period.

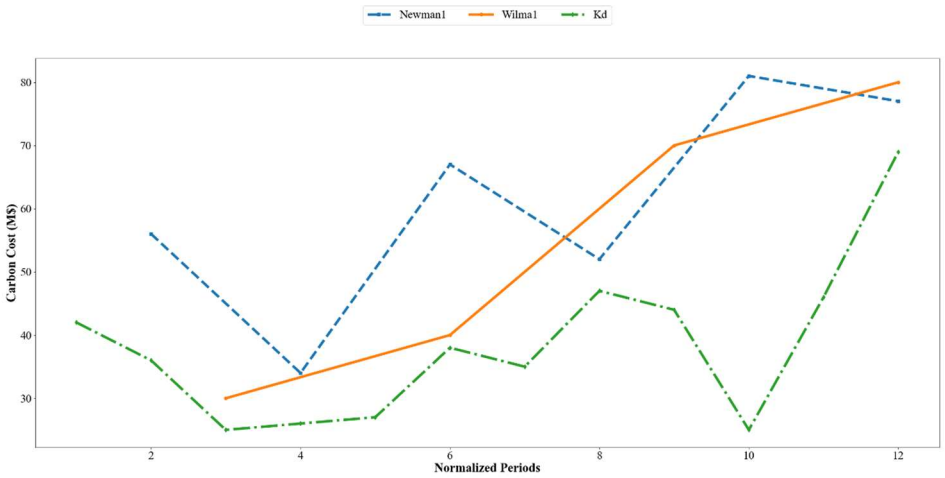

Figure 12. Sensitivity analyses on the carbon emissions generated per period.

Figure 12 illustrates the carbon emissions generated per period, with an upper bound set at 10^8. It can be observed that carbon cost increase steadily per period, contrary to the NPV trend observed earlier. As extraction progresses, blocks located in lower layers typically incur higher carbon emissions compared to those in upper layers, as described in Eq. (1). This trend underscores the importance of balancing economic objectives with environmental sustainability goals, necessitating the development of strategies that optimize both financial returns and reduce carbon emissions.

6. Conclusion

This paper introduced an efficient ALNS algorithm to tackle the PCPSP. The method was tested on three real-world mining datasets of varying complexity. We introduced carbon costing into the scheduling model and used adaptive heuristic selection strategies to improve solution quality. The results showed that the ALNS algorithm achieved near-optimal solutions with small optimality gaps, specifically 0.08 for Newman1, 0.12 for Wilma1, and 0.23 for Kd. This demonstrates its effective performance in dealing with different operating configurations. This demonstrates its effective performance in dealing with different operating configurations.

Future work will investigate how our ALNS approach performs on a stochastic version of the PCPSP. This will involve developing new heuristics to effectively handle uncertainties related to block grades, market pricing, and operational constraints. In addition, we will investigate the integration of real-time data to enable dynamic scheduling decisions. This will improve the strength and usefulness of the system in real-world mining operations.

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Technological Advances in Mobile Equipment for Greenhouse Gas Emission Reduction in the Mining Industry: A Systematic Review

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ABSTRACT

The mining industry faces a critical challenge in reducing greenhouse gas (GHG) emissions, particularly those generated by mobile equipment. This systematic review examines recent technological advances and techniques applied to mining mobile equipment to mitigate GHG emissions. Effective strategies for GHG reduction are identified through a systematic analysis of objectives, methodologies, results, production impacts, gaps, and limitations in various studies. The urgency of meeting the industry's commitments under the Paris Agreement for net-zero emissions by 2050 underscores the importance of these advancements. Additionally, the review analyzes potential modifications and challenges in implementing these technologies to achieve sustainable mining practices. By synthesizing this knowledge, the study contributes to ongoing efforts to align mining operations with global climate goals, emphasizing the crucial role of mobile equipment in achieving a sustainable, low-carbon future for the mining sector.

1. Introduction

The mining industry, a cornerstone of global economic development, now faces the critical challenge of reducing greenhouse gas (GHG) emissions, particularly those generated by mobile equipment. This challenge is not merely a matter of environmental responsibility but a crucial necessity to meet global commitments under the Paris Agreement, which aims to achieve net-zero emissions by 2050 [1].

Currently, the mining sector accounts for approximately 4 - 7% of global GHG emissions, with carbon dioxide (CO2), methane (CH4), and nitrous oxide (N2O) being the primary gases emitted [2]. These emissions are distributed across various activities: extraction and processing (50%), transportation (25%), and other operations such as drilling and blasting (25%) [3].

Historically, the industry relied on rudimentary technologies that were effective for mineral extraction but highly carbon intensive. The advent of the industrial revolution brought significant advances in heavy machinery, which increased productivity and led to a rise in GHG emissions. The reliance on fossil fuels to operate mobile equipment, such as haul trucks and excavators, became a symbol of industrialization and a major contributor to climate change [4].

In recent decades, growing concerns about climate change have driven the mining industry to seek innovative solutions. The motivation for reducing GHG emissions stems from regulatory pressures and the increasing recognition of climate change's environmental impact. As a result, major mining

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companies have pledged to achieve net-zero emissions by 2050, aligning their goals with global climate targets [3, 5].

One of the critical trends in the mining sector is the electrification of mobile equipment. Technologies such as electric haul trucks, catenary systems, and high-capacity batteries exemplify how advancements reduce mining operations' carbon footprint [6]. Additionally, implementing energy management systems and using artificial intelligence (AI) to optimize routes and minimize energy consumption demonstrate the sector's commitment to sustainability [7]. Digitalization and automation also play a significant role in enhancing operational efficiency and reducing emissions [8].

A simple way to measure the quantity of GHG emissions is through the use of emission factors, which quantify the emissions per unit of activity, such as kilograms of CO2 per litre of diesel consumed. These factors are outlined in guidelines provided by the Intergovernmental Panel on Climate Change (IPCC) [9] and the U.S. Environmental Protection Agency [2].

Despite these advances, the transition to a low-carbon future presents several challenges. Technical, economic, and operational barriers persist, limiting the widespread adoption of clean technologies. For instance, the initial investment in electric equipment can be prohibitive for some operations, and developing the necessary charging infrastructure is still in progress [10]. Furthermore, integrating these technologies into existing mining operations requires careful planning and significant adaptations to current processes [11].

This systematic review examines and analyzes the most recent technologies and techniques applied to mobile equipment in mining to mitigate GHG emissions. Effective strategies for GHG reduction are identified through a systematic analysis of various studies' objectives, methodologies, results, production impacts, gaps, and limitations. The urgency of meeting the commitments of the Paris Agreement underscores the importance of these technological advances. Furthermore, the review explores potential modifications and challenges in implementing these technologies to achieve sustainable mining practices. By synthesizing this knowledge, the study contributes to ongoing efforts to align mining operations with global climate goals, emphasizing the crucial role of mobile equipment in achieving a sustainable and low-carbon future for the mining sector [12].

2. Methodology

This systematic review examines recent technological advances and techniques applied to mobile equipment in mining to mitigate GHG emissions. The methodology follows a structured approach based on systematic literature review guidelines tailored to the context of mining engineering.

2.1. Research Questions

The review seeks to answer the following research questions:

1. What are the recent technological advances and techniques applied to mobile equipment in mining to mitigate GHG emissions?
2. How effective are these strategies in reducing GHG emissions?
3. What challenges and potential modifications are required to implement these technologies in mining operations?

2.2. Literature Search Strategy

A comprehensive literature search was conducted across several scientific databases, including Science Direct, Scopus, IEEE Xplore, MDPI, and Google Scholar. The search included papers

published from the year 2000 up to June 2024. The search query was designed to capture relevant studies using the following combination of keywords:

- Keywords related to mobile equipment: "Mobile equipment", "Mining trucks", "Haul trucks".
- Keywords related to GHG emissions: "GHG emissions", "Greenhouse gas", "Carbon emissions".
- Keywords related to technological advancements: "Technological advancements", "Innovation", "Electrification", "Hybrid systems".
- Keywords related to sustainability: "Sustainable mining practices", "Net-zero emissions", "Paris Agreement", "Climate goals", "Carbon footprint mining", "Emissions reduction strategies".

2.3. Inclusion Criteria

The selection of studies for this review was based on the following criteria:

- Only peer-reviewed journal papers or conference proceedings were included.
- Publications from the year 2000 onwards.
- Written in English.
- Studies that specifically focus on the reduction of GHG emissions through technological advances in mobile equipment within the mining industry.

2.4. Exclusion Criteria

- Studies not related to the mining industry.
- Studies that address other aspects of mining operations not related to mobile equipment or GHG emissions reduction.
- Non-peer-reviewed journal, and conference papers.
- Articles not available in full text.

2.5. Data Extraction

Relevant data were extracted from the selected studies, including:

- Study objectives: What the study aimed to investigate.
- Methodologies used: Research methods and approaches used in the study.
- Results and findings: Key outcomes related to GHG emissions reduction.
- Impacts on production: Any reported impacts on mining operations and productivity.
- Gaps and limitations: Identified gaps in research and limitations of the study.

2.6. Selection and Filtering Process Diagram

Figure 1 illustrates the steps in the systematic review and provides a clear overview of the selection and filtering process.

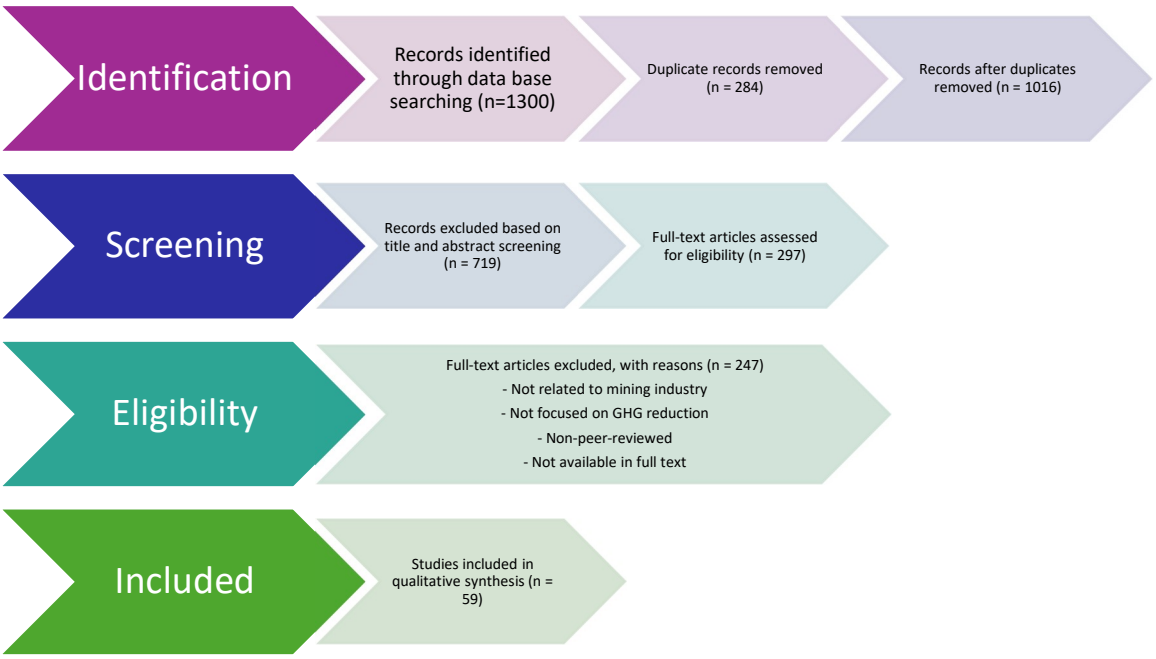

Figure 1. Diagram for Literature Selection and Filtering Process.

3. Results and Discussion

Mining is a carbon-intensive industry, significantly contributing to global GHG emissions. Finding effective strategies to reduce these emissions is essential to align the sector with the goals of the Paris Agreement and other international sustainability initiatives [1]. This study explores key factors contributing to GHG emissions in mining operations, as well as emerging methodologies and technologies that have the potential to mitigate these impacts.

The results section provides a detailed analysis of existing literature, highlighting factors influencing GHG emissions and their reduction strategies. Factors such as fuel type, energy efficiency, equipment electrification, operational practices, and the integration of renewable energy are crucial for developing a comprehensive approach to emission reduction in mining [13].

Additionally, complementary literature and methodological support are incorporated to provide a holistic view of current technologies and practices. This multidimensional approach is essential to capture the complexity of the problem, and the solutions needed for an effective transition to more sustainable mining operations. Integrating digitalization, automation, and implementing environmental policies and regulations are essential elements to promote sustainable practices and reduce GHG emissions in the mining industry [3].

Through a comprehensive analysis of recent publications, this section not only identifies emerging trends in emission reduction research but also evaluates the practical impact of various strategies in real mining operations. The findings underscore the importance of combining multiple approaches to achieve significant and sustainable reductions in GHG emissions.

3.1. Key Factors Contributing to GHG Emissions

The literature review identifies several key factors that significantly contribute to GHG emissions in mining operations. These factors are crucial for developing effective strategies to reduce emissions and improve efficiency in the mining industry. The factors identified in Table 1. Key Factors and GHG Emissions. provide a comprehensive understanding of the various elements influencing GHG emissions in mining operations.

Table 1. Key Factors and GHG Emissions.

Factor	Impact on GHG Emissions
Fuel Type [14], [15]	The type of fuel used in mining equipment directly impacts GHG emissions. Traditional diesel fuel produces higher emissions than alternatives like natural gas or hydrogen.
Energy Efficiency [13], [16]	Improving energy efficiency in mining processes reduces fuel consumption and GHG emissions.
Electrification of Equipment [6], [17], [18]	Switching to electric-powered equipment can significantly reduce GHG emissions associated with diesel fuel combustion.
Equipment Maintenance [19], [20]	Regular and high-quality maintenance of equipment ensures optimal performance and lower emissions.
Operational Practices [10], [12]	Efficient operational practices, including optimized vehicle dispatch and routing, can minimize idle times and reduce emissions.
Renewable Energy Integration [21], [22]	Integrating renewable energy sources, such as solar and wind, into mining operations can drastically reduce dependency on fossil fuels and GHG emissions.
Digitalization and Automation [23], [24], [25], [26]	Implementing IoT, sensors, and real-time data analytics can improve operational efficiency and emission monitoring, leading to lower GHG emissions.
Regulations and Policies [3], [5], [27], [28], [29], [30], [31]	Strict environmental regulations and policies can enforce emission reductions and promote sustainable practices in the mining industry.
Lifecycle Analysis [32], [33], [34], [35], [36]	Conducting lifecycle analyses of mining equipment and operations helps identify emission hotspots and opportunities for reductions.
Alternative Powertrains [15], [33], [37]	Utilizing alternative powertrains, such as hybrid and hydrogen fuel cells, can reduce emissions compared to conventional diesel engines.
Infrastructure for Charging and Refueling [17], [15]	Developing infrastructure for charging electric vehicles and refueling hydrogen-powered equipment is crucial for supporting low-emission technologies.

One of the primary factors influencing GHG emissions in mining is the type of fuel used in mining equipment. Traditional diesel fuel is known for its high carbon footprint. Studies by Cao et al. [14] and Leone [15] illustrate that switching from diesel to cleaner alternatives, such as natural gas or hydrogen, can drastically reduce emissions. Hydrogen, in particular, has the potential to reduce emissions by up to 90%, as its combustion produces only water vapour. This significant reduction was demonstrated through extensive emissions testing in operational mining settings, where the use of hydrogen led to markedly lower GHG outputs compared to diesel.

Complementing the shift in fuel type, improving energy efficiency within mining operations emerges as another critical strategy. Patterson et al. [13] and Saidur et al. [16] have shown that adopting energy-efficient technologies can reduce fuel consumption by 15-20%. This includes measures such as retrofitting machinery with high-efficiency motors, optimizing ventilation systems in underground mines, and implementing energy management systems. These improvements were achieved through comprehensive energy audits and performance optimizations, highlighting that reduced energy waste translates directly into lower emissions [16].

Building on the theme of efficiency, the electrification of mining equipment presents a highly effective method for emission reduction. Varaschin [6] and Bao et al. [17] provide robust evidence from case studies and lifecycle assessments that switching from diesel-powered to electric machinery can cut emissions by more than 50%. This is primarily because electric machinery eliminates direct emissions from diesel combustion. The studies monitored the performance and emissions of electric vehicles in real mining operations, revealing significant environmental benefits and long-term cost savings due to lower fuel and maintenance costs [6].

Similarly, integrating renewable energy sources into mining operations offers another transformative approach. Case studies where solar and wind energy implementation in mining projects reduced fossil fuel use by 40-50% have been documented. This integration was validated through real-time energy consumption data and emission tracking before and after adopting renewable energy sources, showing substantial environmental benefits and the feasibility of reducing GHG emissions in mining operations through renewable energy [21, 22].

Further enhancing the impact of these strategies, implementing digital technologies and automation can significantly optimize operational efficiency and reduce emissions. Yavari et al. [23], Avalos et al. [24], Asa'd and Levesque [25], and Awuah-Offei et al. [26] discuss the use of Internet of Things (IoT), sensors, and real-time data analytics to optimize mining operations. These technologies allow for immediate adjustments to operational parameters, reducing energy consumption and emissions. Pilot projects have shown that automated systems significantly improve operational efficiency by continuously monitoring and optimizing equipment performance, making mining operations more sustainable [23].

Among the strategies analyzed, integrating renewable energy and the electrification of mining equipment provide the most substantial benefits in reducing GHG emissions. These approaches address the primary sources of emissions and offer significant reductions. However, their effectiveness is greatly enhanced when combined with efficient operational practices, regular maintenance, supportive regulatory frameworks, digitalization, and lifecycle analysis. A comprehensive approach incorporating these factors is essential for achieving significant and sustainable emission reductions in the mining industry. The literature supports the potential of these strategies to transform mining operations into more sustainable and environmentally friendly activities.

3.2. Integration of Complementary Literature and Methodological Support

This section aims to incorporate complementary literature and methodological support that enhances the overall understanding of GHG emissions reduction in the mining industry. As shown in Figure 2, integrating four key themes provides a comprehensive view of the various strategies and technologies available. The review captures the full spectrum of current research by adopting this holistic approach.

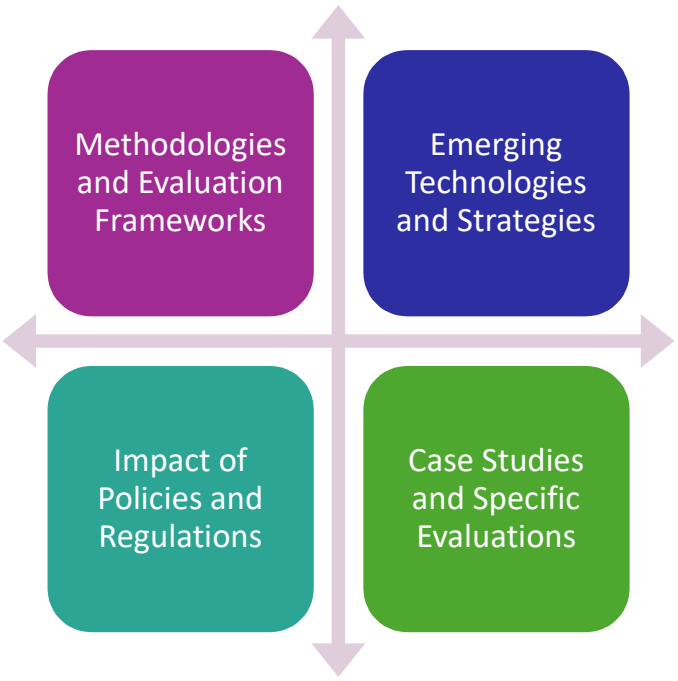

Figure 2. Complementary Literature and Methodological Support.

The advancement of methodologies and evaluation frameworks is crucial for optimizing operations and reducing environmental impacts. Vis [38] focuses on optimizing fuel consumption for hauling mobile equipment through speed optimization using Simulated Annealing, demonstrating significant improvements in fuel efficiency and emission reductions. Complementing this, Kına [39] uses discrete-event simulation to model and optimize the microscopic fuel consumption of haulage trucks, offering a detailed methodology for minimizing environmental impact and operational costs. Both studies underscore the importance of detailed methodologies in achieving operational efficiency and sustainability. Further, Kazemi Ashtiani [40] introduces an integrated stochastic multi-objective simulation framework for fuel-efficient truck dispatching, addressing inherent uncertainties and ensuring reliable and sustainable outcomes.

Building on these methodologies, emerging technologies offer transformative potential in reducing GHG emissions. Yavari et al. [23] explore AI and IoT for real-time emissions monitoring in mining operations, demonstrating how these technologies provide precise data for timely interventions. Similarly, Feng et al. [41] compare various powertrain solutions for mining haul trucks, highlighting that electric and hydrogen fuel cell options significantly reduce operational costs and emissions. Jacobs [42] supports these findings by discussing the strategic integration of new technologies into mining operations, emphasizing the need for structured implementation plans to enhance both efficiency and sustainability. Moreover, Massonini Ngoma et al. [43] evaluate the impact of technological trends on climate change in Congo, underscoring the importance of adopting cutting-edge technologies to address environmental challenges. Widmer et al. [44] and Yip et al. [45] further highlight advancements in engineering solutions, such as extending battery life and hydrogen direct injection, which significantly contribute to sustainable mining operations.

In parallel to technological advancements, environmental policies and regulations are vital in shaping sustainable mining practices. Ulrich et al. [27] demonstrate how carbon pricing incentivizes the adoption of cleaner technologies and practices, aligning economic and environmental goals. Building on this, Wang et al. [46] emphasize the importance of regulatory frameworks in promoting sustainable fleet management practices, ensuring compliance with environmental policies to achieve greater efficiency and lower emissions. Additionally, Kittipongvises [47] underscores the potential

of international mechanisms like the Clean Development Mechanism (CDM) in driving significant emissions reductions, highlighting the importance of global cooperation and adherence to international agreements.

To provide practical insights into these strategies and their real-world impact, specific case studies are invaluable. Widmer et al. [44] present a detailed case study on extending the battery life of hybrid mining trucks, demonstrating how engineering innovations can significantly improve performance and sustainability. Similarly, Carvalho et al. [35] offer crucial data on CO2 emission factors for lifecycle assessment of mining vehicles, which is fundamental for developing effective emission mitigation strategies. Furthermore, Issa et al. [22] discuss the opportunities and challenges of renewable energy and decarbonization in the Canadian mining industry, emphasizing the need for substantial investments in clean technologies and supportive policies to facilitate the energy transition.

By examining these diverse aspects, the review provides a holistic understanding of the current research landscape, highlighting significant achievements in GHG emission mitigation within the mining industry. This comprehensive approach ensures that all facets of emission reduction are addressed, fostering effective collaboration between industry stakeholders, governmental bodies, and the scientific community. Such an integrative effort is essential for advancing sustainable mining practices and achieving meaningful reductions in environmental impact.

3.3. Analysis of Publication Trends in Technological Advancements for GHG Emission Reduction in Mining

Figure 3 shows a marked increase in the number of research articles published in 2022 and 2023, indicating a growing focus on mitigating GHG emissions in the mining sector. This trend can be attributed to several key factors.

First, the Paris Agreement, signed in 2016, set ambitious long-term goals for reducing GHG emissions, which gradually translated into increased research and technological development over the subsequent years. The effects of these commitments became more pronounced in 2022 and 2023 as industries and researchers aligned their efforts to meet these global targets [1].

Second, the period has seen significant technological advancements, including developing battery-electric and fuel-cell hybrid mining trucks, integrating renewable energy sources, and implementing digital technologies such as IoT and AI for real-time monitoring and operational optimization. These innovations have spurred substantial academic and industry research to improve efficiency and reduce emissions [5].

Additionally, the COVID-19 pandemic accelerated the adoption of digital and sustainable practices. The disruption caused by the pandemic prompted industries to seek resilient and adaptive solutions, which included investing in sustainable technologies and practices. Researchers, adapting to new working conditions, were able to focus more on pressing issues such as GHG emissions, leading to a surge in publications during this period [6].

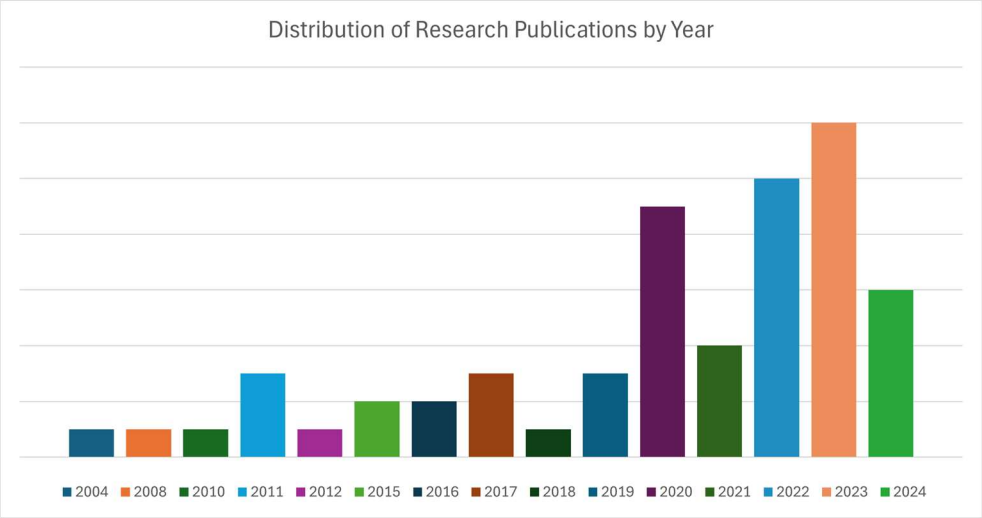

Figure 3. Distribution of Research Publications by Year.

Moreover, increased regulatory pressure and enhanced funding opportunities for sustainability projects have further driven research activities. Governments and private sectors have been providing substantial financial support for green technology initiatives, encouraging more studies and publications in the field of sustainable mining practices [7].

Overall, the combined impact of global environmental commitments, technological advancements, the COVID-19 pandemic, and increased regulatory and financial support has significantly contributed to the rise in research publications. This trend underscores the industry's shift towards sustainability and the critical role of engineering innovations in achieving these goals.

3.4. Final Thoughts

Among the key factors analyzed, the electrification of mining equipment is the most efficient strategy for reducing GHG emissions. Studies by Varaschin [6] and Bao et al. [17] indicate that switching from diesel-powered to electric machinery can reduce emissions by more than 50%, primarily due to eliminating direct emissions from diesel combustion. Additionally, integrating renewable energy sources in mining operations can further amplify these benefits, as demonstrated by Vergara-Zambrano et al. [21].

Considering the ambitious goal of achieving net zero emissions by 2050, current advancements and strategic implementations suggest that the mining industry is on the right track. However, meeting this target will require continuous innovation, substantial investments, and strict regulatory frameworks [3]. Despite significant progress, the full realization of net zero will depend on the widespread adoption of these technologies and practices across the industry.

The fluctuating costs of minerals also play a critical role in reducing GHG emissions. High mineral prices can provide mining companies the financial leverage to invest in sustainable technologies and practices. Conversely, low prices may restrict the ability to make such investments, potentially slowing down progress toward emission reduction goals [4].

Finally, climate change itself poses significant challenges to the mining industry. Rising temperatures and extreme weather events can disrupt mining operations, increase energy consumption, and impact infrastructure stability. These factors highlight the industry's urgent need to mitigate its environmental impact and adapt to the changing climate to ensure operational resilience and sustainability [48].

4. Conclusion

The mining industry is at a critical juncture, facing the imperative to reduce greenhouse gas emissions, particularly those generated by mobile equipment. This systematic review has identified significant technological advances and innovative strategies to mitigate these emissions. Key technologies such as the electrification of mining equipment, integration of renewable energy sources, and implementation of digitalization and automation have demonstrated substantial potential in reducing the carbon footprint of mining operations.

Achieving significant and sustainable reductions in GHG emissions in the mining industry requires a comprehensive approach that combines electrification, renewable energy integration, energy efficiency improvements, digitalization, and robust regulatory support. These strategies not only align with global climate goals but also enhance the sustainability and operational efficiency of mining activities.

The findings of this review underscore the critical role of mobile equipment in achieving a sustainable, low-carbon future for the mining industry. Adopting advanced technologies and innovative practices is essential to align mining operations with global climate goals. Furthermore, continuous research, development, and collaborative efforts among industry stakeholders are urgently needed to drive these advancements. This integrated approach is vital for ensuring the mining industry meets its environmental responsibilities while maintaining productivity and economic viability.

The mining sector can significantly reduce its GHG emissions by leveraging these technological advancements and adhering to stringent regulatory frameworks. This transition not only contributes to global efforts to combat climate change but also positions the industry as a leader in sustainable practices. Ultimately, the path to a low-carbon future in mining hinges on the widespread adoption of these technologies and the collective commitment of all stakeholders involved.

5. Future Work

Future research and development efforts should focus on several key areas to further advance the reduction of GHG emissions in the mining industry:

1. **Cost Reduction and Economic Viability:** Investigate ways to reduce the initial investment and operational costs associated with electrification and other advanced technologies. Economic models and incentives that promote adopting sustainable practices should be explored.
2. **Integration of Renewable Energy:** Continue exploring and expanding the integration of renewable energy sources into mining operations. Research should focus on optimizing the use of renewable energy to power mobile equipment and other mining processes.
3. **Advanced Digital Technologies:** Further develop and refine digital technologies such as IoT, AI, and machine learning for real-time monitoring, operational optimization, and

predictive maintenance. These technologies can significantly enhance efficiency and reduce emissions.

4. **Lifecycle Analysis:** Conduct comprehensive lifecycle analyses of new technologies and practices to identify emission hotspots and opportunities for further reductions. This will provide a holistic understanding of the environmental impact of mining operations.
5. **Policy and Regulatory Support:** Advocate for stringent environmental regulations and policies that enforce emission reductions and promote sustainable practices. Collaboration between industry, government, and academia is essential to drive these initiatives.
6. **Collaborative Research:** Encourage collaboration among mining companies, academic institutions, and technology providers. Sharing knowledge and resources can accelerate the development and adoption of innovative solutions.
7. **Expanded Literature Search:** To complement and strengthen this research, it is necessary to broaden the search for more articles and studies. Expanding the literature review will help identify additional technological advancements, strategies, and best practices that can further reduce GHG emissions in mining operations.

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Dust and Greenhouse Gas Mitigation in Mining: An LCA-MILP Approach to Sustainable Open Pit Planning

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ABSTRACT

As global demand for mineral resources continues to grow, the environmental impact of the mining industry has become increasingly significant. Sustainable mining practices require integrating environmental considerations into all phases of planning and operations. This paper addresses the urgent need to minimize the negative environmental impacts of long-term open pit mine planning, focusing on reducing greenhouse gas (GHG) and dust emissions. We propose an integrated framework that combines life cycle assessment (LCA) data with a mixed-integer linear program (MILP) to optimize mine planning processes. This framework, termed LCA-MILP, quantifies the environmental impacts of mining activities and examines various GHG constraints alongside economic scenarios. To validate the effectiveness of the LCA-MILP framework, we conducted a case study on an open-pit iron ore mine in the Middle East. Our findings emphasize the importance of aligning environmental impact reduction with long-term mine planning, fostering a more sustainable and socially responsible mining industry. For example, it was possible to reduce GHG emissions by 11.05% while achieving 93.66% of the original NPV. In another scenario, the framework achieved the same NPV as the baseline with a 2% price adjustment, while reducing environmental impact by 5.39%. These results provide mining managers with insights into the trade-offs and opportunities of incorporating environmental factors into long-term mine planning, supporting a sustainable and economically viable mining industry.

1. Introduction

Achieving sustainable development goals in the mining industry necessitates maintaining a harmonious equilibrium between economic progress and safeguarding the environment and social well-being. The Mining sector contributes substantial economic and societal advantages to nations by supplying essential raw materials to both domestic and global industries, fostering infrastructure growth, and generating employment opportunities and income for local communities [1]. While the mining industry positively influences economies and societies, which are integral components of sustainable development, it also possesses potential adverse effects on the environment, the third key pillar of sustainability. Adverse environmental impacts of mining activities encompass the destruction of natural habitats, alteration of landscapes, and degradation of air and water resources quality [1].

Approximately 10% of the world's energy-related anthropogenic greenhouse gas (GHG) emissions stem from the primary production of minerals and metals [2, 3]. Projections based on current trends suggest that by 2030, the escalation of iron ore open-pit mining activities to meet the global

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demand for raw materials could significantly increase GHG emissions, leading to more pronounced environmental degradation [4]. Conversely, an increasing number of governments are pledging to achieve net-zero emissions by either 2030 or 2050 [5]. To sustain or decrease current levels of emissions in the future, it is necessary to enhance efficiency by adopting new and improved methods within the mining industry. Enhancing environmental performance can help mining companies mitigate economic risk, especially as there is a growing demand from governments and consumers for greater environmental and social responsibility [6, 7].

The life cycle assessment (LCA) method stands out as a highly promising approach for quantifying the environmental performance of mining operations when seeking to measure environmental impacts [8]. It is an unbiased approach that assesses the environmental loads associated with a product or process throughout its lifespan, considering the supplementary impacts of materials or energy consumed in the analyzed process. An essential characteristic of LCA is its capability to assess the indirect effects of a process, such as the environmental impacts linked to the production of the fuel that powers the process [9]. So, integrating LCA with mine planning attempts to assess the environmental impact of mining activities, serving as a managerial tool for informed and sustainable decision-making.

While the LCA method has traditionally found more usage among policymakers and researchers [10, 11], mining companies have increasingly embraced it in recent times. Chaulya [12] employed a distinct method, conducting visits to three iron ore mines to quantify particulate emission rates and formulate equations for various surface activities. Emission rates during mining activities can be influenced by the physical properties of the ore. These properties, combined with other data like spatial location, constitute the foundation for the calculations in the LCA presented in their method. Ferreira and Leite [13] conducted an LCA technique to produce iron ore in Brazil. Their investigation focused on the environmental expenses associated with producing iron ore concentrate, emphasizing the significant role of grinding media contributing to mines overall environmental impacts. Vahidi, Navarro [14] presented the inaugural LCA of in-situ leach mining for rare earth elements (REEs) extracted from ion adsorption clays in southern China. The study offers novel insights into the environmental consequences and energy demands associated with this extraction approach. Islam, Vilaysouk [15] utilized remote sensing (RS) and LCA to evaluate the environmental impacts of a copper-gold-silver mine in Laos, focusing on land use change, Global Warming Potential (GWP), and Gross Energy Requirement (GER).

Mine planning, a crucial department in open-pit mines, necessitates mining companies to explore potential environmental impact mitigation strategies within this specific division [16].Mine planning involves the selection of specific materials to be extracted and determining the sequence and timing of extraction to minimize costs or achieve a particular business objective [17]. Within a sustainable framework, the alleviation of environmental impacts can be achieved by incorporating environmental constraints into modeling and employing digital technologies to implement and ensure compliance with appropriate limits for environmental footprints [1]. In recent years, numerous studies have addressed open-pit mine planning using deterministic and stochastic approaches [18-23]. However, there has been relatively less emphasis on integrating environmental impacts, including GHG emissions, into these studies. Muñoz, Guzmán [24] introduced a technique for calculating carbon emissions and energy usage at the Economic Block Model (BM) level for key mining activities. They present a new approach that involves integrating a carbon tax, linked to emissions, as supplementary costs for each block within the mine BM. Pell, Tijsseling [6] presented a novel approach to incorporate the environmental impacts into the BM of a deposit. The results demonstrate that integrating environmental constraints into mine scheduling can lead to significant reductions in global warming impact with minimal economic costs. Agosti, Utili [25] investigated the simultaneous financial and environmental implications of a carbon levy on mining and processing activities, uniquely incorporating environmental costs into the Ultimate Pit Limit

(UPL) determination alongside Net Present Value (NPV) maximization. Table 1 presents a synthesis of key studies dedicated to integrating ecological considerations into the design and strategic planning of mining operations.

Table 1. An overview of research for incorporating environmental consideration into mining design and planning.

Research	Parameters	Goal
Munoz et al [24]	Energy consumption, greenhouse gas emissions, freshwater consumption, acid mine drainage generation, and direct employment generation.	Ore resource evaluation and mine planning
Xu et al. [26]	Land area estimation, lost value of direct ecological services, lost value of indirect ecological services, prevention and restoration costs, ecological cost associated with damaged forest land, and cost of carbon emission from energy consumption	Ultimate pit optimization
Xu et al [27]	Lost value of direct ecological services, restoration costs, lost value of indirect ecological services, and carbon emission cost of energy consumption	Production scheduling
Pell et al. [6]	Dust, Carbon dioxide, PM2.5, and PM10	Mine scheduling
Xu et al. [28]	Area of land destruction, ecological costs, spiritual civilization benefit, regional economy promoting benefit, medical care benefit, and safety investment benefit	Open pit limit optimization
Rijsdijk and Nehring [29]	Carbon dioxide emission	Cut-off grade and optimal pit limits
Xu et al [30]	Ecological service value loss, reclamation costs, carbon emission cost, and lost value of direct ecological services	Ultimate pit optimization
Agosti et al [25]	Carbon dioxide emission	Ultimate pit limit and profitability

This study suggests the integration of environmental data derived from LCA into long-term mine planning to quantify the environmental impact of mining activities. An integrated framework (LCA-MILP) for implementing this approach in mine planning has been formulated through a case study of an iron deposit situated in the Middle East region. This study centers on investigating the CO_2 and dust emissions from mining activities and assessing the economic ramifications associated with these emissions. The proactive inclusion of environmental considerations in mine planning is facilitated through the integration of mine planning and LCA, achieved by defining diverse constraints and economic scenarios. The developed sustainable integrated framework provides valuable insights for environmentally responsible raw material extraction in open-pit mines.

2. Material and Methods

The environmental impact data computed through LCA can be incorporated into the mine planning procedure, allowing for the exploration of scenarios and the adjustment of constraints after the initial results generation, as depicted in Figure 1. Hence, the objective of this study is to formulate an integrated approach aimed at mitigating the environmental impacts of mining operations throughout the process of long-term mine planning. Our research seeks to create a holistic framework by integrating various tools and methodologies. This framework aims to empower mining companies to make well-informed decisions that strike a balance between production objectives and environmental sustainability.

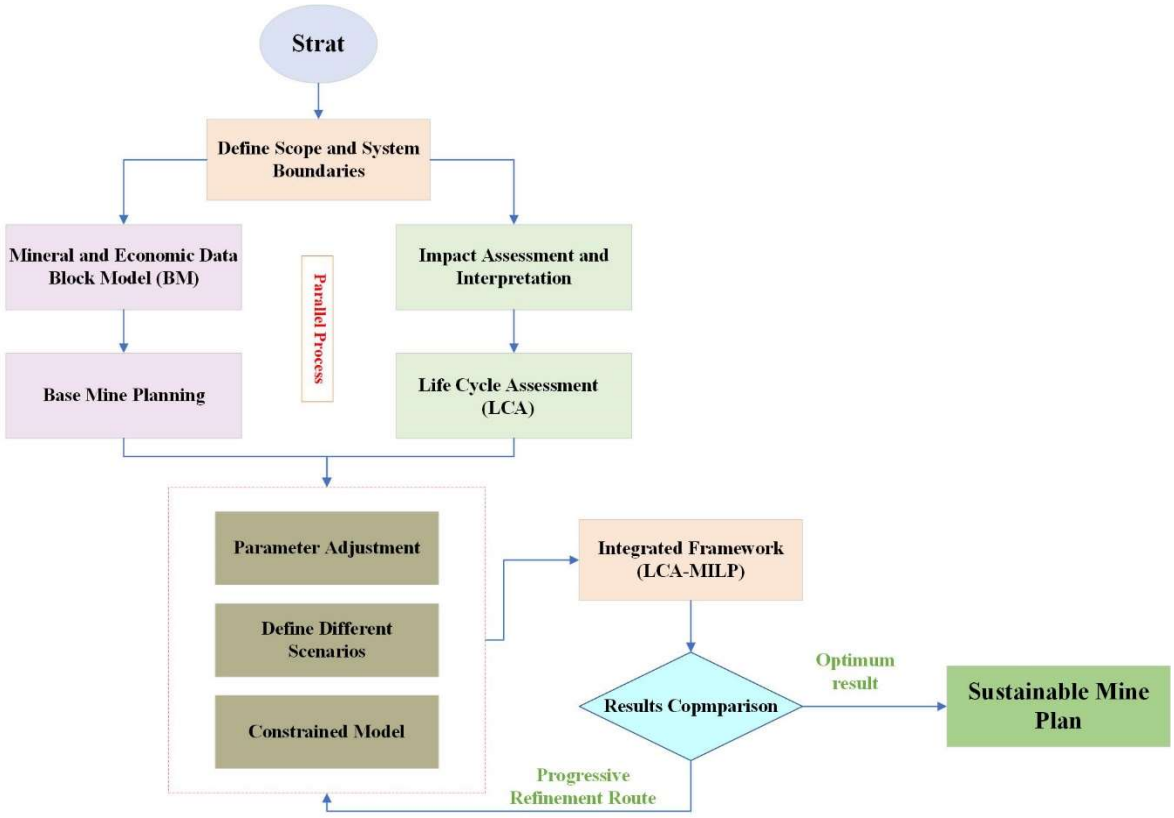

Figure 1. Details of proposed integrated framework (LCA-MILP) in this study.

In summary, the integrated framework for sustainable long-term production planning of open-pit mines commences by defining the scope and system boundaries. The base mine planning phase using a mix integer linear programming (MILP), running in parallel with LCA, establishes an initial production plan devoid of environmental considerations, acting as a reference point for subsequent scenarios. Through parameter adjustment, different scenarios are defined to explore a spectrum of economic and environmental conditions. The culmination of this approach is realized in the integrated framework (LCA-MILP), where LCA information is harmonized with a MILP model to concurrently optimize economic and environmental facets. Results comparison across scenarios facilitates a nuanced evaluation, leading to the formulation of a Sustainable Mine Plan that intricately integrates economic feasibility with environmental responsibility, thereby offering a holistic and forward-thinking strategy for the mining industry.

2.1. Environmental Impacts Measurement

Lately, several studies have emerged in the literature aiming to conduct LCA for open-pit mines [6, 25, 31]. Industries are consistently striving to enhance their environmental sustainability by employing LCA, a methodical approach to assess the environmental impacts of products and processes [1]. The LCA method enables the measurement of impacts and the identification of possibilities for mitigation, either through the exploration of alternative solutions or the improvement of existing products and processes. The objective and focus of LCA part are to evaluate the global warming impact associated with the extraction and transportation of an individual block in the specified case study. The LCA technique from extraction to the gate employed a functional unit of one block of ore or waste. The set of operations, such as drilling, blasting, and loading, remains consistent for each block. The waste block is dumped at the designated waste dump location in the mine, while the ore block undergoes crushing at the crusher, excluding additional processing steps. The LCA system boundary encompasses explosive,

electricity, and diesel inputs, along with the corresponding dust and exhaust emissions occurring at the mine site, as depicted in Figure 2.

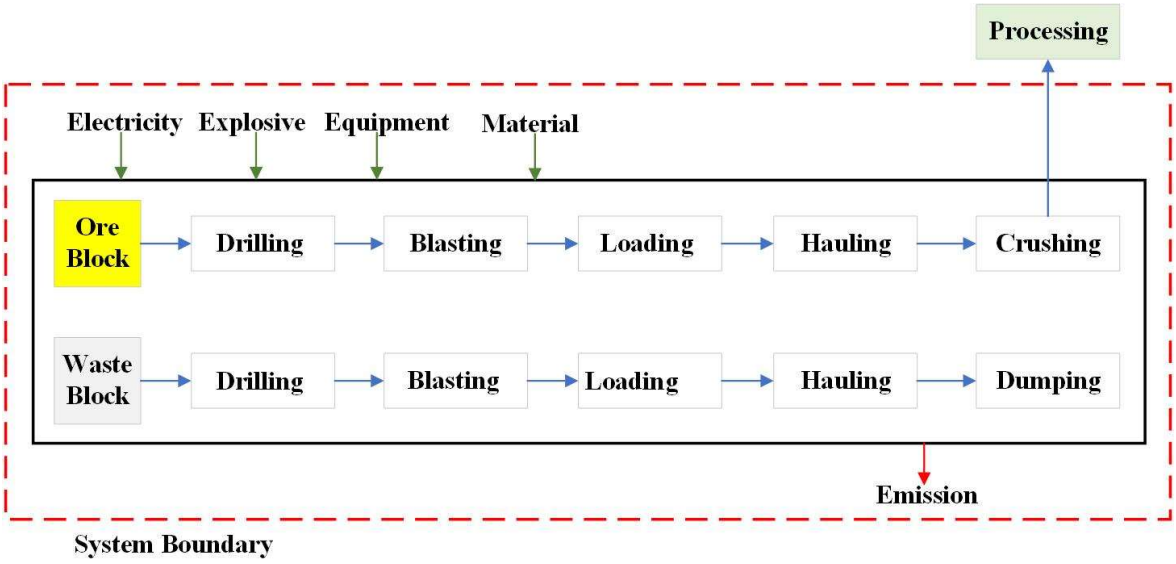

Figure 2. Environmental impact system boundary for each block.

The formulas used for particle emissions follow the methodology outlined by Chaulya [12], while the calculations for emissions related to equipment, diesel, and electricity consumption are based on the approaches by Muñoz, Guzmán [24], NPI [32]. To gain a thorough understanding of the environmental impact quantification, the equation for calculating the GWP of the mining operation can be found in Muñoz, Guzmán [24], NPI [32]. These equations include emission factors and operational parameters that are tailored to this particular study. All variables, excluding the block's physical properties, remained constant. This encompassed the environmental conditions, and the machinery utilized. Unless otherwise specified, diesel equipment is employed, chosen in accordance with the regulations applicable to the region.

Table 2. The inputs and outputs to the process of LCA.

Procedure	Element	Unit	Explanation
Drilling	Diesel	MJ	Input
Blasting	Explosives	kg	Input
Loading	Diesel	MJ	Input
Hauling	Diesel	MJ	Input
Crushing	Electricity	MJ	Input
Entirely	Carbon dioxide	kg	Output
Entirely	Dust	kg	Output

Finally, the findings in this research assess the GWP midpoint indicator using the TRACI 2.2 LCA methodology. TRACI is an application for ecological impact evaluations that can be used for products, processes, buildings, businesses, and communities. It offers characterization elements for Life Cycle effect Assessment (LCIA), industrial ecology, and sustainability measures [33]. Information regarding diesel, explosives, energy consumption, and emissions was sourced from the GaBi® database [34]. The LCA was conducted using GaBi® 6.0 software. Table 2 shows the inputs and outputs incorporated in the LCA method. The provided data comprises the primary

factors contributing to the impact of GWP, a correlation supported by earlier LCA studies on mining operations [6, 35].

2.2. Long-Term Mine Planning

To formulate a mine plan, the essential information needed about the deposit includes the grade of the element of interest and the tonnage of each block. The arrangement of grade and tonnage throughout the deposit is also crucial in the process of mine planning. This study acquired information about the ore body from an iron mine situated in Iran. The authors conducted the Kriging Neighborhood method to generate an impartial estimation of the diverse elements present within the deposit on a mining block scale.

An economic and a waste value has been estimated and allocated to every block based on the elemental grades and tonnage of the block. The economic value is estimated by considering the value of the iron in the block and subtracting mining costs, processing costs, and penalties associated with the present contaminants. The economic value of the iron is determined by multiplying the iron grade with the block tonnage using an iron ore price. The waste cost is computed by multiplying the block's tonnage, determined by multiplying specific gravity by the block's dimensions, with the mining cost per tonnage (Equation 1).

$$V_i = b_i \times \left[(R \times P \times g_i) - C_p - C_m\right] \quad (1)$$

A mixed integer linear programming (MILP) model was developed for the purpose of long-term planning of the ore body. The blocks in the block model are scheduled directly on an annual basis, adhering to operational constraints (e.g., annual extraction or plant capacity) as well as desired constraints, such as product grade or maximum annual environmental impact. The ultimate objective of the optimization process is to maximize the overall NPV of the project.

Equations 2 to 8 illustrate the MILP model for long-term planning [20]. In these equations, T, I, and O denote the indices and the number of time periods, the number of blocks, and the number of ore blocks, respectively. M_{el}^t, M_{eu}^t, M_{pl}^t, and M_{pu}^t represent the minimum and maximum extraction capacities, as well as the maximum and minimum processing capacities. g_i, g_u^t, and g_l^t specify the grade of block i, the maximum required grade, and the minimum required grade for processing, respectively. b_i represents the tonnage of block, ε is the discount rate, and V_i denotes the economic value of block i. I_{pi} is a set of blocks that need to be extracted before block i. Finally, x_i^t is decision variable which equals one if block i is extracted in time period t; otherwise, it is zero.

$$Max \quad \sum_{t=1}^{T}\sum_{i=1}^{I}\frac{V_i}{(1+\varepsilon)^t}x_i^t, \qquad x_i^t \epsilon \{0,1\} \quad (2)$$

$$\sum_{r=1}^{t} x_j^r - x_i^t \geq 0, \quad \forall\, t = 1, \dots, T; i \in I; j \in I_{pi} \quad (3)$$

$$M_{el}^t \leq \sum_{i=1}^{I} b_i\, x_i^t \leq M_{eu}^t, \quad \forall\, t = 1, \dots, T \quad (4)$$

$$M_{pl}^t \leq \sum_{i=1}^{O} b_i\, x_i^t \leq M_{pu}^t, \quad \forall\, t = 1, \dots, T \quad (5)$$

$$\sum_{i=1}^{O} b_i\, x_i^t (g_i - g_u^t) \leq 0, \quad \forall\, t = 1, \dots, T \quad (6)$$

$$\sum_{i=1}^{O} b_i \, x_i^t (g_i - g_l^t) \geq 0, \quad \forall \, t = 1, \ldots, T \tag{7}$$

$$\sum_{t=1}^{T} x_i^t \leq 1, \quad \forall \, i = 1, \ldots, I \tag{8}$$

Where, in the above model, the objective function (Equation (2)) maximizes the NPV. The NPV is determined by adding up the economic value of every block, while taking into consideration the changing economic conditions and extraction costs, by discounting them over time using the discount rate (ε). Equation (3) represents the slope stability constraint. According to this constraint, if block j is a prerequisite for extracting block i, then block j must be extracted before block i. This constraint maintains the integrity of the mining structure and prevents the destabilization of blocks. Equation (4) indicates the maximum and minimum extraction capacities. According to this equation, the total tonnage of waste and ore blocks extracted must adhere to the mining extraction capacity. According to Equation (5), the input feed to the processing plant must fall within the required range for the plant in each time period, constrained by the minimum and maximum processing capacities. Additionally, Equations (6) and (7) establish the grade constraints for the processing plant. Equation (6) ensures that the weighted average grade of the processed ore does not exceed the upper limit, while Equation (7) guarantees that it does not fall below the lower limit. According to Equation (8), each block can be extracted at most once.

In this research, GWP per block and Fe content, contingent on economic values, were computed and assigned to all blocks in the block model. In essence, the integrated framework for sustainable long-term production planning of open-pit mines starts by defining the scope and system boundaries. Initially, we develop a base mine plan using MILP and LCA to establish a production plan without considering environmental factors. Simultaneously, we explore various scenarios by adjusting parameters, leading to the final phase's integrated framework (LCA-MILP). This integrated framework optimizes both economic and environmental factors by merging LCA information with a MILP model. It assesses the economic performance of the operation, determines metal production tonnages, and calculates annual environmental impact. By comparing results across scenarios, we can evaluate the framework comprehensively and formulate a sustainable mine plan that combines economic feasibility and environmental responsibility. In the upcoming sections, we will delve into each aspect of the framework, providing a detailed exploration of its components and implications.

2.3. Parameter Adjustment and Scenarios Definition

The initial pit scheduling was conducted without any environmental constraints, establishing the baseline for the study, and serving as a basis for subsequent assessments. Within the integrated framework, supplementary constraints were introduced, imposing an upper limit on the annual emissions output (Equation (9)). As a limitation, six levels ranging from 5 to 30 percent of the annual baseline output were selected. The chosen constraint levels were carefully selected to explore the trade-off between reducing environmental impact and economic costs. This range was chosen for two reasons. Firstly, it allows for a detailed examination of the impact at different levels, helping us understand when environmental improvements become significant. Secondly, by incorporating a range of constraint levels within our existing operational capacity, we can assess the feasibility of making changes without major alterations to our facilities. This approach provides valuable insights into the practicality and adaptability of the proposed environmental constraints within our current mining infrastructure. Overall, the selected range ensures a thorough analysis of the relationship between environmental sustainability and economic considerations, providing actionable insights for the industry. The levels of reduction of GHG emissions are presented in Table 3.

$$\sum_{i=1}^{I} E_i \, x_i^t \leq Upper\ Limit, \quad \forall\, t = 1, \ldots, T \tag{9}$$

Where E_i represents the emissions associated with block i.

Table 3. The levels of environmental constraints.

Level	Environmental threshold
Base	None
Level 1	5% reduce
Level 2	10% reduce
Level 3	15% reduce
Level 4	20% reduce
Level 5	25% reduce
Level 6	30% reduce

Moreover, the economic value of Fe was modified by augmenting the base Fe price of $120 per ton by 1%, 2%, 3%, 4%, and 5%, respectively. Thus, scenarios were defined by combining environmental constraints and price adjustments. The justification for assigning added value to Fe in evaluations involving global warming thresholds is grounded in the findings of numerous studies, which indicate that integrating environmental constraints into mining operations can enhance the overall value of minerals [1, 6, 36]. By incorporating a heightened economic value for Fe, it becomes feasible to assess the potential additional value a company could theoretically add to a product with reduced carbon emissions. With this clarification for future evaluation, Table 4 outlines the defined scenarios.

The procedure outlined in the mine planning section was adhered to, incorporating the environmental constraints detailed in Table 4 for all scenarios. An augmented economic value for the block was also implemented within the constraints elucidated in Table 4 for scenarios 2–6. This was done to comprehend the elevated block value necessary to align with the baseline under environmentally constrained conditions. Subsequently, the data generated from the integrated framework (LCA-MILP) can be evaluated in terms of both environmental impact and its corresponding influence on the NPV. In this phase of comparing results, it is also feasible to picture relationships between scenarios and adjust constraints for additional assessment.

Table 4. The details of scenarios employed in this study.

Scenario	Symbol	Goal	Price adjustment	Environmental threshold
1	S1	Max NPV	None	Base and All levels
2	S2	Max NPV	1%	Base and All levels
3	S3	Max NPV	2%	Base and All levels
4	S4	Max NPV	3%	Base and All levels
5	S5	Max NPV	4%	Base and All levels
6	S6	Max NPV	5%	Base and All levels

3. Results

In this section, our proposed integrated framework is implemented in various scenarios to showcase its efficacy. The implementation was carried out using Python® programming language [37] and the CPLEX® solver [38]. All experiments were conducted on a Windows 11 workstation

equipped with an AMD Ryzen 7 5800H CPU and 16GB of RAM. To validate and test the developed LCA-MILP, we applied it to a case study involving an open-pit iron mine. This iron deposit is located in the Middle East region. The reserve modeling, planning activities, and long-term production planning were grounded in drill-hole prospecting data.

3.1. Mine Planning Without Environmental Issues

As previously stated, the initial mine plan was formulated without environmental constraints, establishing the study's baseline and providing a foundation for subsequent evaluations. Hence, Figure 3 illustrates the financial and environmental aspects of this approach. The mine planning, conducted without environmental constraints, resulted in annual emissions ranging from 80,000 to 95,000 equivalent ton, with a cumulative total of 439,000 equivalent ton. Emissions exhibit an ascending trend from the outset, peaking in period 4, and subsequently experiencing a substantial decrease toward the end. At the same time, CO2 accounted for 55% and dust for 45%, equating to 241,000 equivalent ton and 198,000 equivalent ton, respectively. Figure 3 illustrates the cumulative NPV, showcasing the optimization of the target cut-off grades. By the end of period 5, the baseline achieved an NPV of $1,188 million.

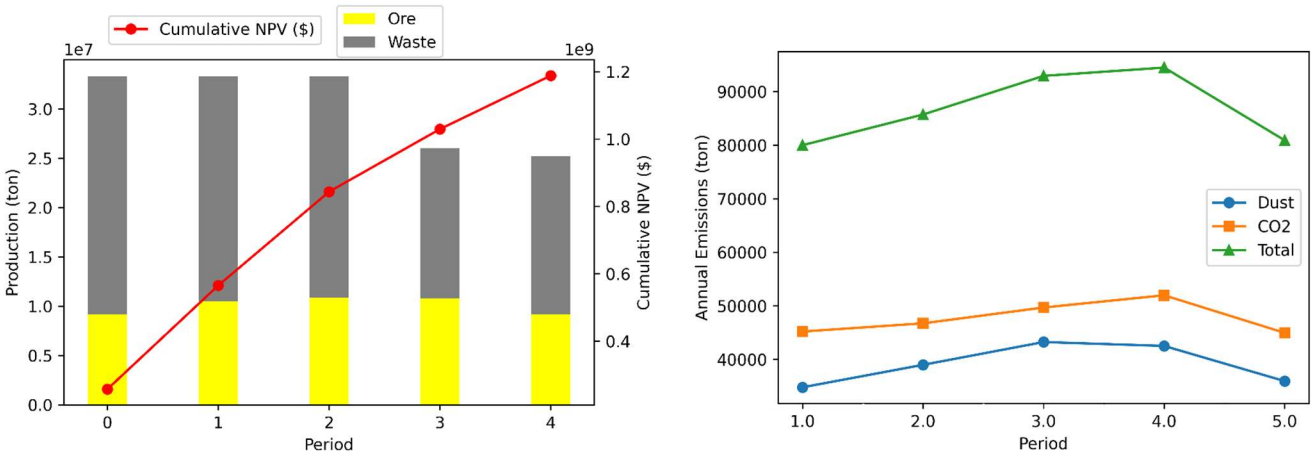

Figure 3. Annual production and cumulative NPV (left) alongside annual emissions (right) in the baseline.

3.2. Environmentally Constrained Mine Planning

Implementing annual environmental constraints in the mine planning framework has an impact on both the annual and cumulative global warming potential emissions as well as NPV. Table 5 presents cumulative emissions and NPV values under various environmental constraints. In these scenarios, the constraint is defined to restrict the global warming impact up to 30% of the average global warming value for all threshold levels. The first level witnessed a 6.24% decrease in emissions, leading to a corresponding NPV reduction of $37.9 million, equivalent to a 3.19% decrease compared to the baseline. At the second level, similar to the first one, there is a slight decline in financial returns with an 11.05% reduction, resulting in an NPV decrease of $75.29 million. This signifies a 3% difference between the two levels. However, as the threshold increases, the differences become more pronounced. For instance, the disparities between levels 4 and 5, as well as levels 5 and 6, were 5.8% and 5.91%, respectively. This results from the more stringent constraint restricting the extraction of blocks with higher impact. The relationship between NPV and environmental impact rate is non-linear, as shown in Table 5. This distinction serves as a crucial factor for planners in crafting strategic plans, allowing them to assess how deviation from desired financial outputs can be minimized alongside emission reductions. This suggests the potential for finding an optimal solution through the exploration of various constraints and economic values.

Table 5. Impact of environmental constraint on financial and environmental outputs.

Detail	Environmental threshold	Emissions		NPV	
		Amount (ton)	Decrease (%)	Amount (M$)	Decrease (%)
Mine Plan	Base	439133	0.00	1188.46	0.00
	Level 1	411728	6.24	1150.56	3.19
	Level 2	390630	11.05	1113.18	6.33
	Level 3	368750	16.03	1062.47	10.60
	Level 4	347000	20.98	1000.45	15.82
	Level 5	326772	25.59	931.54	21.62

This paper seeks to explore the possibilities of reducing environmental emissions and the associated economic consequences without the need for facility modifications. One bottleneck in mining operations lies in meeting the plant's feed requirements. To address this concern, Figure 4 illustrates the influence of each environmental constraint level on the incoming feed to the plant. In the initial and final periods of the first and second levels, the annual ore production remains comparable to the baseline, while there is a more pronounced reduction in the middle periods. For the third level, the reduction exhibits an irregular pattern, and the fourth and fifth levels demonstrate a consistently significant reduction. However, in the sixth level, non-compliance with the minimum plant feed is observed throughout the periods except for the last one, based on the specified threshold. For this reason, the sixth level of environmental constraint is not considered in further analysis.

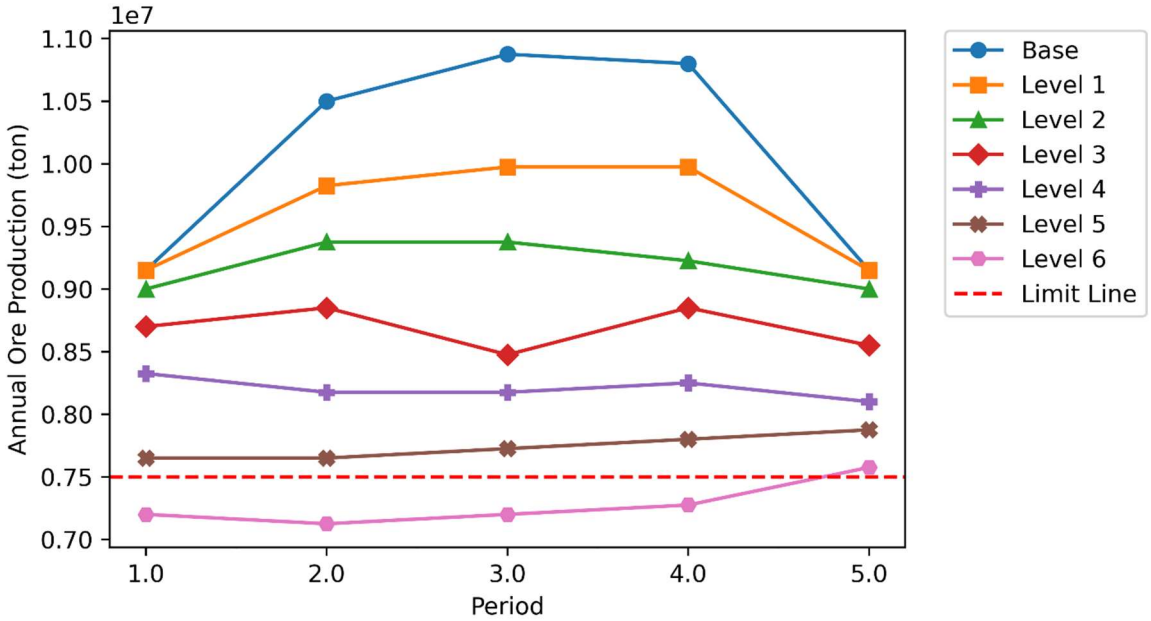

Figure 4. Annual ore production for each level of environmental constraint.

Figure 5 depicts the relative carbon emissions from mining processes for two selected blocks. Transportation emerges as the key contributor to carbon output, with each block's transport emissions calculated separately. An increase in the depth of the pit is projected to amplify carbon emissions from hauling, as longer haul cycles will require more fuel per ton of material transported. Additionally, the process of crushing is responsible for 27% of the total carbon emissions produced by mining activities for ore blocks.

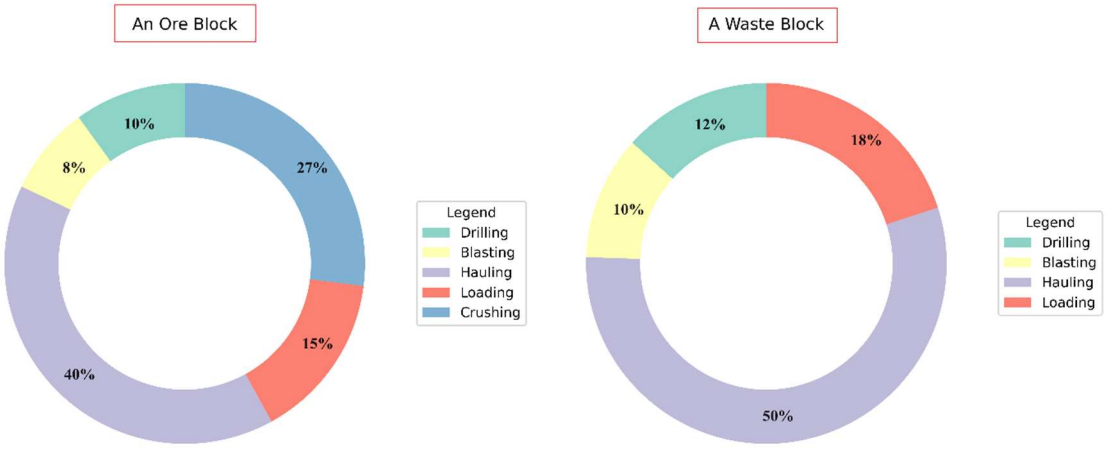

Figure 5. Distribution of carbon dioxide emissions among various mining processes.

3.3. Scenario Results Comparison

Some mining companies voluntarily adhere to environmental standards and carbon dioxide emission limits, offering their raw material products at premium prices due to a reduced global warming footprint. In certain regions, like Canada, carbon taxes have been implemented, creating economic incentives for the reduction of CO2 emissions. Scenarios are defined by introducing environmental thresholds alongside a gradual increase in the economic value of Fe, ranging from 1% to 5%. This approach enables us to assess the necessary value increase to sustain the baseline NPV while simultaneously reducing the GWP impact. Table 6 presents the outcomes for the six scenarios incorporating elevated Fe values and emissions constraints.

As depicted in Table 6, the NPV performance is contrasted between scenarios, comparing the baseline with the outcomes of incorporating environmental constraints. In scenario 1, the outcomes pertain to the condition where the mine plan runs without any price adjustment. This provides insights to managers regarding the costs associated with reducing emissions in operations. For instance, by implementing an environmental constraint, it was feasible to attain 88.95% of the global warming impact while achieving 93.66% of the NPV compared to the baseline. The change highlighted in Table 6 is derived by subtracting the baseline NPV, and the negative value indicates that this condition has a higher NPV. In scenario 3, it is viable to achieve nearly the same NPV as the baseline while attaining a 94.61% reduction in global warming impact through a 2% price adjustment. In scenario 5, introducing a 4% price adjustment resulted in achieving 91.37% reduction in global warming impact. For a better understanding of the impact of applied changes, Figure 6 illustrates the NPV performance in scenarios one and six.

According to Figure 6, it is evident that in the scenario with a 5% adjustment, in addition to the first level of emission constraint, which has a higher NPV compared to the baseline, the second level of constraint also accurately covers both the annual and cumulative NPV of the baseline. Incorporating price adjustments into the modeling process leads to variations in financial outcomes, block sequencing, and emission levels. At lower percentages (1% and 2%), the outcomes suggest that the fundamental optimization is making minimal change to the selection and order of block extraction. However, in scenarios with 4% and 5% adjustments, the heightened economic value of Fe opens new economically viable areas within the deposit, even while adhering to emission thresholds. These alterations can substantially influence the overall cumulative emissions.

Table 6. The outcomes for the six scenarios incorporating elevated Fe values and emissions constraints.

Scenario	Environmental	Price Adjustment	NPV

	threshold		Amount (M$)	Change (%)
Scenario 1	Base	-	1188.46	0.00
	Level 1	-	1150.56	3.19
	Level 2	-	1113.18	6.33
	Level 3	-	1062.47	10.60
	Level 4	-	1000.45	15.82
	Level 5	-	931.54	21.62
Scenario 2	Base	-	1188.46	0.00
	Level 1	1%	1167.58	1.76
	Level 2	1%	1129.58	4.95
	Level 3	1%	1078.11	9.29
	Level 4	1%	1015.20	14.58
	Level 5	1%	945.35	20.46
Scenario 3	Base	-	1188.46	0.00
	Level 1	2%	1184.59	0.33
	Level 2	2%	1145.97	3.58
	Level 3	2%	1093.74	7.97
	Level 4	2%	1029.96	13.34
	Level 5	2%	959.17	19.29
Scenario 4	Base	-	1188.46	0.00
	Level 1	3%	1201.60	-1.11
	Level 2	3%	1163.26	2.12
	Level 3	3%	1110.26	6.58
	Level 4	3%	1045.60	12.02
	Level 5	3%	973.87	18.06
Scenario 5	Base	-	1188.46	0.00
	Level 1	4%	1218.62	-2.54
	Level 2	4%	1179.67	0.74
	Level 3	4%	1125.91	5.26
	Level 4	4%	1060.37	10.78
	Level 5	4%	987.70	16.89
Scenario 6	Base	-	1188.46	0.00
	Level 1	5%	1235.63	-3.97
	Level 2	5%	1195.17	-0.56
	Level 3	5%	1140.65	4.02
	Level 4	5%	1074.22	9.61
	Level 5	5%	1000.61	15.81

4. Discussion

The results of this research have implications for mining managers who are working towards creating strategic mine plans that balance economic goals with environmental responsibility. Our study offers insights to decision makers who want to align mining operations with sustainability objectives by integrating environmental impact assessment into long term planning for open-pit mines. The main purpose of incorporating factors into the mine planning process is to enable mining companies to make decisions that consider both production goals and environmental sustainability. The findings emphasize the role of decision making in achieving a harmonious equilibrium between economic performance and its impact on the environment.

As previously discussed, the introduction of price adjustments results in variations in emitted emissions. Table 7 illustrates the environmental performance and adjustment justifies spending money to decrease emissions across diverse scenarios. The difference within a column between the

two scenarios is inconspicuous, while the variance between Scenario 1 and Scenario 6 is approximately 2%. Thus, Figure 7 visually depicts annual emissions in relation to Scenarios 1 and 6. The improvement in costs serves as an additional criterion for managers to evaluate, determining which strategies align with the company's policies in this domain. The presence of negative values indicates a profitable outcome for the scenario. This is attributed to the enhanced value assigned to the block, surpassing the baseline in terms of economic performance in these scenarios.

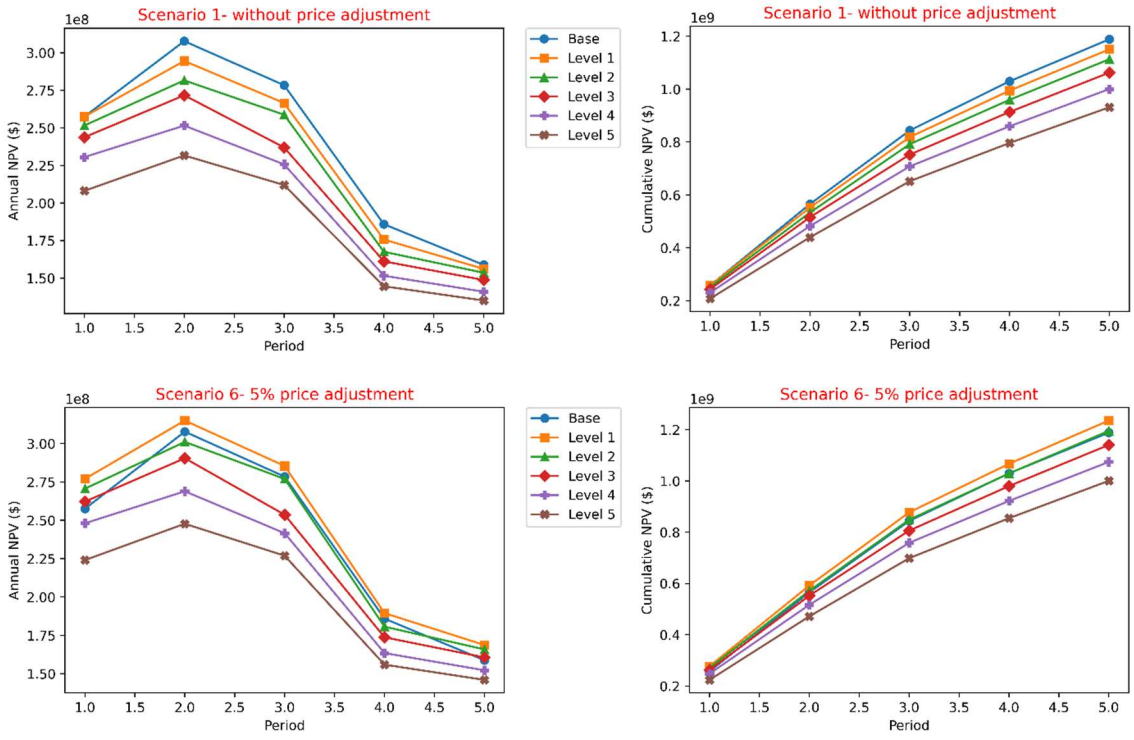

Figure 6. The obtained NPV of scenarios 1 and 6 relative to base.

Table 7. Comparative analysis of environmental impact and cost enhancements across various scenarios.

Scenario	Emission amount with each level					Emission per ton of iron ore	$ Per kg emission saved
	Level 1	Level 2	Level 3	Level 4	Level 5		
Scenario 1	411728	390630	368750	347000	326772	8.44 to 8.56	1.38 to 2.29
Scenario 2	414020	392801	370799	348924	328568	8.49 to 8.61	0.83 to 2.2
Scenario 3	415432	394155	372088	350139	329725	8.52 to 8.64	0.16 to 2.10
Scenario 4	416400	395077	372978	350973	330427	8.55 to 8.67	-0.58 to 1.97
Scenario 5	418227	396820	374616	352515	331950	8.58 to 8.71	-1.44 to 1.87
Scenario 6	419863	398368	376069	353885	333238	8.61 to 8.74	-2.45 to 1.77

The LCA scores for various scenarios suggest that for a ton of iron ore extracted emissions were between 8.44 and 8.74 at the mine. Pell et al [6] computed a value of 8.22 kg per ton of extracted ore, considering scenarios without the inclusion of crushing in the cycle and under various mine conditions. These values fall within the range reported by Norgate and Haque [39], who determined a CO_2 emission of 11.9 per ton of Fe concentrate, and Ferreira and Leite [13], who calculated 13.32 kg CO_2 per ton of Fe concentrate [40, 41].

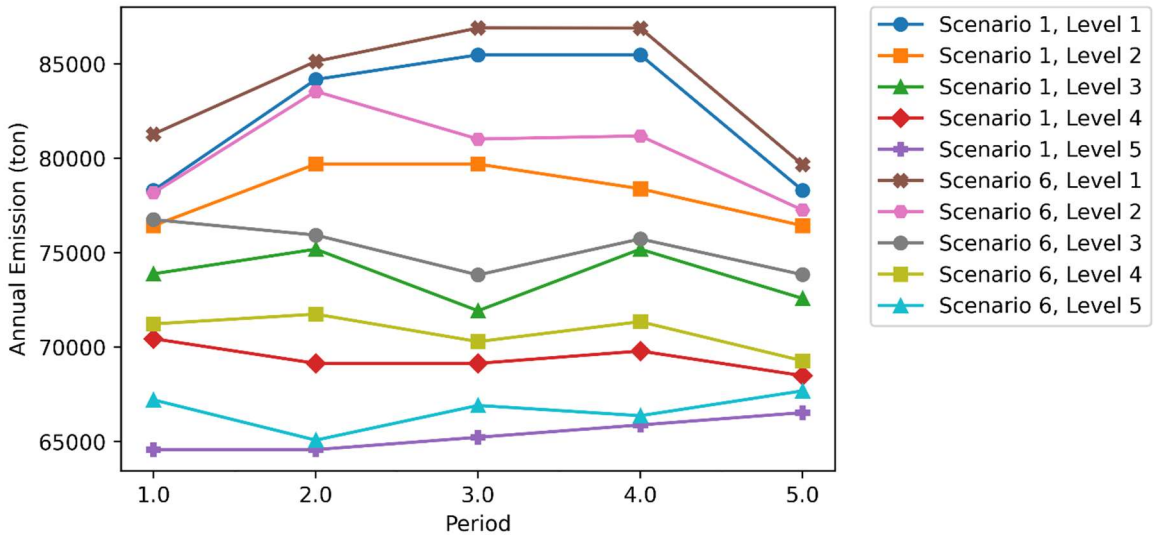

Figure 7. The obtained NPV of scenarios 1 and 6 relative to base.

One important finding is the non-linear relationship between NPV and environmental impact, especially when emission constraints are imposed. Mining managers face the challenge of optimizing NPV while adhering to environmental limitations in their long-term planning. Our study examines various scenarios to understand how different levels of environmental constraints and economic adjustments affect the economic and environmental performance of mining operations. The research shows that sustainable mining practices can be achieved without sacrificing economic viability. By introducing environmental constraints and making incremental adjustments to the economic value of iron ore, we discovered a range of feasible scenarios. This insight is invaluable for managers who want to develop mine plans that not only meet financial targets but also contribute to environmental stewardship. The study highlights the importance of assigning a higher economic value to iron ore (Fe) in successfully implementing environmentally constrained mine plans. Under certain scenarios, the additional value attributed to Fe can lead to profitable outcomes that surpass the baseline economic performance. This finding gives managers a strategic lever to explore economically viable options while minimizing the ecological footprint.

The analysis of ore production within environmental constraints highlights operational challenges, particularly in meeting plant feed requirements. This understanding prompts mining managers to not only consider the economic feasibility of extraction, but also the practicalities of maintaining consistent production levels under varying environmental limitations. The study's comparative environmental analysis provides insights into the cost benefits associated with different scenarios. The presence of negative values in certain scenarios indicates profitable outcomes, emphasizing that environmentally responsible practices can align with economic success. This information serves as a valuable criterion for managers to evaluate strategies that adhere to the company's sustainability policies. By drawing on real-world case studies and emerging trends, our research contributes to the evolving landscape of sustainable mining practices. The defined scenarios, along with economic adjustments, offer mining managers a practical roadmap to navigate the complexities of integrating environmental considerations into mine planning.

The results of this research provide mining managers with a strategic framework to effectively address the changing demands for sustainable and socially responsible mining. By demonstrating the viability of mine plans that prioritize environmental constraints, the study contributes to a transformative shift in the industry, where economic success and ecological responsibility are intertwined objectives. These findings empower mining managers to actively shape the future of

mining operations, promoting a more sustainable and socially responsible mining industry. While our study establishes a strong foundation, future research should explore the integration of social impacts, regulatory considerations, and community engagement into mine planning strategies. Additionally, investigating the applicability of the proposed methodology in different mining contexts and commodities could further enhance its practical usefulness

5. Conclusion

This study highlights the importance of considering environmental impacts in long-term mine planning to promote sustainability in the mining industry. The results show that by strategically implementing environmental constraints, it is possible to reduce global warming potential emissions by 25.59% without compromising the lower limit of processing plant. Additionally, NPV shows a decreasing trend of up to 21.62%. The integrated framework (LCA-MILP) developed in this study, which incorporates environmental impact factors as constraints in mine planning, is a valuable tool for mining managers. It helps them navigate the complex trade-offs between economic objectives and environmental responsibility. The findings of this study provide practical insights on how mining operations can minimize their ecological footprint while optimizing economic performance.

Additionally, by exploring scenarios that consider both environmental limitations and adjustments in the economic value of the extracted resource, a more comprehensive understanding of potential strategies can be gained. This knowledge can be utilized by mining managers to develop sustainable and economically feasible mine plans, taking into consideration factors such as emission reduction targets and economic implications. By quantifying the outcomes, this research provides tangible strategies that can be used by stakeholders in the mining industry to make well-informed decisions. The study aims to promote a shift towards responsible and sustainable resource extraction, aligning with global efforts to address environmental challenges. Given the increasing scrutiny faced by the mining sector, the insights from this research contribute to the ongoing conversation about balancing economic objectives with environmental stewardship to create a resilient and socially responsible mining industry.

6. References

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Sustainable Mine Planning: An Integrated Framework for Balancing Economic and Environmental Costs in Open-Pit Mining

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ABSTRACT

As global demand for mineral resources grows, the mining sector faces increased scrutiny over its environmental impact, necessitating a shift towards sustainable practices. This research presents an innovative framework for long-term open-pit mine planning that integrates economic and environmental considerations. By incorporating carbon pricing into the decision-making process, the framework addresses financial risks and introduces two scenarios: one focused on minimizing environmental costs and the other on maximizing adjusted Net Present Value (NPV). Applied to an open-pit iron ore mine in the Middle East, the framework's impact on block sequencing, greenhouse gas emissions, and financial outcomes was evaluated. The minimization scenario achieved 90.54% of the global warming impact and 90.48% of environmental costs while maintaining 96.25% of the adjusted NPV compared to the maximization scenario. Sensitivity analyses highlighted the framework's adaptability to varying carbon pricing scenarios. This research offers a sustainable approach to mine planning, balancing economic returns with ecological responsibility, and provides valuable insights for decision-makers in the mining industry.

1. Introduction

Mining industries contribute substantial economic and societal advantages to a nation by providing essential raw materials for both domestic and global industries, fostering infrastructure development, and generating employment opportunities and revenue for the local community [1, 2]. While the mining industry significantly contributes to economic and societal aspects, which are essential pillars of sustainable development, it also harbors potential adverse effects on the environment, representing the third crucial facet of sustainability [3]. The adverse environmental effects of the mining industry encompass the depletion of natural habitats, contamination of water and air, and the displacement of indigenous communities [4]. Achieving sustainable development in the mining sector necessitates striking a harmonious balance among economic advancement, as well as environmental and social preservation [5, 6].

Mine planning is a part of process design in mining, and it allows for the use of eco-design principles in the strategic decision-making stage. Mine planning in general and long-term production scheduling in particular, involve the selection of specific materials for extraction and determining the sequence and timing of extraction to minimize costs or achieve a particular

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business objective. This procedure can take place long before operations commence and can be revised throughout the mine's lifespan. Typically, the process entails collecting geological data through methods such as drill holes or other sampling techniques. Using this information, it is possible to construct a block model that includes details about the position and mineral composition of the deposit. The selection of ore and waste is determined by their economic value, and their arrangement is planned to guarantee a consistent marketable grade for the products [7-14].

In recent years, the prime focus of research on the production scheduling problem has been to minimize the scale of problem and account for uncertainties [7, 15-20]. The initial objective is to enhance the efficiency and practicality of the optimization algorithm, while the secondary goal is to achieve the highest degree of stability between investment return and risk. Also, the primary objective function of production scheduling optimization consistently revolves around maximizing economic benefit. Unfortunately, environmental concerns closely tied to production scheduling have garnered less attention in this context.

Previous studies have addressed the environmental impacts of mining in mine design or planning, particularly greenhouse gas (GHG) emissions, through two main approaches: 1) quantification, applied as constraints, and 2) incorporation into economic parameters through taxes or costs. For the first category, Chaulya [21] utilized a unique methodology, conducting site visits to three iron ore mines to quantify rates of particulate emissions and derive equations for different surface activities. The emission rates during mining activities are subject to influence from the physical properties of the ore. Muñoz, Guzmán [22] introduced an approach to estimate comparable carbon emissions and energy consumption resulting from key mining activities at the Block Model (BM) level. They proposed a new method that involves incorporating a carbon tax, proportionate to the emitted amount, as supplementary costs for each block within the mine BM. This cost accounts for the emissions generated by all emitting mining activities. Pell, Tijsseling [23] introduced an innovative approach to Life Cycle Assessments (LCA) by generating spatially explicit data for environmental impact modeling in mining projects. The findings demonstrate substantial reductions in global warming impact with minimal economic costs, emphasizing the potential of incorporating environmental constraints in strategic mine planning.

Limited research exists in the public domain that evaluates the technical and economic implications of integrating a carbon price into the operations of resource projects. Liu, Ren [24] explores the impact of carbon pricing on an iron ore mine, specifically examining whether transitioning from open-pit to underground operations can mitigate the effects of a carbon price. Rijsdijk and Nehring [25] examine the economic consequences of carbon pricing on a copper-cobalt mine in the Democratic Republic of Congo, revealing that a $30/t carbon price moderately impacts mining and processing costs. The study emphasizes the intricate relationship between carbon pricing, operational expenses, and the economic feasibility of mining operations. Agosti, Utili [26] pioneer a simultaneous incorporation of carbon tax in Ultimate Pit Limit (UPL) determination, exploring its impact on Net Present Value (NPV), ore extraction, and carbon emissions. Examining the Marvin copper deposit, the research advocates for optimal pit wall profiles, showcasing substantial gains of up to 215 million AUD without compromising safety.

The correlation between mining plans and the environmental impacts on a particular mining project is evident. Nevertheless, as outlined earlier, conventional open-pit mine planning continues to prioritize maximizing economic gains as the primary objective, neglecting the ecological expenses incurred through resource extraction. Simultaneously, mining operations do not account for the environmental repercussions they generate. While the laws in numerous countries mandate environmental assessments for mining projects, there persists a degree of autonomy in mine design.

This paper introduces an innovative integrated framework that incorporates the minimization of environmental costs, specifically Global Warming Potential (GWP), into strategic mine planning, diverging from conventional approaches. So, this paper quantifies the environmental costs of open-pit mining and incorporates such costs in a mine plan optimization model to demonstrate the influence of environmental costs on the outcomes. Furthermore, a model emphasizing NPV maximization that accommodates environmental costs was developed for comparative analysis of results. This study employs a case analysis of an iron ore deposit situated in the Middle East to evaluate the impact of the integrated framework on an operational site. Considering the widespread adoption of carbon pricing as a significant environmental concern in various global jurisdictions, it is crucial to quantify the economic implications of a harmful environmental pollutant for long-term strategic optimization.

2. Material and Methods

This study began by assessing the energy consumption and measuring greenhouse gas emissions in open-pit mining activities, using recent researches. Our analysis included drilling, blasting, loading, hauling, ancillary tasks, and crushing, taking into account factors such as drill meters, explosive usage, and diesel consumption. A crucial step involved integrating carbon pricing into our analysis, accounting for potential financial risks. We adopted a unique approach, distinguishing emissions based on block destinations. To ensure a comprehensive understanding of the environmental impact, we developed an integrated framework for long-term mine planning, addressing economic and ecological considerations. This framework introduced innovative strategies, such as minimizing environmental costs and maximizing adjusted NPV. The integrated framework captures the complex relationship between economic value and associated carbon costs. To visually illustrate our methodology, we propose a flowchart (Figure 1) that outlines the sequential steps, starting from quantifying emissions to implementing the integrated framework for long-term mine planning.

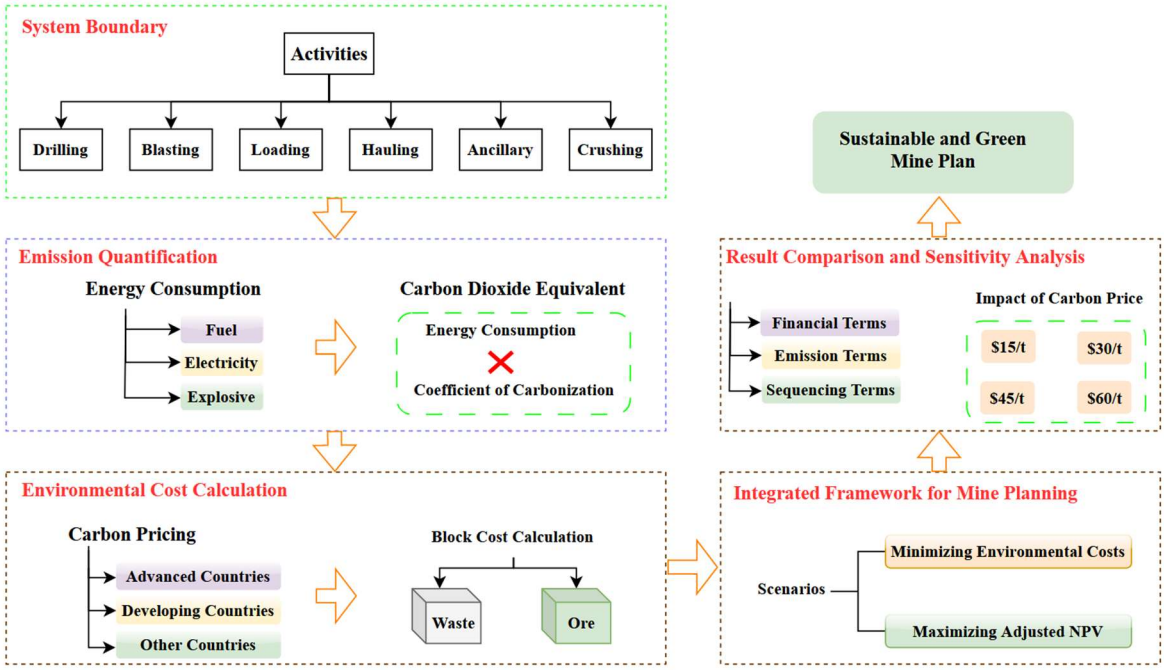

Figure 1. Sequential step of novel integrated framework.

2.1. Emission Quantification

In recent years, there have been a handful of studies focusing on conducting life cycle assessments, quantifying greenhouse gas emissions, and exploring carbon tax and pricing within the operational context of open-pit mines [22, 23, 25-27].

Energy consumption and carbon emissions in the mining process are primarily driven by operational expenditures such as drilling, blasting, loading, hauling, ancillary activities, and crushing. In alignment with Muñoz, Guzmán [22] and Rijsdijk and Nehring [25], our initial step involved assessing the energy consumption of individual blocks by considering the relevant physical processes, followed by the calculation of the global-warming potential (GWP) derived from the estimated energy consumption.

Table 1. The utilized attributes in equations [22, 23, 25-27].

Attribute	Description	value	Attribute	Description	value
$\boldsymbol{R_d}$	The hourly rate of diesel consumption during drilling	40 l/hr.	D_l	The consumption rete of diesel per ton mined	0.18 l/ton
$\boldsymbol{M_d}$	Drill meters needed per ton of mined rock	0.0085 m	S	The distance of block from destination	km
$\boldsymbol{B_F}$	The percentage of mined rock that necessitates drilling and blasting	100%	ζ	Carbonization's coefficient of electrical power	0.56kgCO_{2eq}/MJ
$\boldsymbol{T_A}$	The amount of material extracted	ton	r	The slope of the ramp	10%
$\boldsymbol{P_r}$	The speed at which the drill penetrates	33 m/hr.	R_s	The frictional resistance of the surface	2%
$\boldsymbol{Q_f}$	The amount of CO_{2eq} generated from diesel combustion	2.64 kgCO_{2e}/l	R_i	The estimated internal resistance of the truck	1%
$\boldsymbol{P_F}$	The powder factor needed for the block	0.56 kg/m^3	M_{truck}	The overall weight of the loaded truck	166ton
$\boldsymbol{\rho}$	Density	3 kg/m^3	δ	Carbonization's coefficient	0.61kgCO2e/MJ
$\boldsymbol{R_{ANFO}}$	The proportion of ANFO in the explosive blend	66%	D_a	The consumption rete of diesel per ton mined	0.26 l/ton
$\boldsymbol{Q_A}$	The amount of CO_{2e} generated from ANFO combustion	0.18kg	W_i	The Bond's grindability index	17.325 kWh
$\boldsymbol{R_{Emulsion}}$	The proportion of emulsion in the explosive blend	34%	P_{cr}^{80}	The product sizes where 80% of the material through for the crusher	15 × 103 μm
$\boldsymbol{Q_E}$	The amount of CO_{2e} generated from emulsion combustion	0.137kg	F_{cr}^{80}	The product sizes where 80% of feed material through for the crusher	75 × 103 μm
$\boldsymbol{m_{truck}}$	The truck's loading capacity	92.2ton			

Energy consumption and carbon emission play pivotal roles in the progression of mining projects, given their significant intensity in energy terms. Simultaneously, carbon emission stands out as a critical factor in the realm of sustainability. The determination of energy consumption for each block is contingent upon the unit processes influencing it [22]. The subsequent section outlines the equations employed to compute carbon emissions associated with each activity that contributes to carbon production. Table 1 contains all the required attributes for the equations are presented.

2.1.1. Drilling and Blasting

The initial mining activity involves drilling and blasting, which aims to fragment the rock for subsequent excavation and transportation. The activities of drilling and blasting can have an impact on subsequent processes, potentially reducing the energy demand during the crushing and milling phases. Emissions generated during drilling and blasting activities stem from diesel consumption in mechanical drilling and the release of gases resulting from blasting, which involves the use of ammonium nitrate/fuel oil (ANFO) consisting of 94% ammonium nitrate and 6% diesel.

The term "CO2eq" or "Carbon dioxide equivalent" is employed to characterize various greenhouse gases, providing a means to aggregate the overall impact of all gases produced during blasting activities. This paper excludes non-carbon-based gases from consideration, given their negligible quantities.

Equation 1 represents the amount of CO2eq generated from diesel consumption during the drilling process [25]. This equation considers the meters drilled, patterns drilled, and tons mined.

$$C_{Drill} = R_d \times \frac{M_d \times B_F \times T_A}{P_r} \times Q_f \quad (1)$$

The amount of CO2e generated from blasting activities is expressed in Equation 2 [25]. A combination of ANFO and emulsion is employed in the operation, with the proportion of each varying seasonally depending on whether it is the wet or dry season. The powder factor serves as a variable parameter determined by lithology and weathering, applied individually to each block. This equation relies on the consumption of explosives, the number of loaded holes, and the quantity of material mined.

$$C_{Blast} = \left(T_A \times \frac{P_F}{\rho}\right) \times \left((R_{ANFO} \times Q_A) + (R_{Emulsion} \times Q_E)\right) \quad (2)$$

2.1.2. Loading

Equation 3 represents the CO_{2eq} emissions resulting from diesel consumption during the loading process, where the loading fleet is predominantly powered by diesel.

$$C_{Loading} = T_A \times D_l \times Q_f \quad (3)$$

2.1.3. Hauling

Haulage pertains to the transportation of material from the pit to destinations such as crushers, waste rock dumps, or stockpiles. The energy required to transport one ton of material, and the associated diesel consumption vary based on factors such as the depth of material extraction, the positioning of long-term stockpiles and waste dumps, and the type of ramp system employed. Hence, Equation (4) can be employed to calculate the CO_{2eq} emissions and the specific energy required for transporting one ton of material from the pit to either the processing plant or the waste dump. The determination of the distance of the *i*th block from the comminution plant or waste dump relies on case study and the location of destinations.

$$C_{Hauling} = Specific\ Energy \times carbonization's\ coefficient = \quad (4)$$

$$\left(\frac{9.81 \times S \times \left(m_{truck} \times r + \ (R_s + R_i) \times (2 \times M_{truck} - m_{truck})\right)}{m_{truck}}\right) \times \ \delta$$

2.1.4. Ancillary

An ancillary fleet, comprising front-end loaders, graders, bulldozers, fuel trucks, and excavators with a capacity of less than 300 tons (secondary loading units), is employed for tasks such as bench preparation, maintenance of haul roads, reclamation of stockpiles, rehabilitation of waste dumps, and various other activities. The CO_{2eq} emissions resulting from diesel consumption in ancillary activities can be represented by Equation 5, which translates ancillary activities and their respective diesel consumption into an equivalent ton mined.

$$C_{Ancillary} = \ T_A \times \ D_a \ \times \ Q_f \tag{5}$$

2.1.5. Crushing

The comminution stage, where solid materials are reduced from one average particle size to a smaller size through crushing methods, is exclusively carried out on mined material categorized as ore. Hence, this was implemented solely on a subset of extracted blocks. The CO_{2eq} emissions associated with comminuting a ton of ore can be calculated using Bond's law and Equation 6.

$$C_{Crushing} = \left(3.6 \ \times 10 \ \times \ W_i \ \times \left(\frac{1}{\sqrt{P_{cr}^{80}}} - \frac{1}{\sqrt{F_{cr}^{80}}}\right)\right) \times \ \zeta \tag{6}$$

2.2. Carbon Pricing

Climate change possesses the capacity to impact mining operations, posing risks across environmental, social, and financial dimensions. These risks have the potential to affect operations directly and can also exert an influence on a company at the corporate level due to heightened investor concern and expectations. The primary energy sources utilized in the examined mining operations include diesel, explosives, and electricity, serving various purposes within the mining activities. In assessing the financial risk associated with the potential implementation of a carbon price, the scope outlined in section 2.1 has been considered.

The examined facility is situated in the Middle East and encompasses open-pit mines, a concentrator, and a hydrometallurgy plant. In this investigation, the analysis concludes with the comminution of ore material, and downstream processes are not taken into account. The International Energy Agency (IEA) (2021) has provided a range of possible carbon prices depending on the country and year, as outlined in Table 2. The examination carried out in this paper begins with an assumed average carbon price of $30 per ton and is situated in the Middle East, categorized as a developing country (International Energy Agency, IEA, 2021).

Table 2. USD Carbon Pricing Model (International Energy Agency, IEA, 2021)

Cost of CO2 ($/t)	2025	2030	2040	2050
Advanced countries	75	130	205	250
Chosen developing countries and emerging markets a	45	90	160	200
Other developing countries and emerging markets	3	15	35	55

2.3. Integrating Environmental Costs

In this investigation, we initially assessed the energy consumption of individual blocks by considering the underlying physical processes. Subsequently, we computed the GWP derived from the determined energy consumption. The process of incorporating the CO_{2eq} price into the financial analysis is depicted in Figure 2. In the initial phase, the primary mining operations are categorized into activities that are applied universally to all blocks, irrespective of their destination, and those specifically carried out on blocks directed to the waste dump and crusher. This division is essential for accurately integrating carbon prices into the subsequent process without making approximations in carbon emissions and their related costs.

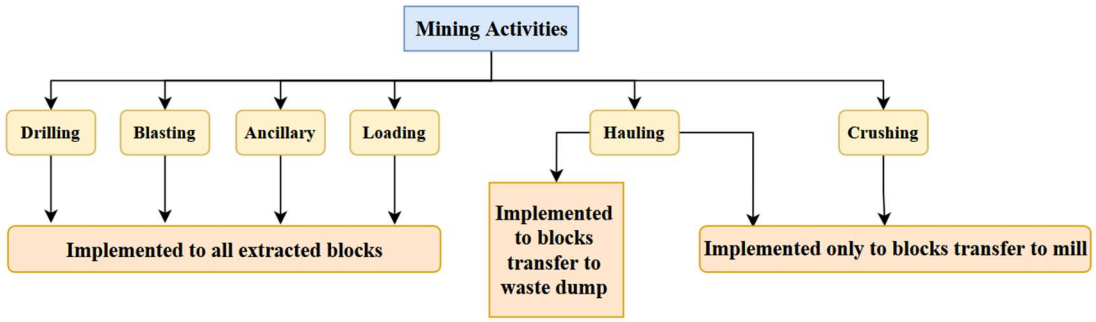

Figure 2. Schematic representation of the approach used to integrate CO2 costs into the mine plan.

Due to this rationale, we opted to combine drilling, ancillary tasks, blasting, and loading. All blocks chosen for extraction undergo these four mining activities. Transporting the extracted material from the pit is unquestionably an essential operation, generating a significant portion of the total emissions directly correlated with the distance covered by the haul trucks to convey the material to either the designated crusher or waste dump. Hence, we distinguished between emissions associated with block transportation to the crusher and those to the waste dump, depending on the respective destination locations. Finally, the crushing phase, involving the reduction of solid materials from a certain average particle size to a smaller average particle size using a crusher, is exclusively conducted on extracted material categorized as ore.

2.4. Integrated Framework for Long-term Mine Planning

Long-term mine planning entails the strategic development and implementation of plans to optimize the value of mineral resources over their entire life cycles. This process involves a comprehensive consideration of geological, technical, economic, environmental, and social factors, incorporating assessments of uncertainties and operational risks. Leveraging sophisticated tools such as strategic options analysis, mine life planning, optimization models, simulations, and scenario planning, professionals evaluate and compare different options to identify the most suitable ones aligned with project constraints. The significance of long-term mine planning lies in its crucial role in ensuring the sustainability, profitability, and safety of mining operations, all while adhering to industry regulations and standards.

When it comes to long-term mine planning, it is crucial to develop strategies that go beyond short-term economic gains and prioritize environmental concerns and sustainable practices. Our approach introduces a novel framework that seamlessly integrates carbon pricing into long-term planning processes. Traditional mine planning often prioritizes economic benefits without considering the environmental costs involved. Our framework lies in systematically incorporating carbon pricing, making sure that the costs associated with CO2 emissions are essential factors in decision-making throughout the entire lifespan of the mine.

Within this integrated framework, we embark on an analysis of environmental costs through two groundbreaking approaches. The first approach involves minimizing the environmental cost, strategically aligning with the growing imperative for eco-friendly mining practices. This signifies a paradigm shift, acknowledging that minimizing the ecological footprint is as crucial as maximizing economic returns. The second approach introduces a cutting-edge method of maximizing adjusted NPV, where the economic value of each mining block is intricately linked with its associated carbon cost. This dual focus on economic and environmental factors represents a groundbreaking advancement in the field of long-term mine planning, offering a comprehensive strategy that pioneers sustainability in the mining industry.

2.4.1. Minimization of Environmental Costs

The integration of Mixed Integer Linear Programming (MILP) in long-term mine planning offers a unique approach to reduce environmental costs. MILP, a mathematical optimization technique, is crucial in making sustainable mining decisions. In this scenario, by using a MILP model to formulate the mine planning problem, the focus shifts from maximizing economic returns to minimizing the environmental impact, particularly in relation to carbon emissions. This innovative framework allows for the consideration of environmental concerns as essential factors in the optimization process, enabling a comprehensive evaluation of mining strategies that balance economic viability with ecological responsibility. The outcome is an optimized long-term mine plan that not only maximizes economic benefits but also actively addresses environmental impacts, demonstrating a forward-thinking approach to mining operations.

Equations 7 to 13 illustrate the MILP model for long-term planning. The integrated framework was developed for the purpose of long-term planning of the ore body. The blocks in the block model are scheduled directly on an annual basis, adhering to operational constraints (e.g., annual extraction or plant capacity) as well as desired constraints, such as product grade. The ultimate objective of the optimization process is to minimize the environmental costs associated with the mining activities of the project. The decision variable x_id^t is assigned a value of one if block i is extracted during time period t and send to destination d, and zero otherwise. C_i represents the associated environmental costs for block i. Table 4 contains all the required set and parameters for integrated model.

$$Min \sum_{d=1}^{D}\sum_{t=1}^{T}\sum_{i=1}^{I}\frac{C_i}{(1+\varepsilon)^t}x_{id}^t b_i, \quad x_{id}^t \epsilon \{0,1\} \tag{7}$$

$$\sum_{d=1}^{D}\sum_{r=1}^{t} x_{jd}^r - \sum_{d=1}^{D} x_{id}^t \geq 0, \quad \forall\, t = 1, \dots, T; i \in I; j \in I_{pi} \tag{8}$$

$$M_{el}^t \leq \sum_{i=1}^{I} b_i\, x_{id}^t \leq M_{eu}^t, \quad \forall\, t = 1, \dots, T, d = 1, \dots, D \tag{9}$$

$$M_{pl}^t \leq \sum_{i=1}^{O} b_i\, x_{id}^t \leq M_{pu}^t, \quad \forall\, t = 1, \dots, T, d = 1, \dots, D \tag{10}$$

$$\sum_{i=1}^{O} b_i\, x_{id}^t (g_i - g_u^t) \leq 0, \quad \forall\, t = 1, \dots, T, d = 1, \dots, D \tag{11}$$

$$\sum_{i=1}^{O} b_i\, x_{id}^t (g_i - g_l^t) \geq 0, \quad \forall\, t = 1, \dots, T, d = 1, \dots, D \tag{12}$$

$$\sum_{d=1}^{D}\sum_{t=1}^{T} x_{id}^{t} \leq 1, \quad \forall\, i = 1, \ldots, I \tag{13}$$

In the presented integrated model, the objective function (Equation (7)) aims to minimize the environmental costs associated with mining activities. The environmental emissions are determined in Section 2.1, which analyzes the necessary processes for each block. The environmental emissions are then translated into financial terms with consideration of carbon pricing, and finally discounted over time using the discount rate (ε). Equation (8) represents the slope stability constraint, ensuring that if block *j* is a prerequisite for extracting block *i*, block *j* must be extracted before block *i* to maintain mining structure integrity and prevent destabilization. Equation (9) outlines maximum and minimum extraction capacities, ensuring that the total tonnage of waste and ore blocks extracted adheres to the mining extraction capacity. Equation (10) regulates the input feed to the processing plant, constrained by the minimum and maximum processing capacities for each time period. Additionally, Equations (11) and (12) establish grade constraints for the processing plant, ensuring that the weighted average grade of the processed ore stays within specified limits. According to Equation (13), each block can be extracted at most once.

Table 3. Sets and parameters of integrated framework.

Term	Description
$\boldsymbol{t}$	The set of time period, t = (0, 1, …, T)
$\boldsymbol{i}$	The set of extraction blocks, *i* = (0,1,…, I)
$\boldsymbol{d}$	The set of block's destination, d = (0, 1, …, D), where d=0 and d=1 denote waste and ore, respectively
$\boldsymbol{I_{pi}}$	The set of blocks that need to be extracted before block *i*
$\boldsymbol{M_{el}^{t}}$	The minimum extraction capacities
$\boldsymbol{M_{eu}^{t}}$	The maximum extraction capacities
$\boldsymbol{M_{pl}^{t}}$	The minimum processing capacities
$\boldsymbol{M_{pu}^{t}}$	The maximum processing capacities
$\boldsymbol{g_i}$	The grade of block *i*
$\boldsymbol{g_u^{t}}$	The maximum required grade for processing
$\boldsymbol{g_l^{t}}$	The minimum required grade for processing
$\boldsymbol{b_i}$	The tonnage of block *i*

2.4.2. Maximization Adjusted NPV

In traditional study, long-term mine planning approaches were employed with the primary objective of maximizing the NPV of the mining operation. NPV functions as a critical financial indicator, signifying the distinction between the present value of cash inflows and outflows throughout the mine's operational lifespan. Within the model, the objective of maximizing NPV is succinctly captured by Equation (14), which considers a range of factors including revenue derived from ore extraction, operational costs, and the discount rate. V_i denotes the economic value of block i.

$$Max \sum_{d=1}^{D}\sum_{t=1}^{T}\sum_{i=1}^{I} \frac{V_i}{(1+\varepsilon)^t} x_{id}^{t} b_i, \qquad x_{id}^{t} \epsilon \{0,1\} \tag{14}$$

Furthermore, the second phase of the MILP approach involves maximizing the Adjusted NPV, a nuanced measure that intricately links the economic value of each mining block with its associated carbon cost. Adjusted NPV considers the environmental impact of mining activities by incorporating the costs associated with carbon emissions into the traditional economic assessment (Equations 15 and 16). AV_i denotes the adjusted economic value of block i.

$$AV_i = V_i - C_i \quad \forall\, i = 1, \ldots, I \tag{15}$$

$$Max \sum_{d=1}^{D}\sum_{t=1}^{T}\sum_{i=1}^{I} \frac{AV_i}{(1+\varepsilon)^t} x_{id}^t b_i, \qquad x_{id}^t \epsilon \{0,1\} \tag{16}$$

Generally, the integrated approach recognizes the importance of environmental responsibility in long-term mine planning, as decision-makers seek a balanced strategy that not only maximizes economic returns but also minimizes the ecological footprint. By concurrently optimizing both economic and environmental facets, the MILP model provides a comprehensive framework for sustainable and responsible mine planning.

3. Results

In this segment, we put into action the innovative integrated framework, considering two primary scenarios: one aimed at minimizing environmental costs and the other at maximizing adjusted NPV. The execution utilized the Python® programming language [28] and the CPLEX® solver [29]. All experiments were applied on a Windows 11 workstation featuring an AMD Ryzen 7 5800H CPU and 16GB of RAM. We applied the developed integrated framework to a practical case study involving an open-pit iron mine in Iran to verify and assess the developed integrated framework. The reserve modeling, planning activities, and long-term production planning were based on drill-hole prospecting data. In this integrated framework, a 5-year plan inside a longer time project is considered. Figure 3 presents aerial images of the case study, along with the location of the crusher and waste dump. This image provides a clear view of the positions of the waste dump and crusher, illustrating their impact on the generated carbon dioxide and associated environmental costs. The determination of the distance of the *i*th block from the comminution plant or waste dump relies on data extracted from Table 4.

Figure 3. Aerial images of the case study, along with the location of the crusher and waste dump

To calculate the distance of each block, the distances between the block and its output point within the pit, considering its destination, are determined. Subsequently, the distance from that point to the center of the destination, whether it be the crusher or waste dump, is measured.

In this study, it is assumed that all models are applied within a predefined ultimate pit limit, and it is highlighted that the carbon tax will not alter this predetermined limit.

Table 4. Location of waste dump and crusher in the case study.

Destination	X	Y	Z
Waste dump	355647	3552027	1687
Crusher	357908	3551267	1774

3.1. Economic and Environmental Block

Figure 4 illustrates a three-dimensional representation of the metal content (Fe grade) for individual blocks within the deposit. Additionally, Figure 5 presents a three-dimensional model showcasing the environmental costs associated with the deposit's operations. This information was employed, as outlined in the methodology, to plan the excavation of the pit, determining the selection and order of blocks for extraction. The geological block model emphasizes the presence of high-value zones situated beneath the deposit, indicating the necessity to initially extract lower-grade material. The values of environmental cost blocks reveal a region with blocks incurring high costs to the right of the deposit base. This is partially attributed to the need for additional transportation to remove these blocks from the pit. Given that the waste dump is located on the left, these materials must be transferred there.

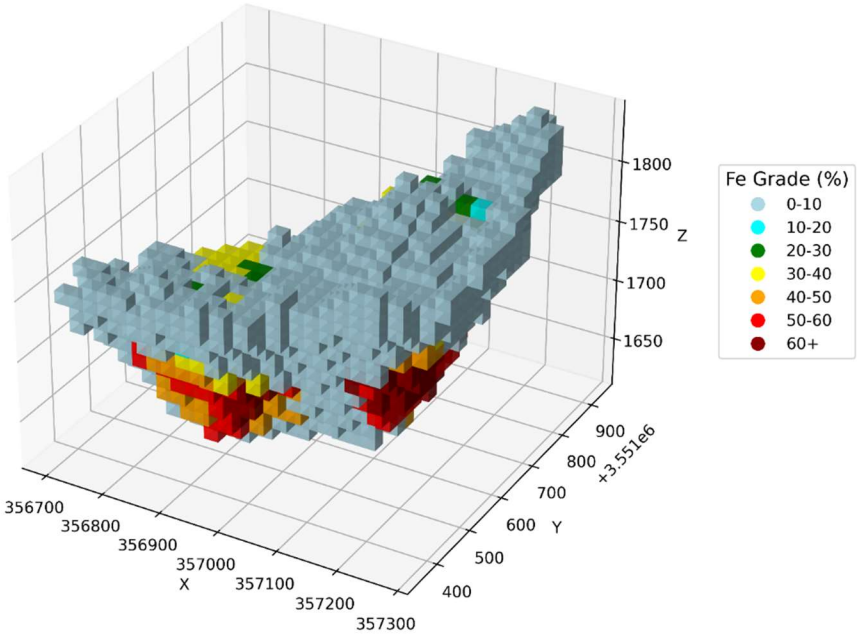

Figure 4. Grade distribution in block model.

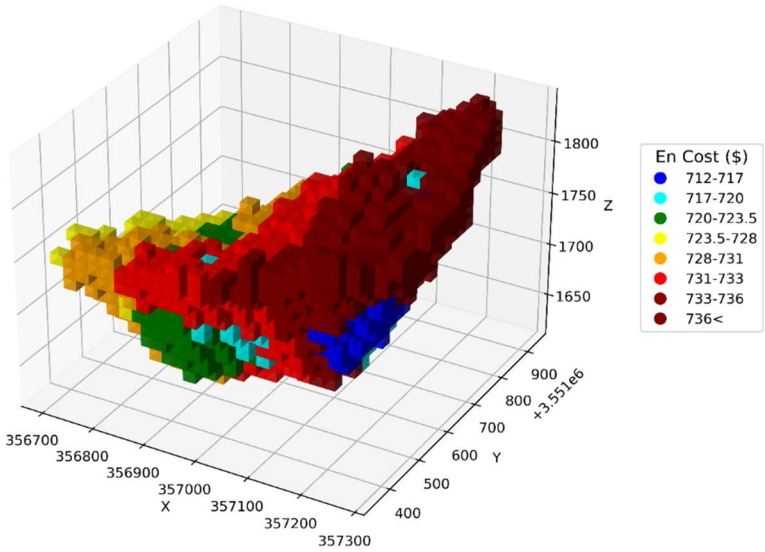

Figure 5. Environmental cost for each block.

Figure 6 illustrates the proportional carbon cost (environmental cost) associated with mining activities for two randomly selected blocks. The primary factor influencing carbon production is transportation, which has been modeled individually for each block. A growth in pit depth will intensify the carbon emissions generated by haulage due to extended cycle times, resulting in a higher amount of fuel needed to transport one ton of material. The ancillary needs account for 29% and 33% of the overall carbon emissions stemming from mining operations for waste and ore blocks, respectively. The ancillary equipment consisted of bulldozers for constructing waste dumps and handling various tasks, graders, water carts, compactors for maintaining haul roads, and front-end loaders for diverse activities.

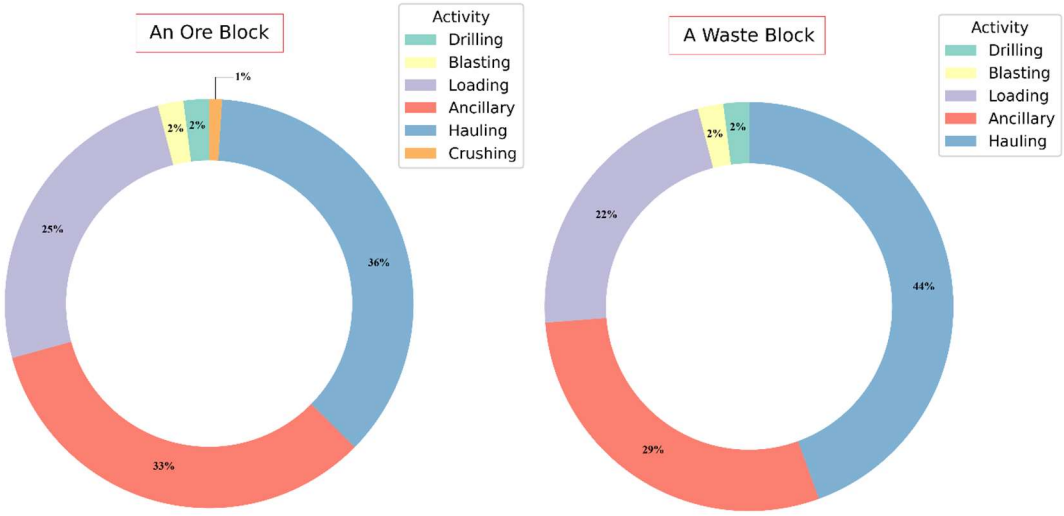

Figure 6. Percentage of carbon costs across mining activities.

Figure 7 illustrates the grade-tonnage distribution alongside the environmental emission distribution. This combined visualization offers readers insights into both the quality of the deposit and the relationship between grade and CO_2eq emission levels.

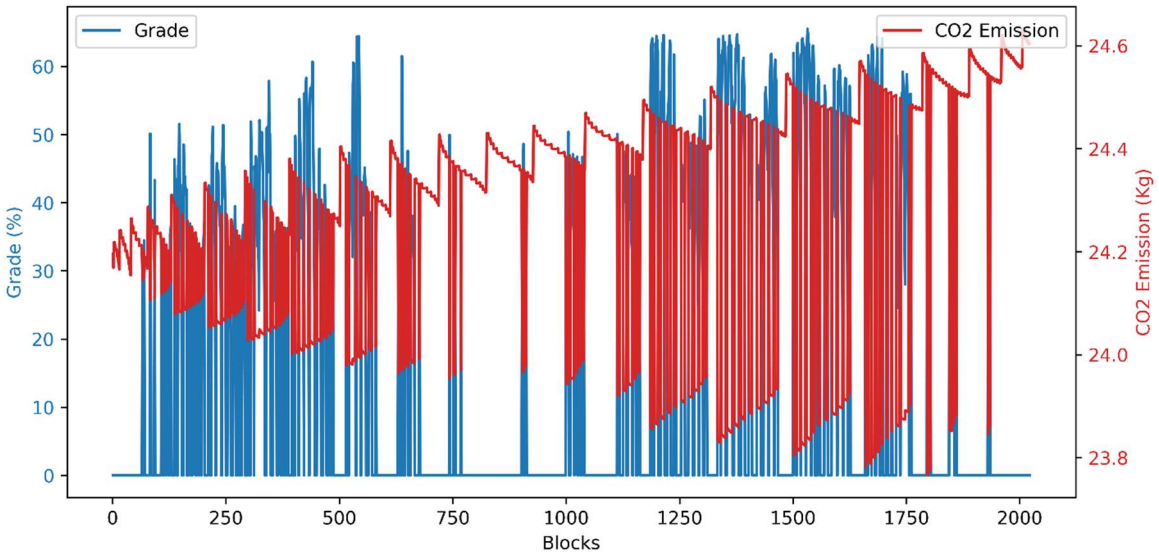

Figure 7. Grade and CO_2eq emission distribution for blocks.

3.2. Integrated Framework Results

The impact of carbon prices on the financial outcomes of mining operations has been examined. Initially, the assessment involves estimating the carbon-related costs associated with mining activities. Then, both scenarios were implemented in the mine schedule simulation by incorporating the carbon cost. In this context, Figure 8 illustrates the annual assignment of ore and waste based on each scheduling approach within the integrated framework. In the scenario focused on minimizing environmental costs, the integrated framework aims to defer blocks with elevated costs, particularly waste blocks associated with higher environmental impacts. By prioritizing the postponement of extraction for such blocks, the integrated framework aims to achieve its goal of reducing overall environmental expenses and promoting sustainable mining practices. Additionally, given the bottleneck nature of the plant's feed requirement, the framework ensures that the deferred actions do not compromise the plant's operational objectives, as depicted in Figure 8 by the presence of the red limit line. On the contrary, in the scenario focusing on maximizing adjusted NPV, the integrated framework aims to prioritize the extraction of the most valuable blocks in the initial periods while deferring the extraction of more costly blocks to subsequent periods. The inherent distinctions between these scenarios, both in nature and theory, result in varying block allocations across periods, thereby influencing GHG emissions, environmental costs, block sequencing, and financial outcomes.

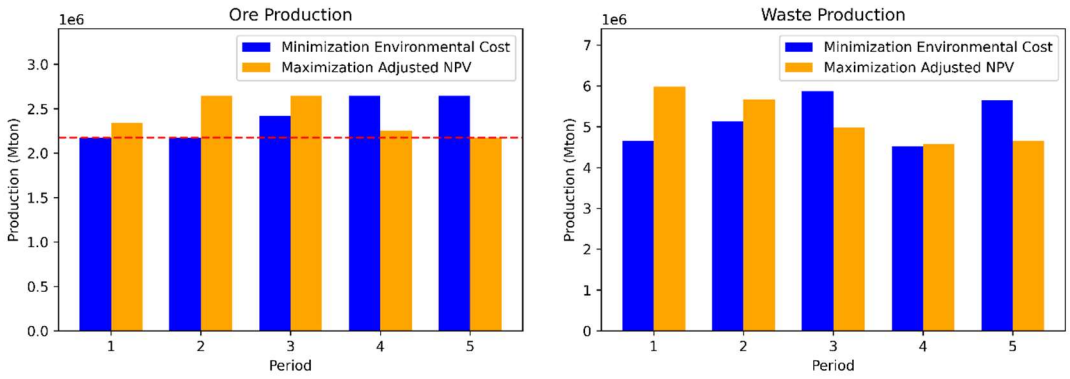

Figure 8. Detail of annual production (Ore and Waste).

The yearly CO_{2eq} emissions and the cumulative environmental costs linked to the two scenarios are illustrated in Figure 9. The yearly CO_{2eq} emissions in the maximization scenario exhibit an annual decline, aligning with the scenario's theoretical basis of maximizing adjusted NPV and block allocation. In contrast, the minimization scenario experiences a notably larger reduction in annual CO_{2eq} emissions and cumulative costs. In this scenario, the yearly emissions data reveals that CO_{2eq} emissions remain lower than those in the maximization scenario until period 3. Subsequently, there is an increase in annual emissions starting from period 3, followed by a reduction from period 4 onward. At the conclusion of the project, there is a notable decline, leading to a divergence in global warming impacts between the two scenarios. The values are 49030t and 44392t CO_{2eq}, representing a 9.5% difference for maximization of adjusted NPV and minimization of environmental costs, respectively. These CO_{2eq} emissions correspond to environmental costs of \$1.3M and \$1M for maximization of adjusted NPV and minimization of environmental costs, respectively.

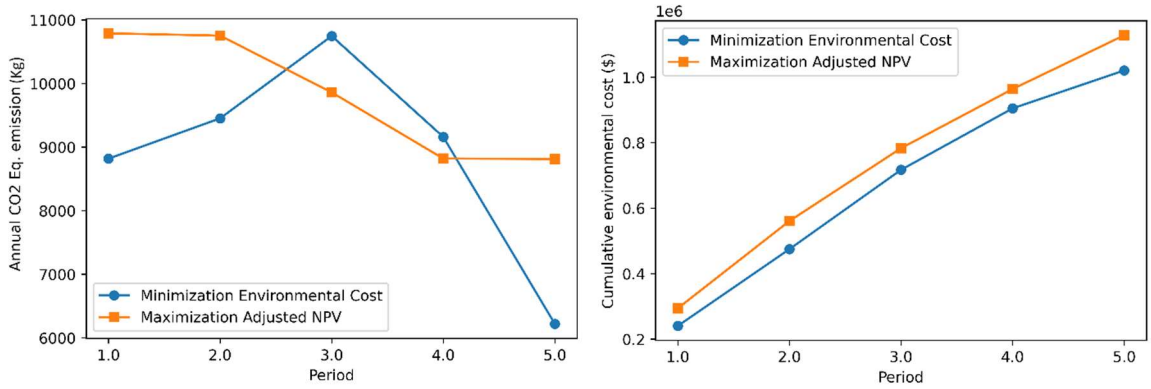

Figure 9. Annual CO_{2eq} emission (left) and cumulative environmental costs (right).

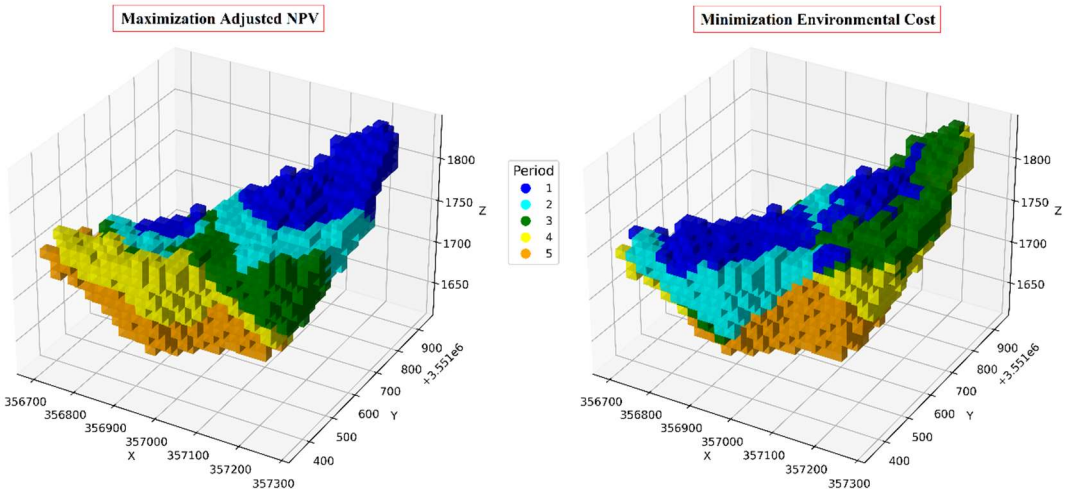

Figure 10. The block extraction sequencing in two scenarios.

As mentioned earlier, the blocks situated on the right side of the deposit exhibit lower grades and need to be transported to the waste dump, which is positioned on the left side of the deposit. Consequently, these blocks incur higher environmental costs compared to others. In this regard, Figure 10 illustrates the block sequencing in each scenario of the integrated framework. It is evident that the mentioned blocks are allocated to different periods in each scenario. In the

minimization scenario, the integrated framework aims to assign blocks with lower costs in the early periods, in contrast to the maximization scenario, which prioritizes the extraction of more valuable blocks in the initial periods.

Clearly, alterations in block sequencing and their associated environmental costs have a notable impact on the net present value of mining operations, a key financial output that is thoroughly examined. Figure 11 depicts the annual and cumulative NPV of the mine plan for each scenario within the integrated framework. The graph highlights that, in the maximization scenario, the early periods exhibit a higher annual NPV, affirming the allocation of valuable blocks. Conversely, in the minimization scenario, the later periods show a higher annual NPV, attributed to an increased production rate and altered block sequencing.

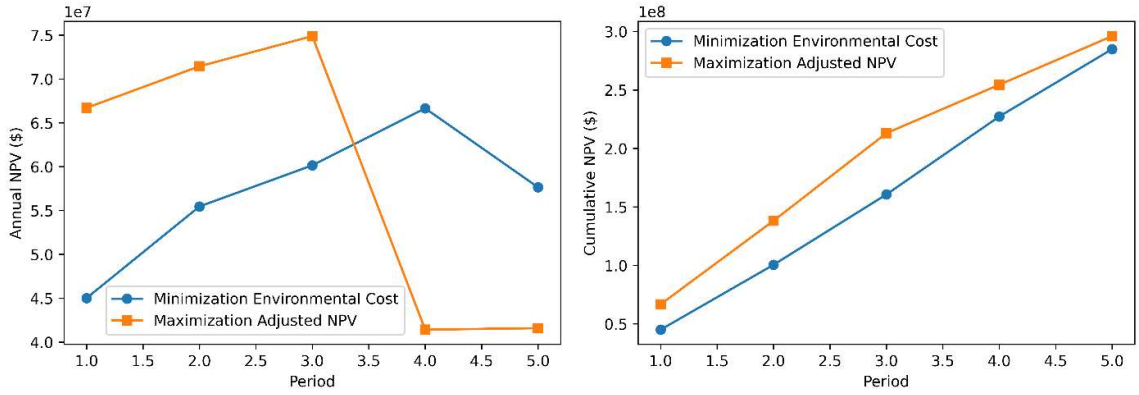

Figure 11. Annual NPV (left) and cumulative NPV (right) for two scenarios.

In general, Table 5 presents the results of the integrated framework for each scenario concerning CO_{2eq} emissions, environmental costs, and NPV. Additionally, Table 5 emphasizes the differences in the obtained results between each scenario. A positive value indicates that the minimization scenario achieves a higher value in those parameters, while a negative value implies the opposite. Based on the results, implementing the scenario aimed at minimizing environmental costs resulted in a reduction of approximately 10% in GHG emissions and environmental costs, while only reducing the adjusted NPV by approximately 4% compared to the scenario focused on maximizing adjusted NPV.

Table 5. Results of integrated framework in two scenarios.

Scenario	Parameter	Period					Total	
		1	2	3	4	5	Value	Dif
Maximize NPV (Base)	CO2eq (Kt)	10.97	10.9	9.77	9.57	9.13	50.4	+2.86
	En costs (M$)	0.299	0.27	0.22	0.196	0.17	1.16	+5.45
	NPV (M$)	67	71.7	75.1	41.6	41.7	297	+0.3
Maximize adjusted NPV	CO2eq (Kt)	10.8	10.8	9.86	8.82	8.81	49	-
	En costs (M$)	0.294	0.267	0.222	0.181	0.164	1.1	-
	NPV (M$)	66.7	71.4	74.9	41.4	41.6	296	-
Minimize environmental cost	CO2eq (Kt)	8.82	9.45	10.7	9.16	6.22	44.4	-9.46
	En costs (M$)	0.240	0.234	0.242	0.188	0.116	1.02	-9.52
	NPV (M$)	45	55.5	60.1	66.6	57.6	285	-3.75

Stripping ratio (SR) serves as a critical indicator in mine planning, directly influencing operational efficiency and resource utilization. Figure 12 illustrates the annual stripping ratios for scenarios.

The Max Adjusted NPV scenario shows a slight increase in stripping ratios in the first two periods, followed by a decrease in later periods. In contrast, the Min Environmental Cost scenario displays a relatively stable trend with minor fluctuations. This indicates that while the Max Adjusted NPV scenario may have higher initial stripping ratios due to environmental factors, it eventually stabilizes, unlike the consistent stripping ratios seen in the Min Environmental Cost scenario.

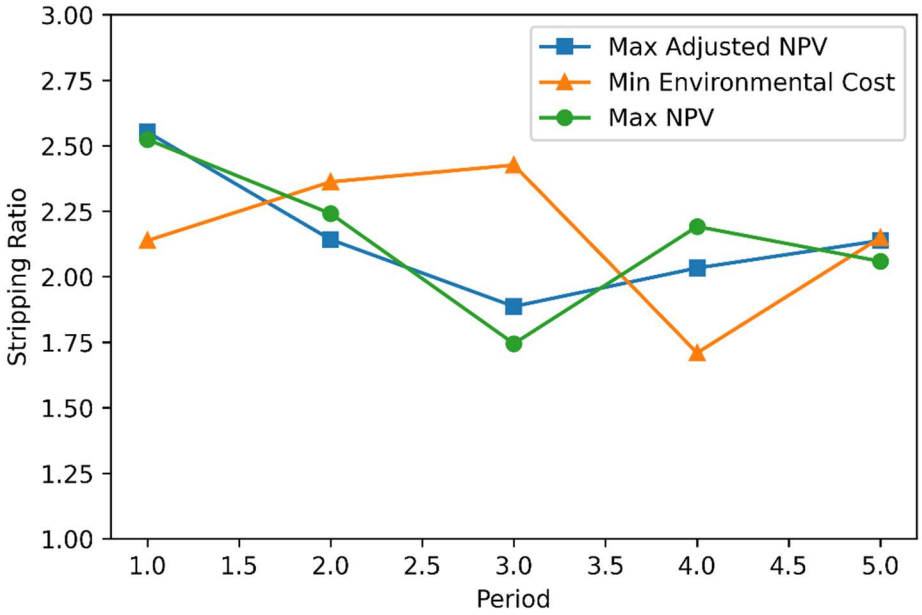

Figure 12. Comparison of stripping ratios for scenarios over time.

3.3. Sensitivity Analysis

Sensitivity analyses have been conducted to quantify the correlation between model performance and crucial parameters. The outcomes of both the minimization of environmental costs and maximization of adjusted NPV scenarios in the integrated framework rely on certain parameters, and any variations in these parameters can influence the application of these models to open-pit mining operations. Therefore, it is essential to study the effects of such variations. The sensitivity analysis relies on the MILP model within the integrated framework, aiming to maximize NPV and illustrates the impact of carbon pricing on the results. Therefore, an alternative schedule is generated using identical parameters to those used in the schedule as mentioned earlier, with the only difference being the carbon pricing set at $15/t, $30/t, $45/t, and $60/t.

As the carbon price rises, it imposes additional costs on the economic value of each block, potentially leading to a decline in financial targets. Figure 13 illustrates the annual NPV risk profile for mining operations, revealing variations compared to Figure 11. Consequently, elevating the carbon price may not enhance project economics but can contribute to advancing sustainability and green initiatives.

Figure 14 illustrates the sequencing of block extraction for NPV, adjusted NPV-30$, and adjusted NPV-60$ methodologies. While there are variations in the generated mine schedules, they generally designate the same areas for mining during corresponding time periods. As anticipated, minor distinctions are likely to diminish when practical schedules are implemented. The most notable difference is observed in periods two (cyan) and three (green).

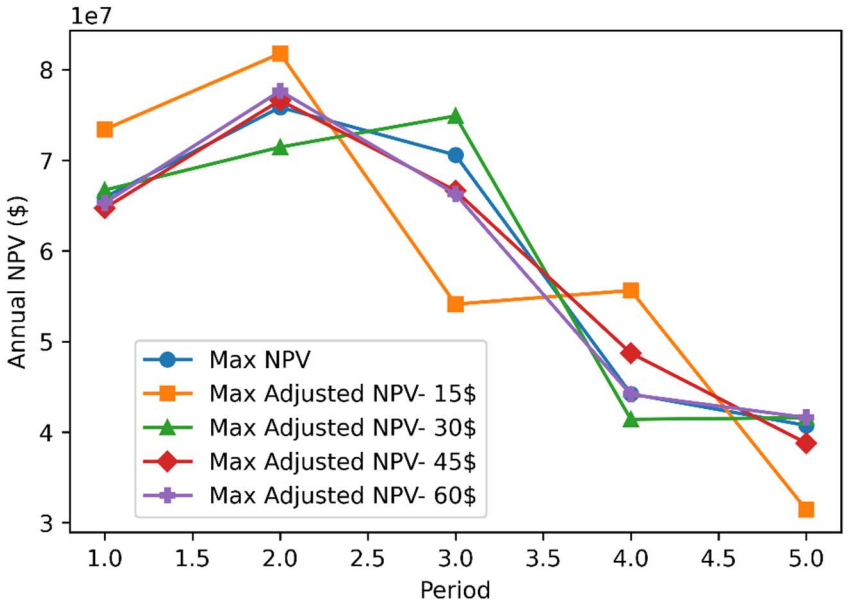

Figure 13. Annual NPV risk assessment for the mine schedule under varied carbon pricing.

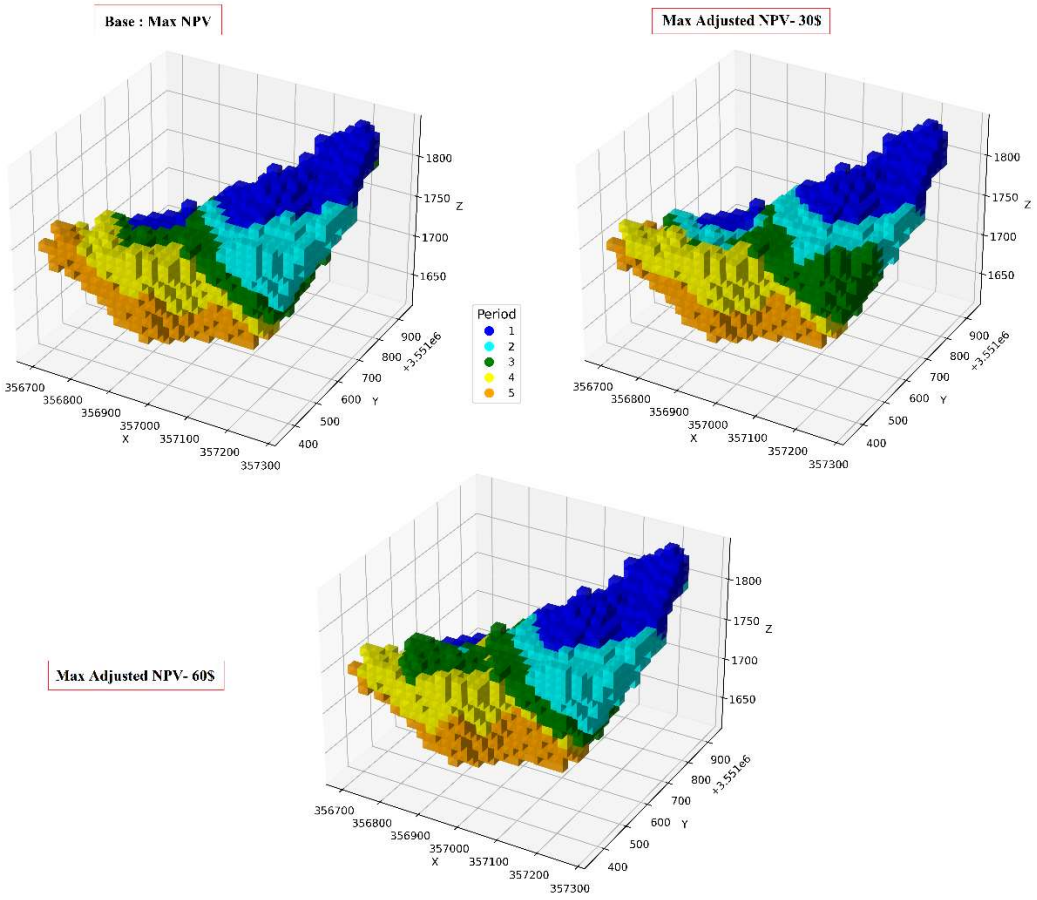

Figure 14. The block extraction sequencing for NPV, adjusted NPV-30$, and adjusted NPV-60$.

4. Conclusion

In conclusion, the presented novel framework for integrating environmental costs and carbon pricing in open-pit mine plans represents a significant step towards promoting sustainability and green practices in the mining industry. The comprehensive methodology, encompassing emission quantification and a sophisticated long-term mine planning approach, provides a holistic understanding of the environmental impact associated with mining activities. Through two distinct scenarios—minimizing environmental costs and maximizing adjusted NPV— the framework demonstrates its versatility in addressing both economic and ecological considerations. The results underscore the framework's effectiveness, showcasing its potential to significantly reduce carbon emissions and environmental costs while still maintaining a competitive economic performance. The sensitivity analysis further emphasizes the adaptability of the framework to varying carbon pricing scenarios, reaffirming its robustness in navigating the dynamic landscape of open-pit mining operations.

Considering the mounting pressure on the mining industry to embrace sustainable practices, this framework presents an innovative solution that surpasses conventional economic factors. By effectively incorporating environmental expenses into the long-term planning of mines, decision-makers can make well-informed decisions that prioritize both economic feasibility and environmental accountability. The demonstrated success of this framework in a practical case study, set in an open-pit iron mine, highlights its applicability and potential for widespread adoption across diverse mining operations. In essence, the pursuit of sustainable and green mining practices in open-pit mines necessitates innovative frameworks like the one presented here. By bridging the gap between economic objectives and environmental concerns, this approach contributes to a more balanced and responsible future for the mining industry.

The current framework proposed provides a thorough examination of how environmental considerations can be integrated into mine planning. However, there are certain limitations that need to be addressed in future research. One key issue is the use of a fixed ultimate pit limit in all models, which requires further investigation into the effects of carbon pricing on different aspects of mining operations, including mine size and profitability. It is also crucial to incorporate other important environmental factors like water usage, dust, vibrations, and disturbance footprint into mine planning models. To promote sustainable mining practices and ensure environmental sustainability and community well-being, it is crucial to consider these key factors. By incorporating these factors into our analysis, we can enhance our understanding of the environmental impacts of mining activities and make better decisions moving forward.

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Balancing Economic Viability and Environmental Stewardship in Open-Pit Mining: A Multi-Objective Optimization Approach

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ABSTRACT

The quest for sustainable development in the mining sector is more pressing than ever, as the industry grapples with the dual challenges of satisfying the global thirst for minerals and mitigating its environmental footprint. This paper introduces a transformative multi-objective optimization (MOO) framework that can balance the economic and environmental aspects of open-pit mining, with a focus on greenhouse gas (GHG) emissions. A case study on an open-pit iron ore mine in the Middle East validates the framework's efficacy. The results demonstrate the potential for significant GHG emission reductions with minimal impact on economic returns. Through comprehensive scenario analysis, we illustrate the trade-offs and synergies between maximizing NPV and minimizing ecological costs. Our findings underscore the importance of integrating environmental considerations into mine planning to foster a sustainable and economically viable mining industry. The proposed MOO framework serves as a blueprint for sustainable practices, ensuring the resilience of the mining sector and its commitment to the planet's future.

1. Introduction

Open-pit mining has been significant in the global extraction of minerals and now stands at a turning moment where the need for sustainable growth is critical. It reconciles the economic imperatives of resource extraction with the moral and ecological imperatives of preserving the environment. This is a paradigm shift from the old ways of mining, which often result in great environmental degeneration to the practices that will sustain the industry and ecological wholeness. With sustainability, open-pit mining can cut its use of energy and consequent emissions, hence contributing to the wellness of the planet without compromising economic growth and development [1, 2].

Environmental stewardship integrated with economic efficiency forms the backbone of modern open-pit mining operations, striving toward a harmonious balance between resource extraction and ecological preservation [3]. This sustainable approach requires comprehensive strategies to be in place that address the most pressing environmental concerns: habitat destruction, water pollution, and soil erosion, while optimizing the economic yield [4]. Mine planning plays an important role in this regard as a strategic tool that lays out mining activities in direct alignment with environmental and economic objectives [5-8]. Weaving environmental considerations into the very fabric of mining operations means that, beyond mere compliance with regulations, it enables the sector to

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invest in a business model that will improve its social license to operate and contribute to long-term profitability. In all, there exists no trade-off between economic and environmental imperatives but rather a synergistic integration, and this is where effective mine planning acts as the blueprint for sustainable practices that ensure the industry's resilience and commitment to the future of the planet [9].

The essence of implementing a multi-objective approach to sustainable open-pit mining is effective mine planning. Planning in such activities is quite complex and includes consideration of ore body characteristics, market conditions, and environmental constraints. With sophisticated planning techniques such as computer modeling and simulation, mining engineers can foresee possible ecological effects and generate strategies to mitigate them. This kind of proactive planning ensures that mining activities are responsibly conducted, balancing economic viability with environmental stewardship, and sets the course for a more sustainable future in the mining industry [3, 10].

The integration of environmental impacts, particularly greenhouse gas (GHG) emissions, into mine planning is a critical part of research that has garnered noteworthy attention recently [2]. Munoz et al incorporated sustainability parameters directly into the ore body block model, mining projects achieved more responsible mine designs and significantly improved their sustainability performance [11]. The cradle-to-gate life cycle assessment (LCA) method was applied by Ferreira et al. for the environmental assessment of Brazilian iron ore mining. The study utilized tools such as SimaPro-7 and Ecoinvent 2.0. Grinding media were reported to have major concerns in the life cycle impacts, affecting most both human health and ecosystem quality [12]. Xu et al. developed an optimization model for open-pit production scheduling that internalizes the ecological costs, including carbon emissions and ecosystem damage, into the economic evaluation formulations. Application to a large-scale open pit mine showed that the integration of the ecological costs led to different mining sequences, lower production rates, longer mine life, and a higher overall net present value (NPV) compared to schedules that treated the ecological costs as externalities [13]. Pell et al. adopted an innovative approach to conducting LCA, which involved generating life cycle impact assessment data and creating an environmental block model of a deposit. This method incorporated spatially explicit data into long-term mine scheduling simulations, showing that significant reductions in global warming impacts can be achieved at minimal economic cost. This allows for the integration of environmental considerations into strategic mine planning [10].

Rijsdijk and Nehring conducted a scenario analysis to examine the impact of carbon pricing on the economic feasibility of a copper mine in Congo. They determined that with prices up to $100/t, higher carbon prices will trigger a cost increment in mining and processing costs, considering both hydroelectric and coal-fired power scenarios, while showing a minor effect on cut-off grades and the optimal pit limits [14]. Agosti et al. used a novel approach to investigate the environmental and financial consequences of introducing a carbon levy in mining activities. By integrating the carbon tax directly into the resolve of the ultimate pit limit (UPL) using the new software OptimalSlope, they demonstrated that relationships between carbon tax value, carbon emissions, ore extracted, and NPV exhibit linearity, and that geotechnically optimal pit wall profiles can result in significant economic gains without compromising safety [15]. Mirzehi et al. used an integrated LCA-MILP framework to compute the ecological effect of mining activities and incorporate these considerations into long-term open-pit mine planning. Their case study on an open-pit iron ore mine demonstrated that framework was able to lower GHG emissions by 11.05% while retaining 93.66% of the initial NPV, highlighting the potential for sustainable and economically viable mining practices [3].

This paper employs a multi-objective optimization (MOO) framework to achieve the goal of balancing economic viability with environmental stewardship by internalizing ecological costs in long-term mine planning. First, the ecological costs of open-pit mining, including carbon emission costs associated with energy consumption, are quantified. Different scenarios are then defined by

assigning various weights to each objective. Finally, a case study on an open-pit mine is presented to compare the mine planning outcomes across these scenarios, demonstrating the framework's effectiveness in achieving a sustainable balance.

2. Material and Methods

In this research, we develop a comprehensive multi-objective framework for long-term planning in sustainable open-pit mining. This approach harmonizes economic viability with environmental stewardship, ensuring that both financial returns and ecological costs are considered during the mine's lifecycle. The framework incorporates carbon pricing into the decision-making procedure, accounting for carbon emissions from all mining activities, including beneficiation and mining and transportation activities. Advanced techniques are employed for assessing options in such a way that NPV is maximized, while minimizing ecological costs. The effectiveness of this integrated framework was confirmed through a case study conducted on an open-pit iron mine located in the Middle East. Moreover, the methodology integrates LCA and quantifies greenhouse gas emissions to conduct a comprehensive evaluation of environmental impacts. This approach ultimately helps to steer mining operations towards sustainability and economic viability.

2.1. Multiple Objective Model for Long-term Planning

Studies highlight the importance of incorporating ecological costs into mine design to mitigate environmental impacts. Optimal carbon emission management across key mining processes—including beneficiation, mining, and transportation—is crucial for achieving carbon peak goals and effectively managing emissions. Moreover, optimal selection of sustainable development strategies for open pit mining enterprises is critical to long-term profits and environmental sustenance [16].

Therefore, we develop a multiple objective framework for sustainable long-term planning, allows for the consideration of conflicting objectives, maximizing NPV while minimizing ecological costs, leading to more comprehensive decision-making. This approach facilitates the reduction of carbon emissions in mining processes, aiding in meeting emission reduction targets and refining emission management strategies. Many mine planning approaches prioritize economic gains over environmental impacts. Our framework focuses on integrating carbon pricing into decision-making processes, ensuring that the costs of CO2 emissions are considered at every stage of the mine's operations.

Mine planning in long-term horizon entails the strategic development and implementing of plans to optimize the value of mineral resources over their entire life cycles. This procedure considers geological, technical, economic, environmental, and social factors, as well as assessments of uncertainties and operational risks. Experts use advanced techniques such as mine life planning, simulations, optimization models, strategic options analysis, and scenario planning to evaluate and compare different decisions, aiming to identify the most suitable ones within project constraints. The significance of comprehensive mine planning lies in its crucial role in ensuring the sustainability, profitability, and safety of mining operations, while also adhering to industry regulations and standards. Table 1 outlines the indices, sets, parameters, and decision variables used to formulate this problem.

Table 1. Elements, set, variables, and parameters of the MOO framework.

Term	Description
$\boldsymbol{p}$	Time period set, p = (0, 1, …, P)
$\boldsymbol{i}$	Block set, i = (0, 1, …, I)
$\boldsymbol{d}$	Block's destination set, d = (0, 1, …, D), where d=0 and d=1 denote waste and ore, respectively

I_{ri}	The precedence set of blocks that must be extracted prior to block i
T_{el}^{p}	The lowest mining capacity threshold
T_{eu}^{p}	The highest mining capacity threshold
T_{fl}^{p}	The lowest plant capacity threshold
T_{fu}^{p}	The highest plant capacity threshold
g_i	Block's grade
g_u^p	The highest-grade threshold for plant
g_l^p	The lowest-grade threshold for plant
b_i	Block's tonnage
V_i	Economic value of block i
C_i	Ecological costs of block i
ε	Discount rate

2.1.1. Objective Function

The model includes two distinct objectives: the first aims to maximize the NPV of the mining operation (Eq. (1)), while the second aims to minimize the total ecological costs associated with CO_2 emissions from energy consumption (Eq. (2)). In addressing the mine planning problem, our focus is on maximizing economic benefits while simultaneously minimizing environmental impact, specifically in terms of carbon emissions. This unique approach integrates environmental concerns as crucial elements in the optimization process, leading to a thorough assessment of mining strategies that strike a balance between economic feasibility and ecological sustainability. The result is a well-optimized long-term mine plan that not only maximizes economic gains but also proactively tackles environmental issues, showcasing a progressive outlook towards mining operations [3, 17].

$$Max \sum_{d=1}^{D}\sum_{p=1}^{P}\sum_{i=1}^{I}\frac{V_i}{(1+\varepsilon)^p}x_{id}^{p}b_i, \quad x_{id}^{p}\epsilon\{0,1\} \tag{1}$$

$$Min \sum_{d=1}^{D}\sum_{p=1}^{P}\sum_{i=1}^{I}\frac{C_i}{(1+\varepsilon)^p}x_{id}^{p}b_i, \quad x_{id}^{p}\epsilon\{0,1\} \tag{2}$$

The objectives in the problem vary in scale and impact on the system. Additionally, the second objective aims to minimize deviation from a target value. To address this, the authors utilized the normalization approach, incorporating the concept of nadir and utopia points to create dimensionless objective functions [18]. This normalized model was then solved using the weighted-sum multiple-objective optimization methodology [18]. Equation (3) illustrates the function of the object representation model, which involves selecting and assigning weights to different goals to achieve desired outcomes. The terms w_1 and w_2 represent the weights assigned to each objective to prioritize and attain the desired results.

$$Objective = w_1 \times objective\,(1) + w_2 \times objective\,(2) \tag{3}$$

2.1.2. Constraints

In the mathematical modeling of goal attainment, it is essential to account for both constraints and resources. For long-term planning, models are executed with a variety of constraints, including precedence relationships, minable reserves, plant production targets, and machinery capacities. Equation (4) enforces the slope stability constraint by stipulating that if block j is necessary for

extracting block i, block j must be extracted before block i to uphold the integrity of the mining structure and prevent destabilization. Equation (5) sets limits on extraction capacities, ensuring that the total tonnage of waste and ore blocks extracted does not exceed or lower than the mining extraction capacity. Equation (6) governs the input feed to the processing plant, considering the minimum and maximum processing capacities for each period. Equations (7) and (8) also set grade constraints for the processing plant to maintain the weighted average grade of the processed ore within certain limits. Moreover, Equation (9) dictates that each block can only be extracted once.

$$\sum_{d=1}^{D}\sum_{r=1}^{p} x_{id}^{p} - \sum_{d=1}^{D} x_{id}^{p} \geq 0, \quad \forall\, p = 1, \dots, P; i \in I; j \in I_{ri} \tag{4}$$

$$T_{el}^{p} \leq \sum_{d=1}^{D}\sum_{i=1}^{I} b_i\, x_{id}^{p} \leq T_{eu}^{p}, \quad \forall\ p = 1, \dots, P, d = 1, \dots, D \tag{5}$$

$$T_{fl}^{p} \leq \sum_{d=1}^{O}\sum_{i=1}^{I} b_i\, x_{id}^{p} \leq T_{fu}^{p}, \quad \forall\ p = 1, \dots, P, d = 1, \dots, D \tag{6}$$

$$\sum_{i=1}^{O} b_i\, x_{id}^{p}\left(g_i - g_u^{p}\right) \leq 0, \quad \forall\ p = 1, \dots, P, d = 1, \dots, D \tag{7}$$

$$\sum_{i=1}^{O} b_i\, x_{id}^{p}\left(g_i - g_l^{p}\right) \geq 0, \quad \forall\ p = 1, \dots, P, d = 1, \dots, D \tag{8}$$

$$\sum_{d=1}^{D}\sum_{p=1}^{P} x_{id}^{p} \leq 1, \quad \forall\, i = 1, \dots, I \tag{9}$$

2.2. Emission Quantification and Pricing

The mining process incurs high energy consumption and carbon emissions mainly due to operational costs associated with activities like drilling, blasting, loading, hauling, ancillary tasks, and crushing.

Our first step was to evaluate the energy consumption of individual blocks by considering the relevant physical processes, as outlined by Muñoz et al. [11] and Rijsdijk and Nehring [14]. This was followed by calculating the global-warming potential (GWP) based on the estimated energy consumption. Energy consumption and carbon emissions are crucial factors in the advancement of mining projects due to their high energy intensity. The calculation of energy consumption for each block depends on the specific unit processes that impact it.

The formulas used in this study are based on the methodology outlined by Muñoz et al. [11] and NPI [23] for calculating emissions from equipment, diesel, and electricity consumption. For a detailed explanation of how the environmental impact of the mining operation is quantified, please refer to Table 2. The equations in Table 2 consider specific emission factors and operational parameters relevant to this study. All variables, except for the block's physical properties, were kept constant, including environmental conditions and machinery used. Diesel equipment was chosen in accordance with regional regulations, unless otherwise specified.

Table 2. Equations for calculating GWP in mining operations.

Operation	Equation	Detail
Drilling	$C_{drilling}\left[\frac{kg_{CO2e}}{t}\right] = \frac{A \times E_v \times L \times N}{\eta_{drill} \times m_b} \times (\alpha + \beta)$	A: The area of the drill hole L: The charged length of the drill hole N: The number of drill holes for each block E_v: The drilling specific energy that depends on rock type η_{drill}: The assumed driller efficiency m_b: The mass of the block in ton α, β: The coefficient of carbonization for diesel, electrical power matrix
Blasting	$C_{blasting}\left[\frac{kg_{CO2eq}}{t}\right] = LF \times E_{expl} \times \delta$	LF: The load factor, defined as the amount of explosive per ton of detonated rock E_{expl}: The specific explosive energy δ: The coefficient of carbonization for explosive
Loading	$C_{loading}\left[\frac{kg_{CO2eq}}{t}\right] = \frac{P_L \times T}{\eta_{loader} \times m_{truck}} \times (\alpha + \beta)$	P_L: The front loader power T: The assumed average time to meet the loading capacity of the dumper η_{loader}: The assumed front loader efficiency m_{truck}: The loading capacity of the dumper
Hauling	$C_{hauling}\left[\frac{kg_{CO2e}}{t}\right] = \frac{9.81 \times S \times \left(m_{truck} \times z + (R_s + R_i) \times (2 \times M_{truck} - m_{truck})\right)}{m_{truck}} \times (\alpha + \beta)$	S_i: The distance of the ith block to destination z: The inclination of the ramp R_s: The rolling resistance of the surface R_i: The assumed internal resistance of the dumper M_{truck}: The total mass of the loaded dumper
Ancillary	$C_{Ancillary}\left[\frac{kg_{CO2eq}}{t}\right] = D_a \times \alpha$	D_a: The consumption rate of diesel per ton mined

Crushing	$C_{crushing}\left[\frac{kg_{CO2eq}}{t}\right] = 3.6 \times 10 \times W_i \times \left(\frac{1}{\sqrt{P_{cr}^{80}}} - \frac{1}{\sqrt{F_{cr}^{80}}}\right) \times \zeta$	**W_i: The Bond's work index** **P_{cr}^{80}: The 80% passing sizes of the product for the crusher** **F_{cr}^{80}: The 80% passing sizes of the feed for the crusher and the mill** **ζ: The coefficient of carbonization for electrical power for comminution**

The facility under review is located in the Middle East and includes open-pit mines, a concentrator, and a hydrometallurgy plant. This study focuses on the process until the comminution of ore material, without considering downstream processes. The International Energy Agency (IEA) [24] offers a range of potential carbon prices based on country and year, as detailed in Table 3. This analysis starts with an assumed average carbon price of $30 per ton and focuses on the Middle East, which is classified as a developing nation according to the IEA.

Table 3. USD Carbon Pricing Model [24, 25].

Cost CO2 ($/t)	2025	2030	2040	2050
Advanced countries	75	130	205	250
Chosen developing countries and emerging markets	45	90	160	200
Other developing countries and emerging markets	3	15	35	55

2.3. Scenarios Definition

The definition of multiple scenarios is essential for assessing model performance related to multi-objective optimization. For example, by assigning different weights to each objective, one can find out how priorities change between the objectives of economic viability and environmental stewardship within the same overall mine-planning strategy. In this way, the trade-offs and synergies between maximizing the net present value and minimizing ecological costs can be examined profoundly.

Here we define eleven scenarios, each applying a different weighting of the two objectives. The first objective maximizes the NPV of the mining operation, while the last objective minimizes the total of the ecological costs associated with CO2 emissions from energy consumption. The scenarios are summarized in Table 4, indicating weights attached to each objective representing different priorities.

By systematically varying the weights assigned to each objective, we can touch base with the full range of potential outcomes, which prove very helpful when identifying optimal strategies that involve a balance between economic and environmental goals and provide insights regarding how different priorities may affect long-term mine planning decisions. Results from such scenarios will portray the flexibility and robustness of the multi-objective optimization framework in making sure that sustainable and economically viable mining operations are attained.

Table 4. Scenario definitions with varying weights for economic viability and environmental stewardship objectives.

Scenario	Symbol	Weight	
		Objective 1 (NPV)	Objective 2 (Ecological costs)
1	S1	1	0
2	S2	0.9	0.1
3	S3	0.8	0.2
4	S4	0.7	0.3
5	S5	0.6	0.4
6	S6	0.5	0.5
7	S7	0.4	0.6
8	S8	0.3	0.7
9	S9	0.2	0.8
10	S10	0.1	0.9
11	S11	0	1

2.4. Case Study

The framework was tested in a practical case study at an open-pit iron mine in Iran to evaluate its effectiveness. The reserve modeling, planning, and long-term production activities were conducted using drill-hole prospecting data. The framework includes a 10-year plan within a larger project timeline. Aerial images in Figure 3 show the location of the crusher and waste dump at the mine site.

Figure 1. Aerial views of the case study area, showing the crusher and waste dump locations.

In Figure 2 a 3D depiction of the content (Fe grade) and ecological costs associated linked to various blocks within the deposit. This information was utilized to plan the pit excavation and establish the sequence of block extraction. The block model (geological) highlights high-value zones beneath the deposit, suggesting that lower-grade material should be extracted first. Blocks with high ecological costs are located to the right of the deposit, mainly due to the extra transportation required to extract them from the pit. These blocks must be transported to the waste dump where is situated on the left part.

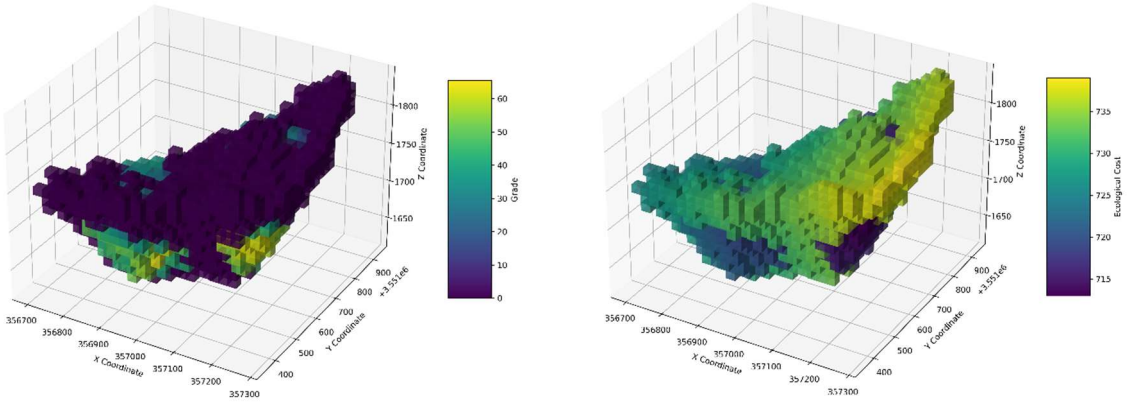

Figure 2. Distribution of grades and ecological costs across blocks.

3. Results

This section demonstrates the efficacy of MOO framework through its implementation in different scenarios. The model was created using the CPLEX® solver [26] and the Python® programming language [27]. To assess the framework's performance, we employed it in a case study focusing on an open-pit iron mine.

3.1. Economic Impacts

Economic impacts for various mining scenarios are evaluated through an analysis of the annual and cumulative NPV. The following data can be taken as examples of NPV values for ten periods for eleven different scenarios. To have a more intuitive way to show the economic impacts, Figure 3 presents the annual and cumulative NPV for each individual scenario. In this way, a visual result can show how each specific scenario impacts the global economic viability of a mining project.

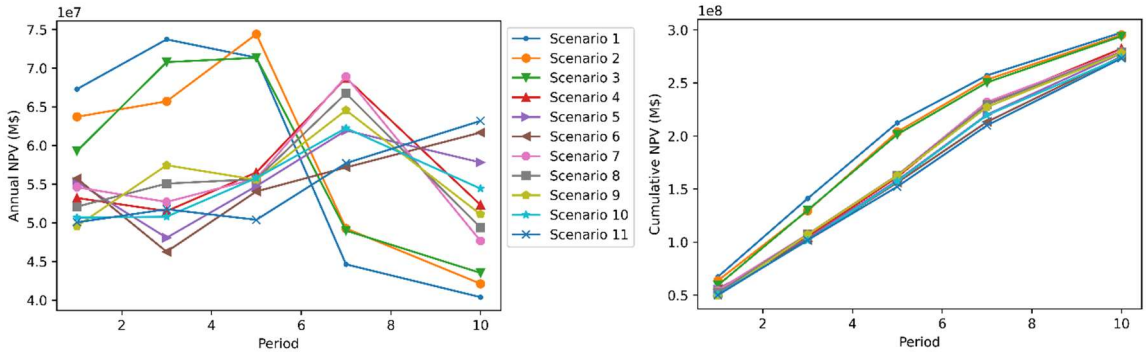

Figure 3. Annual NPV (left) and cumulative NPV (right) for scenarios.

The annual NPV data clarifies how each scenario performs economically over ten periods. High NPV scenarios, such as Scenario 1, strongly start and experience diminishing returns over time, while lower NPV

and higher ecological cost scenarios, like Scenario 6, perform more steadily. This might indicate that scenarios granting more consideration to environmental cost offer more consistent return, although at a lower overall NPV. Generally, higher NPVs at the beginning show a higher cumulative NPV with benchmarks of more accentuated and profitable trajectory growth. That said, the differences between the cumulative NPVs across scenarios are not overwhelming, meaning even the lowest-ranked initial NPVs produce significant long-term profitability.

These results show the importance of scenario selection that will meet both economic and environmental objectives. Tradeoffs between short-term profit and long-term sustainability must be very well thought out. Therefore, Figure 3 reserves a graphical representation of these trends, particularly showing the effects of each scenario on overall project economic viability.

3.2. Emission Outcomes Analysis

The emission results analysis provides a broader outlook on the environmental effects of each scenario. The scenarios demonstrate how variable the focus of ecological costs affects the overall emissions. In Figure 4, detailed emission results for all scenarios are provided.

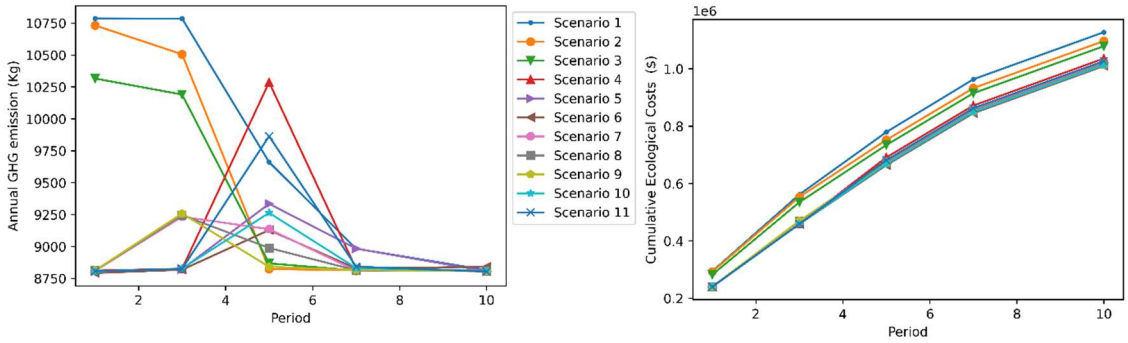

Figure 4. Annual GHG emission and cumulative ecological costs for scenarios.

The data clearly shows that GHG emissions vary across scenarios and, in most cases, are higher for corresponding to scenarios with lower ecological costs weights. Scenario 1 has the highest emission of 49,030 units and prioritizes NPV with minimum ecological costs. Scenario 6, which strikes a middle path between the two objectives, resulted in a cumulative emission of 44,410 units. Cumulative ecological cost trends involve a similar pattern as GHG, rising as priority on NPV goes up. Scenario 1 has the most significant cumulative, while Scenario 6 was more in balance. These results of this analysis underline, as far as possible, the tradeoffs between economic benefits and environment impacts, showing that a balanced development path must be sought—such that the least ecological cost is acquired at the highest level of profitability.

3.3. Block Sequencing Analysis

In this section, we examine the block sequencing variations for the different scenarios. Block sequencing is entirely important in mining operations since it affects the economic returns but also environmental costs. By examining the sequences, we can realize the optimal extraction order that allows for the maximization of NPV but also considers the impacts ecologically. To demonstrate the sequencing variations, we examined four scenarios for more significant details. Figure 5 selected scenario sequence of block extraction over ten periods indicates how the blocks are selected and extracted over time.

Earlier, it was observed that the blocks on the right side of the deposit possess lower grades and need to be transported to the waste dump on the left side. This results in higher environmental costs for these blocks. The model is designed to prioritize the extraction of lower-cost blocks in the

initial stages by emphasizing the ecological cost objective, as opposed to scenarios that prioritize maximizing NPV and extracting more valuable blocks in the beginning (Figure 5).

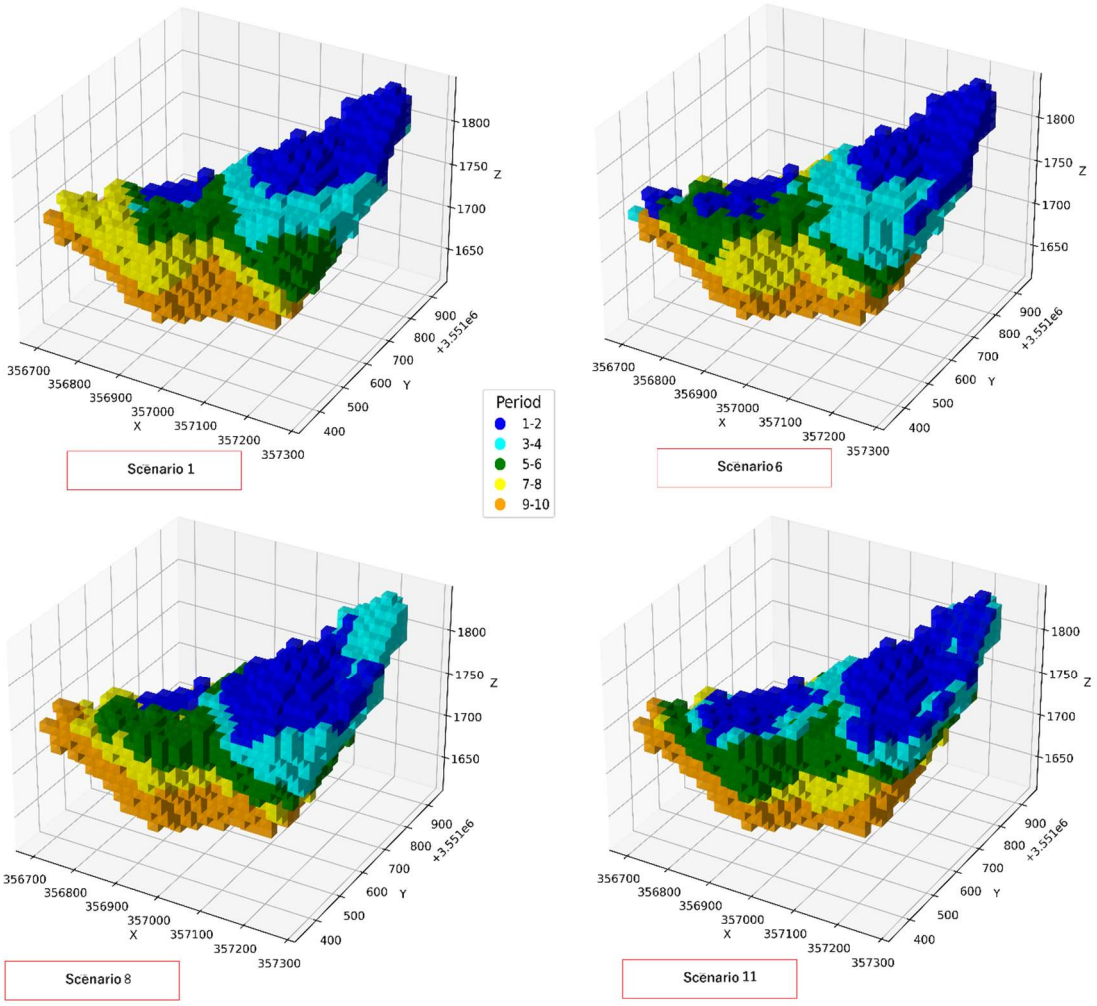

Figure 5. Block extraction sequences for selected scenarios.

3.4. Production Analysis

The production analysis offers an overview of each period's allocation of ore and waste blocks across different scenarios. The analysis highlights the impact of prioritizing economic versus ecological objectives on production levels and financial returns. Figure 6 provides detailed production outcomes for all scenarios.

Based on Figure 6, all scenarios with higher weights of economic elements depict relatively high constant production in the early periods but decrease slightly during the latter periods. The decline of economic priorities sees scenarios with high production but great fluctuation, especially during the middle periods. Scenarios 4, 5, and 6 remain balanced with as constant a level of production as possible to meet the minimum requirements of the plant. Finally, high-ecological-weight scenarios such as 10 and 11, maintaining the lowest plant requirement, vary very little in their production levels. Generally, all scenarios can work on the assurance of the minimum requirements for the plant, opening the possibility of balancing interests between the economic and ecological perspectives.

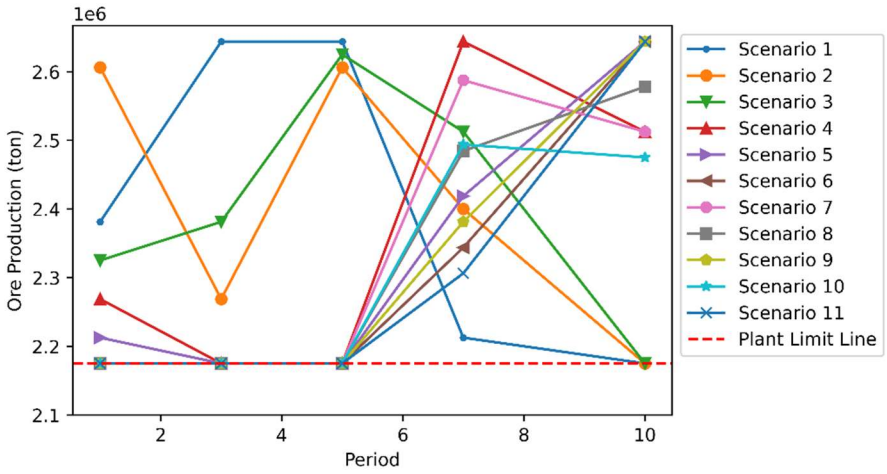

Figure 6. Annual ore production with lower threshold of plant.

3.5. Stripping Ratio (SR) Analysis

The stripping ratio (SR) is a crucial factor in mine design and planning, impacting resource utilization and operational efficiency. Figure 7 shows the annual stripping ratios for different scenarios. Firstly, high SR values obtained for the scenarios mean that a considerable amount of waste is removed relative to ore extraction. Scenario 1, for example, starts with an SR of 2.496, decreasing to 1.830 before rising again slightly. This pattern of high initial SR values, followed by a reduction, is common in the early scenarios, which are focused more on economic goals, and probably this reflects an initial phase of considerable overburden removal to access the ore. Moving to the later scenarios, with a greater emphasis on ecological goals—scenarios 10 and 11—the trend of the SR values is more modest and less variable.

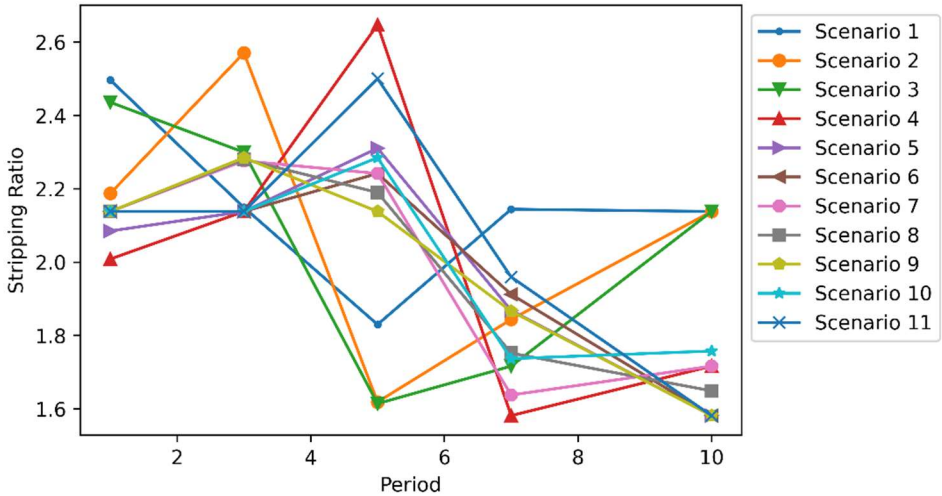

Figure 7. Stripping ratio analysis for scenarios over time.

Overall, the change from scenarios with high economic weight to scenarios with high ecological weight bolds a shift toward more balanced and efficient mining operations. High SR values initially depict a function of significant promotion to access ore bodies, while for the later scenarios, these will be optimized, with more consistent and manageable SRs within targets keeping output while minimizing environmental impact and operational costs is the objective.

Table 5 provides an overview of the outcomes from the MOO framework for various scenarios, including CO_{2eq} emissions, NPV, environmental costs, and SR. Furthermore, Table 5 highlights the variations in outcomes across different scenarios.

Table 5. Results of integrated framework in two scenarios.

Scenario	Ore (Mt)	Waste (Mt)	SR	GHG (Kg)	Eco cost (M$)	NPV (M$)
Scenario 1	12.06	25.86	2.14	49030	1.13	297.37
Scenario 2	12.06	24.83	2.06	47688	1.10	295.19
Scenario 3	12.02	24.34	2.02	46999	1.08	293.91
Scenario 4	11.78	23.46	1.99	45553	1.04	282.27
Scenario 5	11.63	22.99	1.98	44753	1.02	277.84
Scenario 6	11.51	22.84	1.98	44409	1.01	274.87
Scenario 7	11.63	23.03	1.98	44802	1.02	279.57
Scenario 8	11.59	22.96	1.98	44668	1.02	278.90
Scenario 9	11.55	22.89	1.98	44535	1.01	278.23
Scenario 10	11.49	22.95	2.00	44535	1.01	273.91
Scenario 11	11.46	23.44	2.04	45142	1.02	273.08

4. Conclusion

This paper addresses the critical requirements of sustainability practices in open-pit mining through the development of a multi-objective optimization framework that balances the economic and environmental goals. An open-pit mine in the Middle East has been tested to prove this proposed framework, proves its ability at harmonizing economic viability and ecological stewardship. Results indicate that while increasing importance given to economic-oriented objectives increases the initial NPV, it significantly increases the long-term variability of profitability for a mine. Conversely, high-ecological-weight positioning scenarios ensure more stable economic returns, besides effectively reducing GHG emissions. Block sequencing and production analyses further reiterate the framework's ability in optimum resource extraction, besides maintaining stable production levels with reduced environmental impacts. Stripping ratio analysis confirms the efficiency of the framework in managing overburden removal and ensures sustainable utilization of resources. Overall, this research emphasizes the significance of environmental considerations into mine planning that will lead toward economic success and sustainability.

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Integrated Stochastic Discrete-Continuous Simulation-Based Optimization Framework for GHG Mitigation in Mining Operations

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ABSTRACT

This paper presents an integrated stochastic discrete-continuous simulation-based optimization framework specifically designed to address greenhouse gas (GHG) mitigation in operational decision-making processes in open pit mines. Our framework not only addresses the economic imperative of minimizing transportation costs but also prioritizes environmental sustainability by concurrently reducing carbon dioxide emissions. A case study is conducted on a specific copper mine to address the challenge of determining the optimal size of the transportation fleet, while concurrently minimizing transportation costs and the fleet's CO2-equivalent emissions. Furthermore, a novel approach for allocating trucks to shovels is introduced in this work. This method not only contributes to cost reduction and carbon emission mitigation, but also leads to the enhancement of key performance indicators, such as tonnage hauled and cycle time. Sensitivity analysis is performed to examine the influence of various parameters on the objective functions and performance indicators. The findings provide valuable insights for researchers focused on GHG mitigation in mining and contribute to the development of sustainable mining practices.

Keywords: *Sustainable production, GHG emission control, equipment selection and sizing, allocation problem, stochastic simulation-based optimization*

1. Introduction

Mining operations, crucial to global economic activities, heavily rely on fleets of trucks and shovels for material handling, constituting a significant portion of operational costs. The main material handling system in open pit mines is the truck-shovel system [1] which consumes over 50% of the operational budget [2-4]. Adding to the operational cost, these operations come with a hefty environmental cost, marked by substantial greenhouse gas (GHG) emissions, necessitating urgent mitigation efforts in the face of climate change concerns. Besides, the transportation fleet is accounted to consume around 30% of total energy in an open pit mine [5, 6]. Therefore, proper selection, sizing, and utilization of truck and shovel fleets not only will have substantial economic gains but also could lead to mitigating the possible environmental footprints. As presented in the literature section of this paper, several research papers addressed the selection, sizing, and the utilization problems in open pit mines.

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Lack of a proper tool accounting for the associated operational uncertainties and decisional conflicts while sizing the fleet and simultaneously considering economic gains and environmental footprints while utilizing the fleet motivated the authors to conduct this research resulting in introduction of a hybrid stochastic simulation and optimization framework taking a step closer to responsible open pit mining operations.

In the past few years, we have seen a growing emphasis on the development of sustainable mining practices aimed at minimizing environmental impact while maximizing economic efficiency [7-11]. Despite its inevitably crucial role, mine planning has not received its deserved attention in this regard. Developing and applying fleet management systems (FMSs) can be named as a cost-effective strategy widely used to improve overall fleet utilization. The main purpose of implementing an FMS is to apply mathematical models helping to efficiently utilize the equipment leading to production increase [2]. This implementation subsequently causes a reduction in GHG emissions as well as the operational costs, [12] addressing the two fundamental pillars of sustainable practices namely economic and environmental impact.

By considering economic and environmental objectives simultaneously, alongside factors such as uncertainty in maintenance and repair, downstream processes, and conducting sensitivity analysis, our framework offers a holistic approach to sustainable mining practices. The significance of our research lies in its ability to provide practical applications for both academics and industry professionals, fostering the development of mining strategies that balance economic viability with environmental responsibility, thus contributing to the long-term sustainability of mining operations. The presented framework was applied to a case study of a copper mine for performance evaluation. In addition, we performed sensitivity analysis to examine the impact of different parameters on the legitimacy of the framework and accuracy of the performance indicators. The analysis identifies important and influential parameters in economic productivity as well as environmental issues, further enhancing the applicability and effectiveness of the framework.

The following section of this paper includes an extensive review of the literature related to the topic. Following that, a step-by-step elaboration on the components of the framework including the simulation modelling and the optimization algorithm is presented. Model verification and validation using the case study are discussed in the fourth section. Section five provides a detailed comparative representation of results, and subsequently, in section six, results of the sensitivity analysis are laid out. Finally, section seven provides conclusions and proposes possible directions for future research in the field.

2. Literature Review

Finding optimal solutions for the equipment selection and sizing (ESS) problem plays a critical role in open pit mining operations, significantly influencing operating costs and the efficiency of the production fleet [13-14]. Over the years, diverse methodologies have emerged to address the ESS problem, which can be categorized into: considering the concept of equipment matching factor, applying the operations research techniques, implementing the artificial intelligence approaches, introducing the new life cycle costing techniques, and utilizing the discrete event simulation method [15]. This review focuses on research related to operations research techniques and simulation methods.

Early attempts, such as the application of linear programming models by Edwards et al., and the linear programming model by Burt et al., primarily aimed to optimize the selection of shovels and minimize costs. Ta et al. introduced a mathematical model focused on reducing truck fleet size, limited by its applicability to homogeneous fleets [16-18]. Addressing this limitation, Moradi Afrapoli et al. presented a framework integrating the optimization approach and the simulation

modeling considering FMS and operational uncertainties. Mohtasham et al. implemented a two-stage framework to optimally dispatch trucks, making decision on the size of the transportation fleet, allocation of the available equipment, and dispatching of the transporters in real-time [4, 19]. Their subsequent work [15] explored strategies to optimize fleet size, emphasizing matching factor targets. Souza et al. [20] utilized a mixed-integer programming (MIP) model with incorporation of truck dispatching to reduce the possible deviations from the tonnage and grade targets. Yeganejou et al. [21] integrated the Monte-Carlo simulation technique with the MIP to optimize truck fleet allocation leading to enhancement of the fleet productivity. Meanwhile, Mohtasham et al. [22] applied multi-objective decision making technique to develop a framework with which production is maximized while fuel consumption and grade deviations are minimized. Zhang and Xia [23] minimized operating costs by employing the integer programming, considering truck capacities and travel distances. Ahangaran et al. [24] defined transportation cost as the decision variable and used integer programming to minimize it, albeit with a constraint on the number of available trucks. Alexandre et al. [25] explored multi-objective genetic algorithms for minimizing transportation costs and maximizing production. Afrapoli et al. [3] proposed a multi-objective model optimizing truck allocation based on assignment request time, addressing idle time, cumulative truck wait time, and deviations from flow rates.

Mohtasham et al. [12] presented a chance-constrained goal programming model for truck destination optimization, considering uncertainties and minimizing total operating costs. Ta et al. [26] and Afrapoli et al. [27] also presented stochastic models, addressing uncertainties in operational parameters and quality requirements. Both and Dimitrakopoulos [28] introduced a stochastic optimization model considering geological and operational uncertainties trying to investigate impact of short-term strategic plans on the allocation of trucks.

Studies examining environmental factors in open-pit mining include Topal and Ramazan, Peralta et al., Mane et al., Walnum and Simonsen, Aksoy et al., Alinaghian and Naderipour, Winebrake and Green, and Montiel and Dimitrakopoulos [29-36]. These studies investigated the impact of factors such as truck age, maintenance, driver behavior, infrastructure, and vehicle specifications on fuel consumption and greenhouse gas emissions.

The limitations of deterministic models in handling uncertainties, as highlighted by Dindarloo et al., led to the adoption of discrete event simulation (DES). Rist pioneered the application of DES in mine haulage, followed by notable studies by Kolonja and Mutmansky, Ataeepour and Baafi, Yuriy and Vayenas, Que et al., and Chaowasakoo et al., Upadhyay and Askari-Nasab, Forsman et al., Torkamani and Askari-Nasab, Hashemi and Sattarvand, and Moradi Afrapoli and Askari-Nasab [2, 37-47].

Recent studies by Awuah-Offei et al., Suglo and AlHassan, Tan et al., Ortiz et al., Tiile et al., Kaba et al., Zeng et al. and Chaowasakoo et al. have applied simulation to optimally address open-pit mining operational and strategic problems [48-55]. Readers are encouraged to navigate the work by Burt and Caccetta [14] for further investigation on ESS problem.

Recent works by Anaraki and Afrapoli [11] propose a multi-objective optimization model for fleet management, incorporating carbon emission minimization. Mohtasham et al. [15] introduce strategies for equipment sizing using mixed-integer non-linear programming (MINLP) models. Abolghasemian et al. [56] present a modified-NBI optimization method for copper open-pit mine extraction systems, emphasizing multi-objective optimization. Another work by Abolghasemian et al. [57] focuses on the hauling system in an Iranian copper mine, employing a simulation-based optimization approach for increased production. Table 1provides a detailed high level comparative analysis of the current advancements in the field.

Table 1. High level comparative representation of available models.

Year	Paper	Contributions						Model	Objective functions								Software
									Economic				Environmental				
		Simulation	Optimization	Case study	Discrete	Continues	Maintenance problems		#	Min	Max	Type	#	Min	Max	Type	
2013	[18]	*	*		*		*	LIP	1	*		Total number of allocated trucks					C# / CPLEX
2015	[23]		*		*		*	IP	1	*		Total truck operating costs					
2019	[3]	*	*	*	*			MILP	3	*		idle and wait time of equipment and deviation from target production					Arena / CPLEX / VBA
2019	[25]	*	*		*	*			2	*	*	Min: Total cost of the trucks in operation / Max: Total production					
2020	[56]	*	*	*	*			MINLP	1		*	Total production					Arena / OptQuest
2021	[15]	*	*	*	*			MINLP	1	*		Match factor					GAMS / Arena / OptQuest
2021	[12]		*	*	*	*	*	CCGP	4	*		Deviation from production, grade requirements, ore tonnage, total operating costs					MATLAB / CPLEX / Visual C#
2021	[22]		*	*	*			MILGP	4	*		Difference between production / material content / material sent / fuel consumption					CPLEX / GAMS
2021	[27]	*	*	*	*	*	*	FLP	3	*		Deviation from the production target / idle and wait time of equipment					Arena

2022	[57]	*	*	*	*		*	MINLP	2	*	*	Max: total extraction amount / Min: travel time					Arena / Maple / Lingo
2022	[19]	*	*	*	*			NLP	1	*		Deviation in the match facto					Arena / OptQuest
2023	[11]		*	*	*			MILP	1	*		Transportation costs	1	*		CO2 emission	CPLEX
2024	This study	*	*	*	*	*	*	MILP	1	*		Transportation costs	1	*		CO2 emission	Arena / OptQuest

LIP: Linear integer program, MILP: Mixed-integer linear programming, MILGP: Mixed-integer linear goal programming, MINLP: Mixed-integer nonlinear programming, CCGP: Chance-constrained goal programming, NLP: Nonlinear programming, IP: Integer programming, FLP: Fuzzy linear programming.

In conclusion, the literature provides a rich landscape of methodologies and models addressing equipment selection, sizing, and allocation in open pit mining. While various studies have made significant contributions, gaps remain in addressing uncertainties, environmental considerations, and integrating fleet management systems. The proposed framework aims to bridge these gaps and contribute to the advancement of sustainable and efficient mining practices. The following are the key contributions of our research work:

- Considering both environmental and economic issues;
- Considering stochastic maintenance parameters to account for uncertainties;
- Modelling downstream processes; and
- Sensitivity analysis in identifying effective parameters.

3. Framework and Formulations

The proposed framework consists of several interactive models and sub-models imitating open pit mine planning and operational activities, simultaneously simulating the way material handling systems in mines work and optimizing the decisions mining engineers make considering stochastic factors that impacting the operational excellence. 1 conceptualizes a high-level scheme of the proposed framework, illustrating the integrated stochastic discrete-continuous simulation-based optimization framework and highlighting the dynamic interactions between the optimization and simulation models.

We present a multi-objective optimization algorithm that optimizes decision making both economically and environmentally. The model considers various parameters, including fleet size, maintenance and repair of shovels and trucks, post-crushing processes, and allocation of trucks to shovels. One of the principal contributions of our research is the comparison and investigation of truck allocation methods. In this paper, we not only employ the locked-in method based on the match factor [2] but also introduce a novel approach for allocating trucks to shovels. This method not only leads to cost reduction and carbon emission mitigation but also improves key operational performance indicators such as tonnage hauled and cycle time.

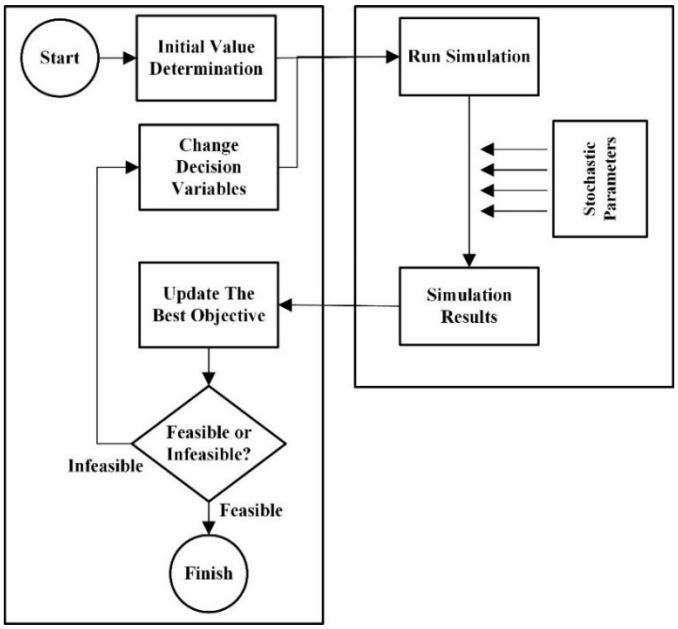

Figure 1. High-level schematic representation of the proposed simulation-based optimization framework.

3.1. Optimization Model

Our proposed multi-objective model aims to minimize transportation costs and enhance environmental sustainability by reducing carbon dioxide emissions. This MILP approach considers various aspects of FMS, such as transportation costs, truck types, ages, and velocities, as well as the emissions generated by each truck. It is important to note that costs, emissions, and velocities vary based on the specific truck type and its age. This model seeks to identify the most efficient set of trucks, including their quantity and age within each closed system (Loading point to Dumping point). However, driver proficiency and weather conditions are not accounted for in this model. The subsequent section outlines the specified indices, sets, parameters, decision variables, the objective function, and the constraints of the optimization model.

i	Indices for truck type (i ϵ {1, 2, … I})
j	Truck age group indices (j ϵ {1, 2, … J})
s	Indices for closed system (s ϵ {1, 2, … S})
o	Ore sites indices (o ϵ {1, 2, … O})
w	Waste sites indices (w ϵ {1, 2, … W})

Parameters

FC_{ijs}	Fix cost of truck of type *i* age *j* in closed system *s*
CL_{ijs}	Cost of trucks of type *i* age *j* in closed system *s* when loaded per kilometer
CUL_{ijs}	Cost of trucks of type *i* age *j* in closed system *s* when unloaded per kilometer
D_{ijs}	Distance traveled by truck *i* age *j* in closed system *s*
NL_{ijs}	Average loaded trip numbers of trucks of type *i* age *j* in closed system *s*
NU_{ijs}	Average unloaded trip numbers of trucks of type *i* age *j* in closed system *s*
CL_{ijs}	Amount of carbon produced by loaded trucks of type *i* age *j* in closed system *s* per trip
CE_{ijs}	Amount of carbon produced by unloaded trucks of type *i* age *j* in closed system *s* per trip
TN_{ijs}	Average tonnage hauled by trucks of type *i* age *j* in closed system *s*
LPR	Lower bound of production requirement
UPR	Upper bound of production requirement
T_i	Total number of truck type *i*
T_j	Total number of truck age *j*
T_s	Total number of truck in closed system *s*
SR	Stripping ratio

Decision Variable

X_{ijs}	Number of trucks of type *i* with age *j* in system *s*

$$Min\ Z1 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s=1}^{S}\left(FC_{ijs}X_{ijs}\right) + \left(CL_{ijs}NL_{ijs}D_{ijs}X_{ijs}\right) + \left(CUL_{ijs}NU_{ijs}D_{ijs}X_{ijs}\right) \quad (1)$$

$$Min\ Z2 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s=1}^{S}\left(CL_{ijs}X_{ijs}NL_{ijs}\right) + \left(CE_{ijs}X_{ijs}NU_{ijs}\right) \quad (2)$$

Subject to:

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s=1}^{S}\left(TN_{ijs}X_{ijs}NL_{ijs}\right) \geq LPR \quad (1)$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s=1}^{S}\left(TN_{ijs}X_{ijs}NL_{ijs}\right) \leq UPR \quad (2)$$

$$\sum_{j=1}^{J}\sum_{s=1}^{S} X_{ijs} = T_i \quad \forall i \in I \quad (3)$$

$$\sum_{i=1}^{I}\sum_{s=1}^{S} X_{ijs} = T_j \quad \forall j \in J \quad (4)$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J} X_{ijs} = T_s \quad \forall s \in S \quad (5)$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s=1}^{W} X_{ijs} = SR\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s=1}^{O} X_{ijs} \quad (6)$$

$$X_{ijs} \geq 0 \quad (7)$$

The first objective function, as illustrated in Equation **Error! Reference source not found.**), focuses on reducing transportation costs. This involves considering the cost differential between using new and used trucks, and loaded and empty trucks, as well as the distance between shovels and dumpsites. Furthermore, as demonstrated in Equation **Error! Reference source not found.**), the second objective function aims to reduce carbon emissions by assessing the amount of carbon generated. Constraints (1) and (2) are implemented to guarantee compliance with the plant capacity requirement in terms of the number of trucks. In fact, these refer to the targeted upper and lower limits of material tonnage to be transported during each shift. Constraints (3), (4), and (5) represent the cumulative count of trucks for each category, the aggregate number of trucks within distinct age brackets, and the collective count of trucks within individual systems, respectively. These represent operational constraints concerning the quantity, type, and age combinations of trucks. For instance, in constraint 5, it ensures that the total count of type i trucks across various ages and systems does not exceed the planned number. Constraint (6) controls the standard ratio of trucks in the ore closed system to the waste closed system. Finally, Constraint (7) guarantees that the solution is an integer number.

3.2. Simulation Model

One major part of the framework was built applying the DES modelling techniques which itself includes several sub-models for proper imitation of cradle-to-gate processes and operations. One of the significant aspects here is the integration of discrete and continuous process modelling techniques, making the framework capable of simulating various aspects of mining operations, including comminution processes, slurry transfer, and plant processes as a cohesive package. Figure 2 and Figure 3 provide an operational level descriptive layout of integrated DES package where two scenarios were simulated to compare different allocation methods. The first allocation

method is a locked-in method based on the match factor [2] (Figure 2), while the second method is a new allocation method that considers trucks' waiting time and loading process queue length (Figure 3).

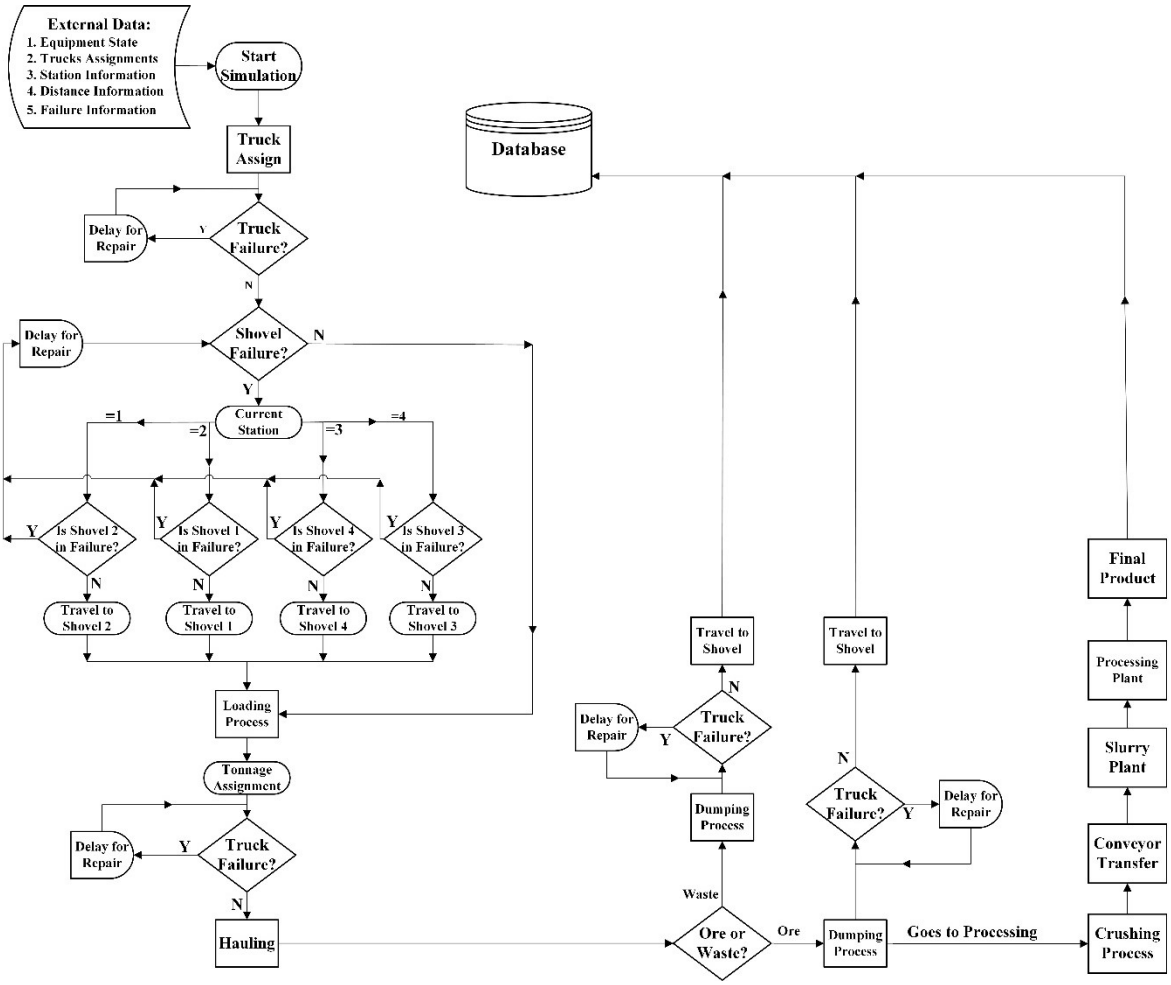

Figure 2. Flow chart of locked-in method.

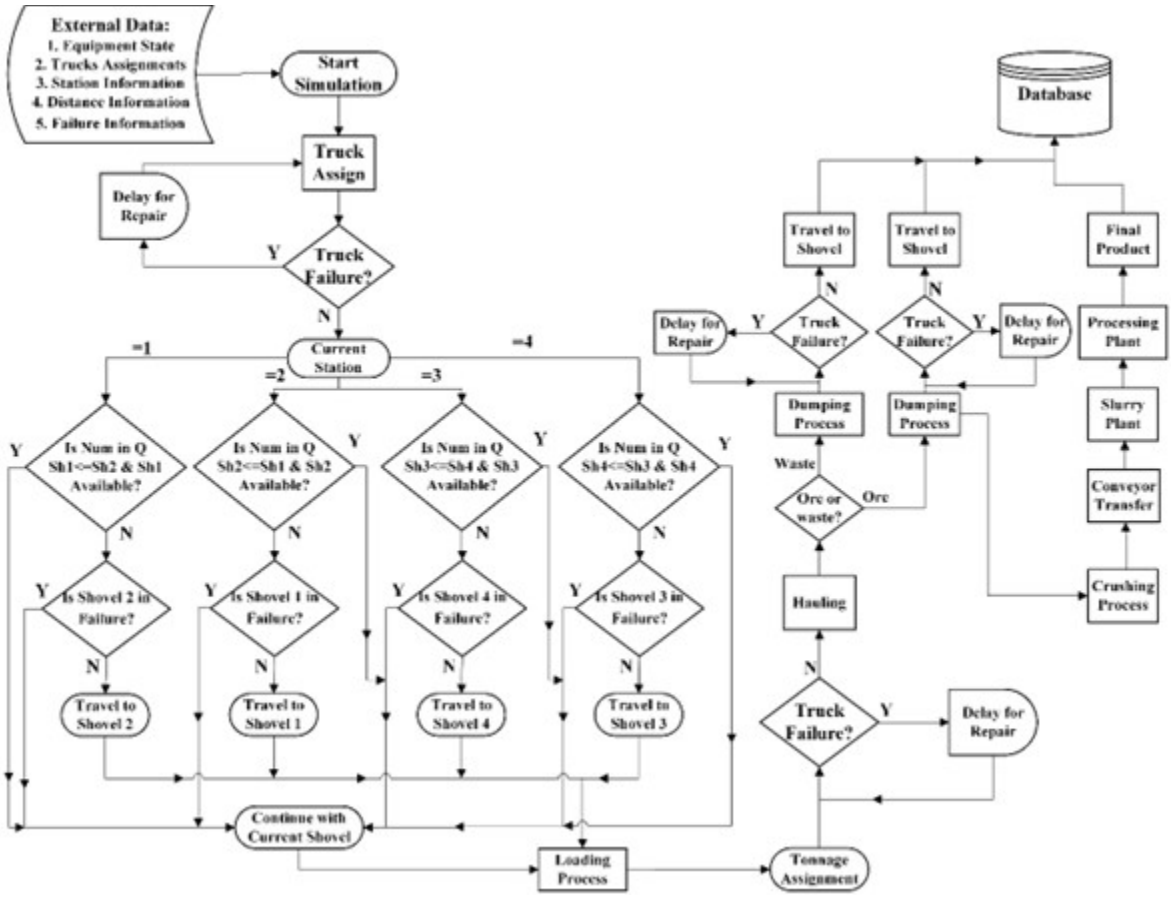

Figure 3. Flow chart of new allocation method.

First, external data, including equipment state, truck assignments, station information, distance information, and maintenance information, is entered into the model before starting the simulation process. Trucks are assigned to fixed shovel stations based on the pre-defined external data. Then, imitating the operation starts with the first step being loading, after two logic controls are performed to check the maintenance program such as emergency or preventive maintenance for trucks and shovels. If a truck fails, it will be taken out of service until the repair or inspection process is completed. However, when a shovel fails, logic control is implemented to ensure that the process does not stop and the trucks do not wait in a queue, allowing them to travel between stations.

After the failure controls, trucks travel to and are loaded by shovels and the loading tonnage is determined. The loaded trucks then haul materials (ore or waste) to a specific dumpsite, where they dump the materials and return to their initial station. Simultaneously, a continuous process is conducted. The ore fed into the crusher undergoes crushing before being conveyed to the slurry plant through a conveyor system. The output of the slurry plant is then transferred to the processing plant, where the final product is produced. It is noteworthy that the framework, as shown in Figure 2 and Figure 3, has an integrated databases built on Microsoft SQL Server, that seamlessly works together with the simulation models to record and store statistics and results of all the production steps.

4. Framework Validation and Evaluation

In the previous sections, authors established a comprehensive framework for optimizing and simulating mining methods. In this section, the proposed framework is first verified and then validated, and the results of its performance evaluation are presented. In this regard, the framework was implemented in a copper mine case study, illustrated in detail in the following sections, considering both abovementioned dispatching methods, and the consequent results served as a benchmark for subsequent evaluation. The validation process performed in this paper started with running the framework for 10 replications (calculated based on the desired production half-width). Subsequently, a comparison was made between the results and actual operating records in various aspects to confirm the efficacy of the framework. After validation, an extensive comparison was conducted between the locked-in method and the new allocation method, resulting in the determination that the new allocation method performs better than the locked-in method across multiple indicators.

4.1. Case study

To assess the efficacy of the hybrid stochastic simulation optimization framework proposed, Sungun open pit copper mine, situated in the northwestern region of Iran and renowned as a leading copper mine globally, has been selected for analysis. Figure 4 demonstrates a specific segment of the mine profile, showcasing the road network and the tasks related to trucks and shovels, which are responsible for the transportation of materials from loading to dumping points [15] Table 2 presents a concise overview of the gathered data.

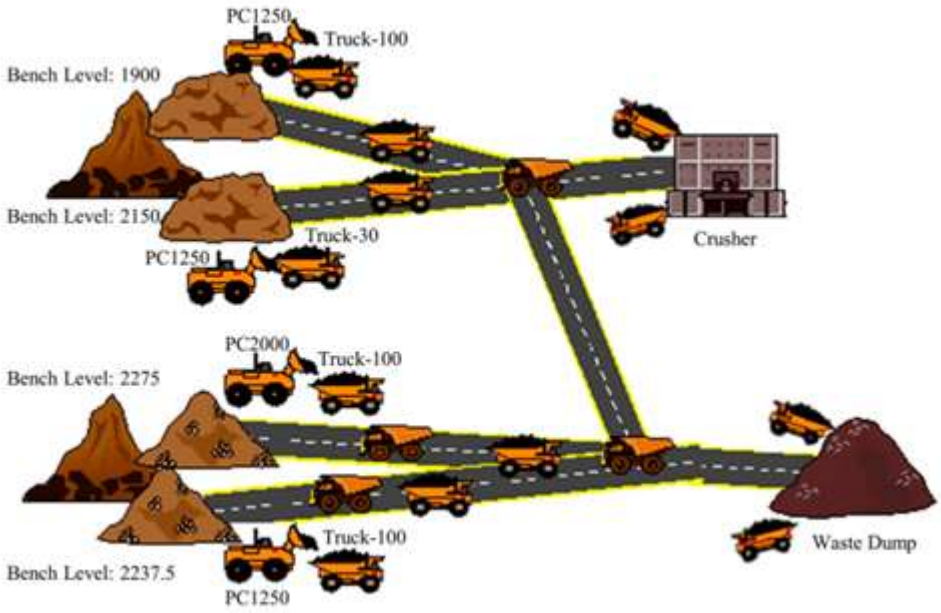

Figure 4. Schematic of the mining operation in the Sungun mine (reproduced after [15]).

Table 2. Main production and transportation systems and their components [11].

Closed system	Loading point	Dumping point	Distance (km)	Mean head grade	Loaders (Komatsu)		Hauler		
					Type	No	Type	Capacity (ton)	No
1	1900	Crushing unit	2.1	0.75	PC-1250	1	HD-785	100	3
2	2150	Crushing unit	3.15	0.42	PC-1250	1	HD-325	30	4
3	2275	Waste disposal	2.5	-	PC-2000	1	HD-785	100	5
4	2237.5	Waste disposal	3.65	-	PC-1250	1	HD-785	100	7

Furthermore, it is necessary for the crusher to maintain a copper grade ranging from 0.62% to 0.63% per shift. The designated tonnage of materials that should be moved during each shift is established at a minimum of 15300 tons and a maximum of 26600 tons. Moreover, the extraction process necessitates a stripping ratio within the range of 2 to 3. The mine operates round-the-clock with three 8-hour shifts, operating 363 days annually.

To categorize the trucks, they are separated based on their working years into two distinct groups. Trucks with under fifteen years of service are categorized as new, whereas those exceeding fifteen years are deemed old. Additionally, the hourly carbon emissions, transportation costs, and cycle time are all equally regarded for both types of trucks within the mine. A summary of the trucks' age groups information is provided in Table 3.

Table 3. Trucks age groups information.

Closed	Hauler (Komatsu)			New trucks	Old trucks
system	Type	Capacity (ton)	No	No	No
1	HD-785	100	3	2	1
2	HD-325	30	4	2	2
3	HD-785	100	5	3	2
4	HD-785	100	7	4	3

It is noteworthy that the Equation **Error! Reference source not found.** was used to calculate the carbon emission of trucks on truck fuel consumption [5].

$$F\left(\frac{L}{cycle}\right) = 1.37071 + 0.00483 \times PL + 0.00398 \times LT + 0.00499 \times ES + 0.01471 \times ETR + 0.00278 \times LS + 0.0519 \times LTR \quad (10)$$

F: Fuel consumption (liters per cycle)

PL: Payload (metric tons)

LT: loading time (seconds)

ES: Empty idle time (seconds)

ETR: Empty travel time (seconds)

LS: Loaded idle time (seconds)

LTR: Loaded travel time (seconds)

4.2. Validation

Verification is to double check if the conceptualized model of the real operation works properly. The main question answered in verification step as mentioned by Banks et al is: *"Is the conceptual model accurately represented by the operational model?"*[58]. Validity testing assesses the model's compatibility with the real system. To validate the framework, the head grade criteria are examined by comparing them between the actual system and the computer framework. This process confirms the model's validity. To do so, an assumption test is conducted on the mean of the normal population with an unknown variance. The alpha level for this test is set at 0.05, with a sample size of 10, representing simulation replications. Table 4 presents percentage information, averages, and standard deviations for both scenarios in the real system.

Table 4. Information about averages and standard deviations.

Closed system	Case study	Scenario 1 (locked-in method)		Scenario 2 (new allocation method)	
	Average	Mean	std	Mean	std
1	0.75	0.74	0.0085	0.74	0.0087
2	0.42	0.42	0.0084	0.42	0.0075

Assumption tests are applied to each closed system, calculating the test score as follows:

$$H_0: \mu = \mu_0 \tag{8}$$

$$H_1: \mu \neq \mu_0 \tag{9}$$

$$t_0 = \frac{x - \mu_0}{\frac{S}{\sqrt{n}}} \tag{10}$$

If the test statistic falls within the range $\left[-t_{\frac{\alpha}{2}.n-1}.\, t_{\frac{\alpha}{2}.n-1}\right]$, there is no basis to reject the H_0 hypothesis, confirming the model's validity. Referring to the t-distribution table, the acceptance interval for a two-tailed test with 9 degrees of freedom and a significance level of 0.05 is [-2.26, 2.26]. Table 5 displays the test statistics for each system.

Table 5. Test statistics for each system.

Closed system	Test score	
	Scenario 1	Scenario 2
1	-1.57	-1.59
2	1.84	1.91

Thus, there is no grounds to reject the null hypothesis for this test, meaning the head grade percentage resulting from the simulation model implementation is not significantly different from the percentages obtained in the case study at the 5% significance level.

The key performance indicators (KPIs) are defined, as presented in Table 6, to analyze the state of two models.

Table 6. Key performance indicators.

KPIs
Total tonnage hauled to dumpsite (Ore and Waste)
Average waiting time per shovel
Average cycle time
Average fuel consumption per cycle
Average CO2 emission per cycle

5. Results and Discussion

The proposed framework with several simulation models and sub-models and a multi-objective optimization model with one decision variable was developed and evaluated using Arena 16.1 software on a windows 10 operating system, equipped with an Intel 7 Core CPU of 2.20 GHz and an 8GB RAM.

OptQuest solver provides a potent tool that uses tabu search and scatter search heuristics to choose an optimal candidate for each decision variable in each simulation run [59]. The assessment of the objective function for each potential solution is conducted by the Arena model, which operates over a period of 12 months with a warm-up period lasting 15 days. To minimize errors and enhance the reliability of results, this process is repeated 10 times. OptQuest employs a variable number of replications, allowing for swift elimination of poor-quality solutions after ten replications to expedite the overall search time. Utilizing the current assessment of the candidate solution and the list of previously examined solutions, OptQuest determines the subsequent candidate solution to be evaluated. The search process continues until the specified stopping criterion is satisfied. A visual representation of the search methodology employed by OptQuest is presented in Figure 5.

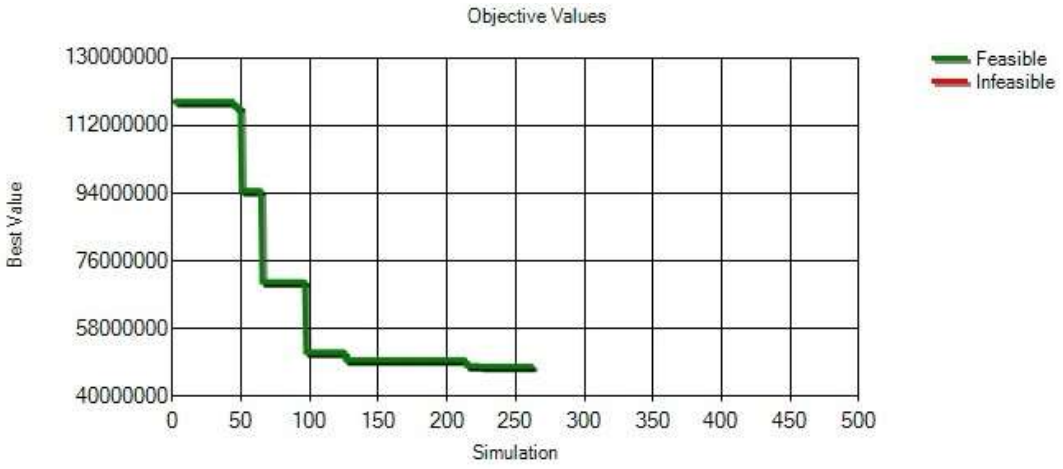

Figure 5. Search method in OptQuest.

Finally, after approximately 500 simulation runs, the optimal results were found in run number 224, as illustrated in Table 7 and Table 8.

Table 7. Optimum size of the truck fleet in different systems.

Item	Quantity
Type 1 trucks	9
Type 2 trucks	10
Closed system 1: sum of trucks	4
Closed system 2: sum of trucks	3
Closed system 3: sum of trucks	5
Closed system 4: sum of trucks	7

Table 8. Optimum number of trucks per each age group to be present in each closed production system

Closed System	Truck type 1		Truck type 2		Total
	Age bin 1	Age bin 2	Age bin 1	Age bin 2	
1	1	2	1	0	4
2	1	0	1	1	3
3	1	1	2	1	5
4	1	2	2	2	7

After obtaining the optimal values, we applied the new allocation method for the same period. The differences in objective functions among the three models are illustrated in Table 9 and Table 10, as well as Figure 6, Figure 7, and Figure 8. The case study model represents the current situation in the mine, whereas the other two models, namely the locked-in and new allocation method, were developed based on optimal values of decision variable. The difference between these models, as discussed in Section 3.2, refers to the logic of truck allocation within each system.

Table 9. Differences between the optimal costs and emissions of the operation using three different decision making models.

Model	Objective 1 (Transportation Costs -$M)	Objective 2 (CO2 Emission – M Kg)
Case Study	37.796	156.234
Locked-In	23.550	47.522
New allocation method	23.059	43.396

Table 10. Optimum fixed and variable costs of the material transportation for each decision making method.

Model	Fix transportation cost ($M)	Loaded travel costs ($M)	Empty travel costs ($M)
Case Study	8.3	15.716	13.78
Locked-In	18.1	2.904	2.546
New allocation method	18.1	2.643	2.316

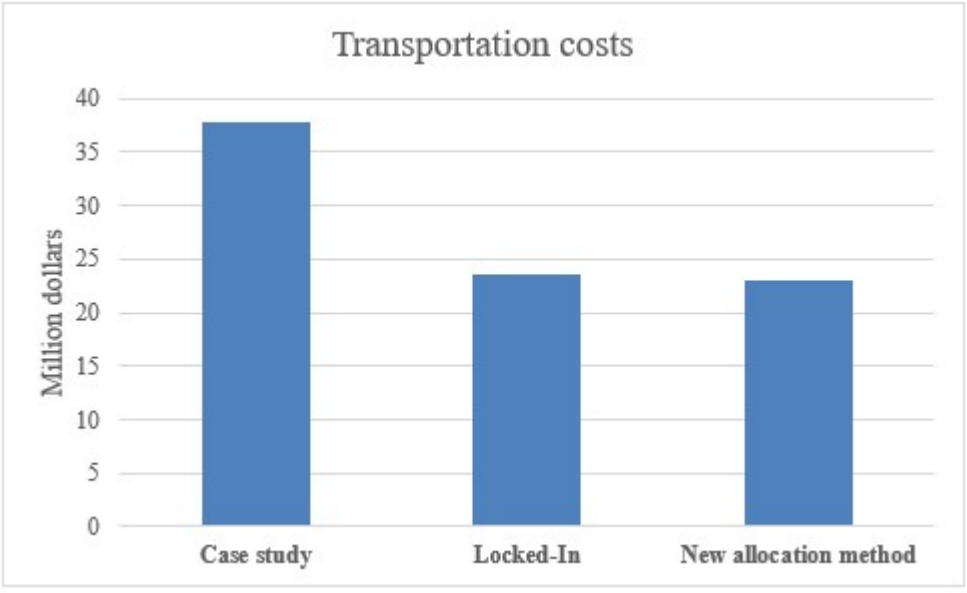

Figure 6. The transportation costs comparison between the case study, locked-in, and new allocation method.

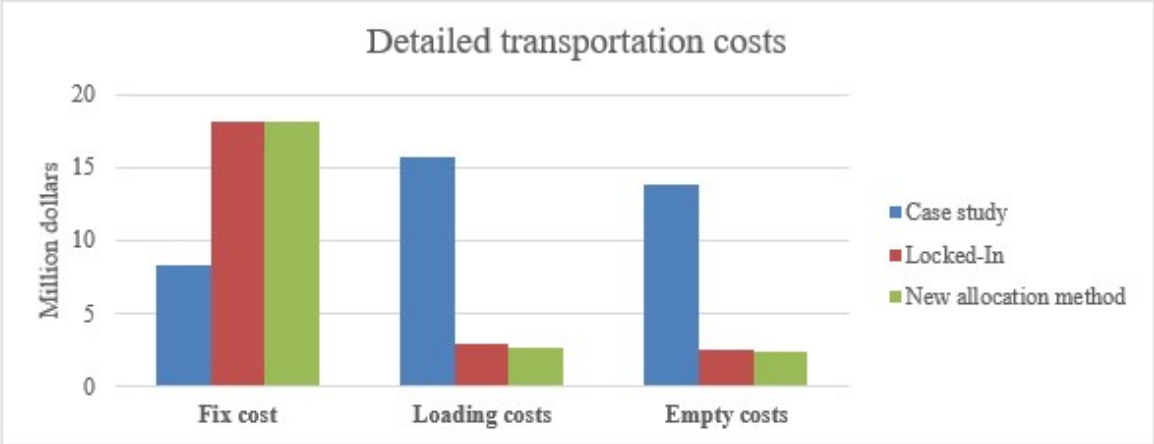

Figure 7. The detailed comparison of transportation costs between the case study, locked-in, and new allocation method.

As shown in Figure 6, the locked-in model and new allocation method have successfully reduced transportation costs by an impressive 38% and 39% respectively. This significant reduction highlights the superior efficiency of these models compared to the current situation in the mine. Furthermore, when referring to Figure 7, we observe a noteworthy 218% increase in fixed costs, attributed to the fleet renewal. However, this increase in fixed costs is counterbalanced by an average decrease of 83% in variable costs, which include loading mode and empty transportation costs.

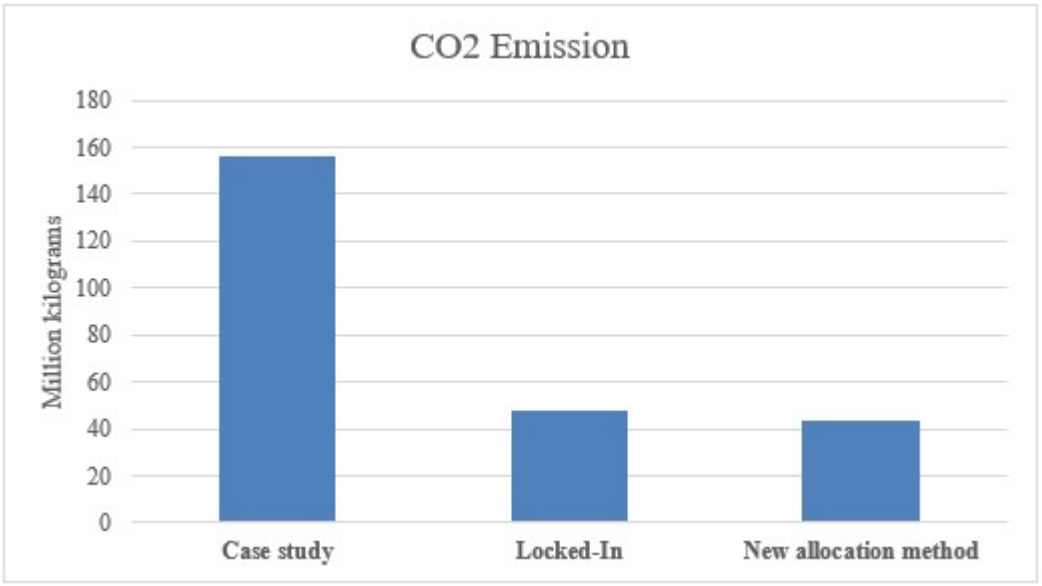

Figure 8. The comparison of CO2 emission between the case study, locked-in, and new allocation method.

As depicted in Figure 8, the renovation of the fleet has led to a remarkable reduction of 70% and 72% in CO2 emissions for the locked-in model and the new allocation method, respectively. These findings highlight the significant impact that the renovation of the fleet has on reducing harmful environmental pollutants. Additionally, these results suggest that investing in fleet renovation can be an effective strategy for combatting climate change and promoting sustainability.

5.1. Comparison of Results

In this section, an evaluation of the outcomes achieved by all three models will be conducted with a focus on defined KPIs. The findings of this comparative analysis are presented in Table 11, along with visual representations in Figure 9.

Table 11. Differences between KPIs.

KPI	Case Study	Locked in	New allocation method
Total tonnage hauled to dumpsite (Ore and Waste) (million tons)	16.803	17.613	18.195
Average waiting time per shovel (min)	3.08	2.73	1.94
Average cycle time (min)	40.33	23.45	22.54
Average fuel consumption per cycle (liter)	56.52	36.72	35.83
Average CO2 emission per cycle (Kg)	146.95	95.47	93.16

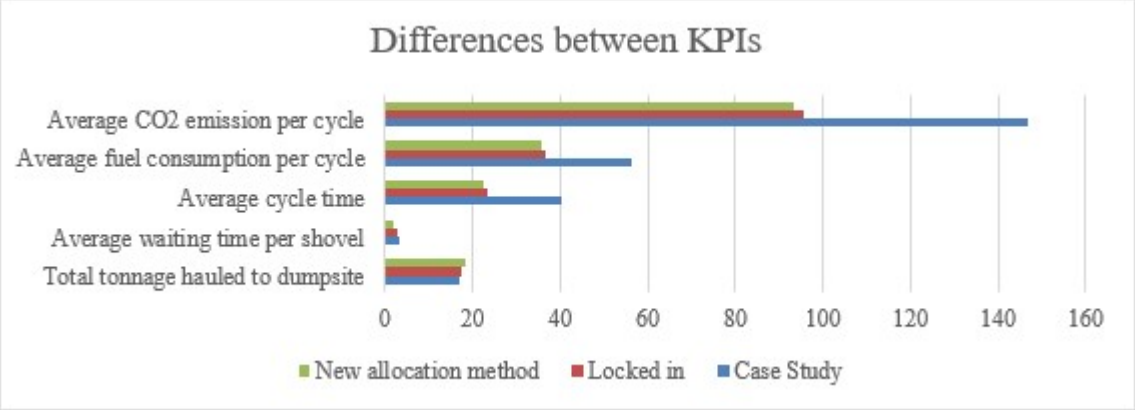

Figure 9. The comparison of KPIs.

By examining Figure 9, it becomes evident that the implementation of both the locked-in model and the new allocation method results in a notable increase in the total tonnage hauled. Specifically, an increase of 5% and 8% is observed respectively for each method, showcasing the significant efficiency improvements brought about by the new approach.

Moreover, it is evident that the locked-in and new allocation method models exhibit a reduction in the average waiting time per shovel by 11% and 37% respectively. Additionally, implementation of different allocation method leads to a significant decrease of 42% and 44%. These findings can be attributed to the adoption of optimal policies for truck allocation, resulting in minimized waiting and cycle times. These significant improvements in efficiency highlight the potential benefits associated with the utilization of advanced allocation strategies.

By analyzing Figure 9 and Table 11, it becomes evident that through fleet renewal and the optimal allocation of trucks, there is a notable average reduction of 36% in fuel consumption as well as carbon dioxide emissions. As a result, this issue demonstrates that fleet renewal has a substantial impact on both the economic and environmental aspects.

6. Sensitivity Analysis

In this section, set pf sensitivity analysis with changes in the parameters of maintenance policies, truck velocity, and changes in the age of trucks has been applied for further analysis of the framework performance. This analysis is done on the new allocation method by examining the objective functions and KPIs. The findings of the analysis are presented in Table 12. As mentioned, the scenarios are categorized into three areas, detailed as follows:

Maintenance:

- Improvement in maintenance policies, entailing a 5% reduction in failures.
- Improvement in maintenance policies, entailing a 10% reduction in failures.

Velocity:

- Increase in truck velocity by 5%.
- Increase in truck velocity by 10%.

Age:

- Depreciation of trucks over 5 years.
- Depreciation of trucks over 10 years.
- Renovation of trucks over 5 years.
- Renovation of trucks over 10 years.

Table 12. Results of sensitivity analysis.

Scenario	Objective 1						Objective 2		KPIs									
	Fix cost ($M)	COV	Loading costs ($M)	COV	Empty costs ($M)	COV	CO2 Emission (M Kg)	COV	Total tonnage hauled (million tons)	COV	Average waiting time (min)	COV	Average cycle time (min)	COV	Average fuel per cycle (liter)	COV	Average CO2 (Kg)	COV
New allocation method	18.1	-	2.643	-	2.316	-	43.396	-	18.195	-	1.94	-	22.54	-	35.83	-	93.16	-
Reduction in failure (5%)	18.1	1.00	2.871	1.09	2.516	1.09	44.791	1.03	19.765	1.09	1.67	0.86	20.59	0.91	36.94	1.03	95.94	1.03
Reduction in failure (10%)	18.1	1.00	2.938	1.11	2.547	1.10	46.686	1.08	21.119	1.16	1.12	0.58	19.36	0.86	38.69	1.08	100.61	1.08
Increase trucks velocity (5%)	18.1	1.00	2.739	1.04	2.409	1.04	46.234	1.07	21.834	1.20	1.90	0.98	19.51	0.87	38.05	1.06	99.87	1.07
Increase trucks velocity (10%)	18.1	1.00	2.995	1.13	2.618	1.13	50.396	1.16	23.504	1.29	1.89	0.97	17.93	0.80	41.48	1.16	108.86	1.17
Increase trucks age (5 years)	15.6	0.86	2.876	1.09	2.499	1.08	48.604	1.12	17.940	0.99	2.08	1.07	23.94	1.06	40.24	1.12	104.53	1.12
Increase trucks age (10 years)	12.8	0.71	3.145	1.19	2.745	1.19	52.510	1.21	16.557	0.91	2.25	1.16	26.37	1.17	43.00	1.20	112.72	1.21
Decrease trucks age (5 years)	20.7	1.14	2.352	0.89	2.108	0.91	39.491	0.91	18.198	1.00	1.86	0.96	22.31	0.99	32.61	0.91	84.78	0.91
Decrease trucks age (10 years)	23.5	1.30	2.061	0.78	1.853	0.80	34.717	0.80	18.326	1.01	1.78	0.92	21.93	0.97	28.66	0.80	74.53	0.80

After reviewing the results of the sensitivity analysis, we have identified the following findings:

- Fixed costs: The age of trucks has the most significant impact on the fixed costs of the project.
- Variable costs: Changes in the age of trucks have the greatest effect on variable costs. Additionally, truck velocity and improved maintenance policies have a similar impact on variable costs.
- The emissions: The age of trucks is the most influential factor in changes to the amount of carbon gas emission. Following this, changes in truck velocity have the most significant effect on pollution levels.
- Amount of hauled tonnage: Truck velocity is the most influential factor in this index, followed by the implementation of improved maintenance policies.
- Average waiting time: Improvement in maintenance policies is the most effective factor in reducing average waiting time.
- Average cycle time: Truck velocity is the main determinant of the cycle time.

6.1. Maintenance Improvement

Improving maintenance policies and reducing the duration of failure times does not affect fixed costs. However, reducing the duration of breakdowns increases the availability time of trucks, which impacts the number of trips they can make. This, in turn, directly increases the values of the objective functions. Generally, improvements in maintenance policies result in a 9 to 10% increase in transportation costs and around 3% to 8% increase in CO2 emissions. It is noteworthy that the increase in the objective function values is primarily due to the reduction in breakdown duration, leading to a potential 9-16% increase in the amount of tonnage hauled. Additionally, this policy improvement significantly affects time related KPIs such as average cycle time and waiting time. The implementation of this policy is expected to result in a 9-14% reduction in cycle time and a 14-42% reduction in expected time. The results of these analyzes are shown in Figure 10.

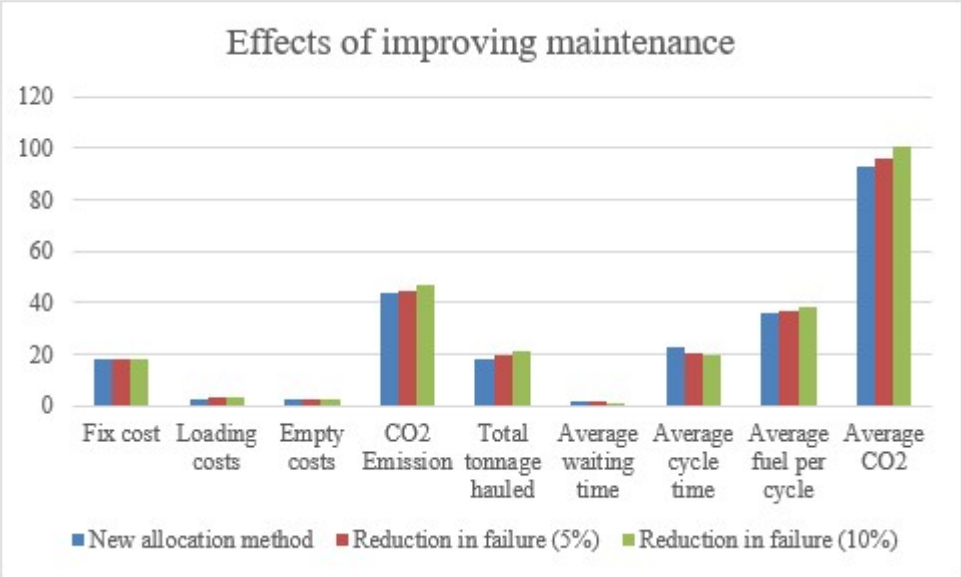

Figure 10. Effects of improving maintenance.

6.2. Increase Truck's Velocity

In this analysis, we examined the effect of increasing the velocity of trucks by 5 and 10 percent. As a result, we observed no change in fixed costs, but we did observe an increase of 4 and 13 percent in variable costs. Furthermore, there was an increase of 7 and 16 percent in carbon emissions. However, the increase in truck velocity had a positive impact on their performance. Specifically, the amount of tonnage carried increased by 20 and 29 percent, while the cycle time decreased by 13 to 20 percent. It is noteworthy that the increase in truck velocity did not have a significant effect on waiting time. In fact, the reduction in waiting time was only between 2 and 3 percent in this scenario. The graph illustrating these changes can be found in Figure 11.

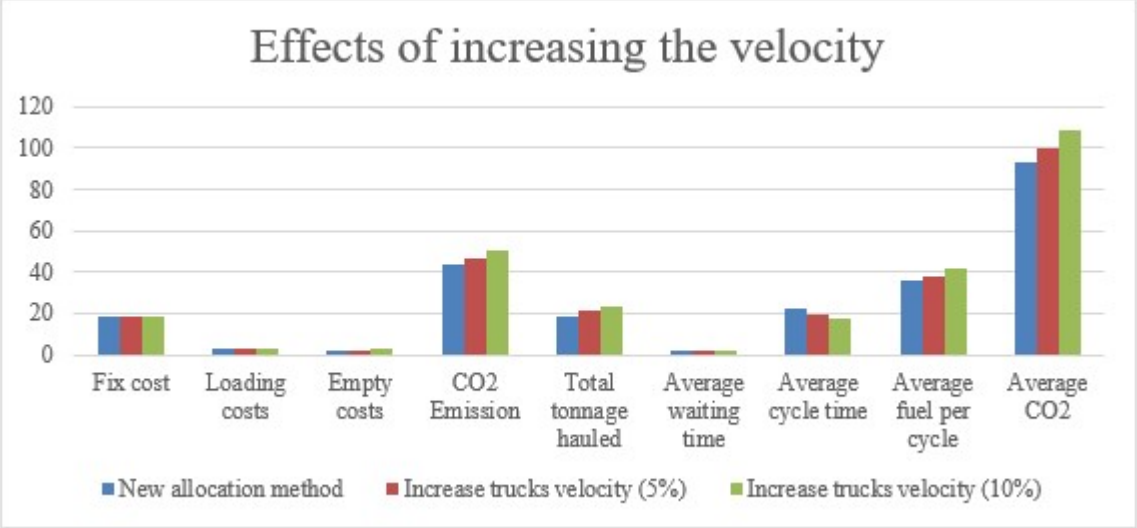

Figure 11. Effects of increasing velocity.

6.3. Changes in the Age of Transport Fleet

In this section, we aim to analyze the impact of truck renovation and depreciation on objective functions and key indicators for our research paper. During this analysis, we tested truck renewal and depreciation over periods ranging from 5 to 10 years. As the trucks' age increases, we observed a decrease in fixed costs, attributed to newer trucks having higher fixed costs initially. This decrease in fixed costs ranged between 14 and 29 percent as the trucks aged. Conversely, increasing the age of trucks led to an increase in variable costs, ranging between 9 and 19 percent. Furthermore, the aging of trucks had a significant impact on carbon emissions, showing an increase of between 12 and 21 percent. Apart from influencing objective function values, aging also negatively affected truck performance. For instance, the amount of tonnage moved decreased by 1 to 9 percent, while cycle time and waiting times increased by 6 to 17 percent.

Now, let us explore the scenario of reducing the age of trucks and considering their renovation. It is evident that truck renovation will result in increased fixed costs, ranging between 14 and 30 percent. However, due to the modernization of trucks and their improved performance, we observed a reduction in variable costs of 9 to 20 percent. Additionally, newer trucks exhibited a 9-20% decrease in carbon emissions. When it comes to measuring truck performance in terms of indicators, the age reduction did not significantly impact the amount of transported tonnage, resulting in a minimal 1% increase. Conversely, cycle time and waiting time experienced a reduction of 4 to 8 percent. These analyses are shown in Figure 12.

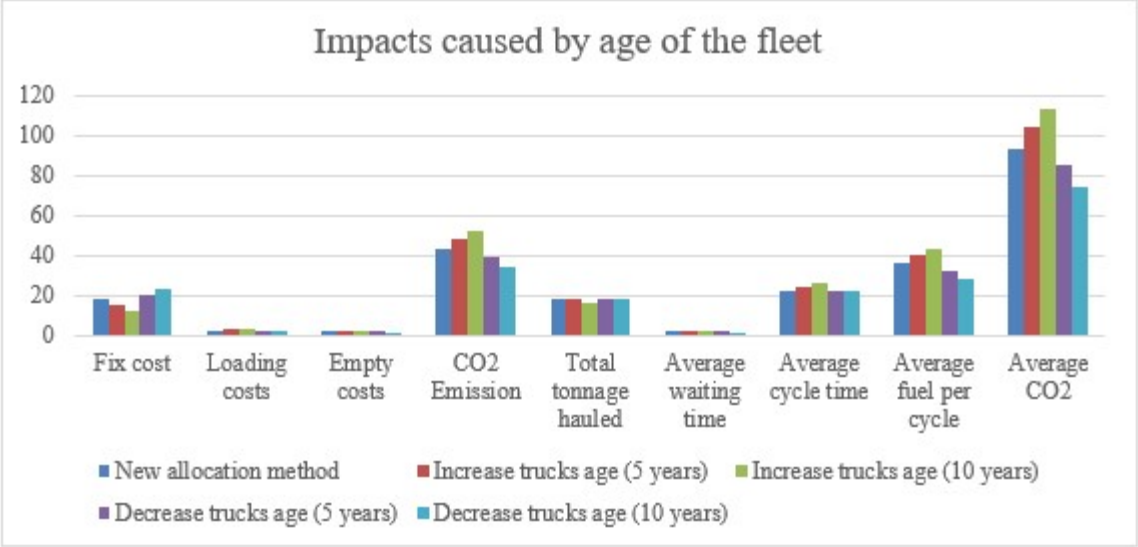

Figure 12. Impacts caused by age of the fleet

7. Conclusion

In this study, we introduced a comprehensive integrated stochastic discrete-continuous simulation-based optimization framework for GHG mitigation in open pit mines. Our framework not only addresses the economic imperative of minimizing transportation costs but also prioritizes environmental sustainability by concurrently reducing carbon dioxide emissions. Furthermore, our novel approach to allocating trucks to shovels stands out for its dual benefits, enhancing both economic efficiency and environmental performance.

The significance and distinction of present work is concurrent addressing of both strategic and tactical level mine planning with simultaneous consideration of economic, environmental, and operational advantages and disadvantages in one frame. Although the presented framework, as the scope mandated, targets the open pit mining operations, the analogy, both the simulation and optimization modeling approaches, and the main structure of the framework can be adapted or translated to other production environments.

In conclusion, the presented framework was effectively evaluated through a real currently in operation copper mine case study. The use of sensitivity analysis allowed for an examination of the influence of factors such as uncertainty in maintenance and repair, as well as downstream processes, on the legitimacy of the framework and accuracy of the performance indicators. Through this analysis, it was possible to identify significant parameters that impact economic productivity and environmental concerns, thus further enhancing the applicability and effectiveness of the framework. Based on our study, the remarkable findings of implementing our novel method for allocating trucks to shovels are as follows:

- Our proposed model led to a significant decrease in transportation costs compared to the existing situation and the use of old truck allocation policies. We observed an 83% reduction in variable costs and a 39% reduction in total costs. These results highlight the economic justification of implementing this model in the strategic planning of the mine.
- Aligned with the growing importance of sustainable development and environmental concerns, a primary accomplishment of our study was the prioritization of these matters. Through the utilization of our new allocation method, we were able to contribute to a 72%

reduction in carbon dioxide emissions. This reduction is crucial for addressing current environmental challenges.

- Our model also demonstrated satisfactory results in terms of time savings and productivity. Notably, we observed a 37% reduction in waiting time and a 44% decrease in the duration of cycle time. Additionally, the model displayed good efficiency, resulting in an approximately 8% increase in tonnage and material transfer. These findings are indicative of the effectiveness and efficiency of our proposed approach.
- Another significant finding of this research was the identification of factors influencing both environmental and economic concerns. Through sensitivity analysis and simulation tests, we discovered that the truck age parameter is the most influential factor in increasing transportation costs, pollution levels, and greenhouse gas emissions.

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Sustainable Open Pit Mining through GHG-Conscious Short-Term Production Scheduling[1]

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ABSTRACT

The mining industry is a notable contributor to global greenhouse gas (GHG) emissions, posing challenges to achieving the Paris Agreement's goal of capping emissions at 30 Gt CO_2-equivalent annually by 2030. This paper introduces a novel Mixed Integer Linear Programming (MILP) model tailored for short-term open-pit mine planning that integrates environmental considerations, particularly GHG emissions, alongside economic objectives. The model manages complex operational challenges including block sequencing, multiple transport destinations, and stockpile management. Additionally, it provides the opportunity to examine the adoption of In-Pit Crushing and Conveying (IPCC) systems as the main transport method, an innovative approach aimed at reducing emissions from haulage—which accounts for over 35% of GHG emissions in open-pit mining. Applied to a case study in an iron ore mine, the model not only considers the environmental benefits of IPCC systems compared to traditional truck and shovel (TS) operations but also highlights significant reductions in haulage costs and carbon tax liabilities. The findings demonstrate that fixed IPCC (FIPCC) systems, in particular, offer substantial decreases in GHG emissions, presenting a compelling case for their broader adoption in the industry.

1. Introduction

The mining sector is pivotal in the global transition to a low-carbon future. However, as a significant contributor to global GHG emissions, the industry faces the urgent need to reduce its environmental impact to effectively combat climate change. Industrial activities, being complex and integrated processes, require holistic approaches when introducing new methods and technologies. Identifying emission hotspots during operations is the first step towards devising actionable and sustainable practices, considering that about 35% of the scope 1 GHG emissions in open-pit mining are due to fuel consumed in hauling [1]. But this alone is not sufficient. It is

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equally essential to consider the economic impacts and the inherent trade-offs of the green solutions to facilitate informed decision-making through considerate strategic and operational planning. Furthermore, it is vital to determine the stages of planning where environmentally friendly solutions can be most effectively implemented. While environmentally considerate planning is gaining traction in the mining field, with some studies addressing long-term [2] and operational planning [3] aspects that incorporate sustainability, a notable gap remains in short-term planning. This paper seeks to address this gap by presenting an environmentally considerate approach specifically designed for short-term production scheduling, thereby contributing a novel perspective to the sustainable transformation of the industry. This paper's primary contribution lies in utilizing a developed mathematical model to assess the environmental and economic performance of novel solutions against traditional methods. Specifically, it evaluates short-term production plans that employ IPCC as the principal mode of material transportation versus TS.

As a response to the pressing demand for sustainable mining practices, mathematical models offer a framework for viewing the entire process in a comprehensive and efficient manner. The advent of mathematical programming has marked a significant milestone in mining, particularly with the application of integer programming and MILP models, enhancing the intricacies of mine production scheduling. The seminal work by Smith et al., which introduced integer programming to mining optimization, the field has seen significant advancements, leveraging both traditional and novel computational techniques to enhance operational efficiency and decision-making [4]. Kumral and Dowd's exploration of simulated annealing and Caccetta's discussion on the broad applications of optimization in mining indicate the versatility and critical importance of these techniques in tackling the sector's complexities, from ore-body modeling to equipment selection [5-6]. Rehman and Asad, and Li and Knights further contribute by introducing MILP models and integrating real options into mine planning, respectively, showcasing the potential of mathematical programming to navigate economic uncertainties and optimize production schedules [7-8]. Bley et al. fortified the formulations for mine production scheduling and Newman et al. providing a comprehensive review of operations research in mine planning, highlighting the sector's growing reliance on sophisticated analytical models to drive efficiency and profitability [9-10]. The innovation extends to methodologies for block aggregation by Tabesh and Askari-Nasab, and multi-destination routing optimization by Eivazy and Askari-Nasab, each contributing to the refinement of production scheduling and operational logistics within mining [11-12].

Despite these advancements, L'Heureux et al. point out the computational challenges inherent in large-scale applications, a sentiment echoed by others in the field seeking more scalable and efficient solutions [13]. Responding to this need, Kozan et al. and Lambert et al. introduce innovative scheduling methodologies and block-sequencing tutorials, respectively, pushing the envelope in mining optimization and planning [14-15]. Recent contributions by Mousavi et al., Blom et al., and Matamoros and Dimitrakopoulos showcase the diversification of optimization techniques in mining, from metaheuristic approaches for block sequencing to multi-objective algorithms for short-term scheduling, each aiming to maximize operational value while navigating the sector's uncertainties and constraints [16-18]. The adoption of portfolio optimization models and dynamic shovel allocation approaches by Osanloo and Rahmanpour, and Upadhyay and Askari-Nasab further illustrate the sector's movement towards integrating advanced optimization tools with detailed operational models to achieve strategic alignment and enhance mine productivity [19-22]. The culmination of these efforts is evident in the works of Otto and Lindeque, and Pathak and Samanta, who demonstrate the practical application and benefits of these advanced mathematical programming techniques in real-world mining operations, underscoring the critical role of integrated planning and optimization in driving the future of mining efficiency and sustainability [23-24]. In reviewing the emerging trajectory of mathematical modeling in mining as outlined by Blom et al., it is apparent that the emphasis has been on the economic aspects of the industry [17]. There has been less focus on utilizing it as a potent tool for investigating sustainable

practices. This study bridges this gap by introducing a novel Mixed Integer Linear Programming (MILP) model for GHG considerate short-term open-pit mine planning. The developed model transcends mere economic optimization by explicitly incorporating environmental considerations. This includes the impact of carbon taxes and the potential of In-Pit Crushing and Conveying (IPCC) systems on emissions reduction.

To showcase the effectiveness of the proposed mathematical model in identifying sustainable strategies, we validated the proposed model using a real mining case study that reflects an actual iron ore mining operation. Given that the model considers both the tonnage and distances for block extraction and transportation, the case study develops yearly plans for an open-pit mine to evaluate the effectiveness of both SMIPCC and FIPCC systems in comparison to conventional TS material handling systems, with an emphasis on economic feasibility and reduction of GHG emissions. This practice is supported by early studies such as the one by Mohammadi et al., which highlight the cost-effectiveness of IPCC systems, which can account for up to 50% of mining expenses [25]. These systems are praised for their energy efficiency and reduced operational costs, making them particularly beneficial for large-scale operations dealing with high fuel and labor costs. Environmental considerations, specifically GHG emissions, play a crucial role in the adoption of IPCC. Norgate and Haque's life cycle assessment indicates that IPCC systems can significantly lower GHG emissions compared to conventional TS systems [26]. This reduction is even more pronounced when electricity from cleaner sources replaces diesel fuel [26]. Nehring et al. further emphasize the environmental benefits of IPCC, including notable decreases in CO_2 emissions and dust and noise pollution, contributing to a more sustainable mining environment: operational efficiency is another critical aspect of IPCC systems [27]. Dzakpata et al. demonstrate that conveyors, a key component of IPCC, outperform TS in terms of efficiency, particularly in valuable operating time [28]. This efficiency translates into significant improvements in loading equipment productivity [28].

The strategic integration of IPCC systems into mining operations requires careful planning and consideration of several factors. Nehring et al. detail crucial prerequisites for the effective integration of IPCC systems, which encompass: (1) A desirable material movement exceeding 4 Mtpa to validate the initial CAPEX, with a preference for amounts exceeding 10 Mtpa. (2) A mine lifespan extending beyond 10 years to ensure the lower OPEX compensates for the elevated initial CAPEX. (3) Electricity expenses ($/kWh) that are less than a quarter of the diesel cost ($/L) [27]. These elements are instrumental in evaluating the feasibility of replacing traditional TS systems with IPCC systems. Recent studies have further explored the economic and operational implications of IPCC systems. Hay et al. provide a methodology for determining the ultimate pit limit when considering semi-mobile IPCC (SMIPCC) systems, showing that these systems can achieve higher net present value (NPV) despite smaller pit sizes due to reduced mining costs [29]. De Werk et al. conduct a cost analysis showing that despite higher initial investments, IPCC systems offer substantial operational cost savings in the long run, particularly as mine depths and haul distances increase [30]. The choice of an appropriate IPCC system—whether fixed, semi-mobile, or fully mobile—is critical and must be based on the unique operational and economic challenges of each mining project. Nasirinezhad et al. emphasize the need for a meticulous selection process to ensure that the chosen IPCC system aligns with the project's specific requirements and maximizes operational efficiency and sustainability [31]. In terms of energy consumption, Purhamadani et al. emphasize the significant energy savings achievable with IPCC systems, projecting considerable reductions in energy consumption and associated costs, thereby enhancing the overall mining economy [32]. Advancements in short-term mine planning have also been influenced by IPCC. The review by Al Habib et al. highlights significant advancements in integrating IPCC systems into short-term mine planning, emphasizing their potential for reducing operational costs and GHG emissions.

Despite these benefits, challenges such as high initial capital costs, the need for skilled labor, and reduced operational flexibility remain significant barriers. The imposition of carbon taxes enhances the economic attractiveness of IPCC systems due to their lower emissions. The review identifies a gap in short-term planning methodologies that integrate IPCC systems and proposes a theoretical framework to address this. The authors recommend expanding research on short-term IPCC planning models and developing strategies to overcome implementation challenges [33]. Al Habib et al. introduces a methodology focusing on shovel allocation that highlights the economic benefits of IPCC, particularly in terms of haulage cost savings. This approach highlights the operational cost advantages of IPCC over traditional TS systems [34]. The paper by Al Habib et al. proposes a mixed-integer programming model for short-term planning in open-pit mines using SMIPCC, demonstrating higher profits and lower operational costs compared to traditional truck-shovel systems through a case study [35]. Nehring et al. explore strategic planning approaches for both IPCC and traditional systems [36]. They demonstrate the environmental advantages of IPCC, including lower CO2 emissions, reduced dust, and noise pollution [36]. Their comparative analysis shows that IPCC systems can achieve higher net present value (NPV) despite smaller pit sizes due to reduced mining costs [36]. Shamsi and Nehring corroborate these findings, emphasizing the cost-effectiveness and energy efficiency of IPCC systems, especially for large-scale operations with high fuel and labor costs [37]. Wachira et al. investigate the productivity of SMIPCC systems using the mine productivity index (MPi), finding that scenarios with more loading equipment have higher productivity compared to traditional truck-shovel systems [38]. Their study suggests that SMIPCC systems can significantly reduce operational costs by minimizing the use of trucks [38]. Nunes et al. provide a decision-making method to assess the benefits of SMIPCC early in mining projects [39]. They highlight that while the initial capital expenditure (CAPEX) for IPCC is higher, the operational expenditure (OPEX) is lower, resulting in overall cost savings and environmental benefits over the life of the mine [39]. Hay et al. focus on the ultimate pit limit determination for SMIPCC systems, demonstrating that these systems can optimize pit designs by reducing haul distances and lowering overall costs [40]. Similarly, Liu et al. introduce a framework for production scheduling in open-pit mines using SMIPCC, emphasizing the need for models that integrate economic, technical, and environmental factors to optimize short-term planning [41]. Further comparison by Bernardi et al. between fixed and mobile IPCC systems with truck-shovel systems reveals that IPCC systems offer greater operational savings due to more efficient energy use and lower labor requirements [42]. Osanloo and Paricheh discusses the application and benefits of IPCC technology in open-pit mining operations, noting significant improvements in cost efficiency and environmental impact [43]. Collectively, these studies highlight the substantial economic and environmental benefits of IPCC systems, while also highlighting the need for further research to develop robust short-term planning models that effectively integrate these systems. Addressing challenges such as high initial costs, operational flexibility, and the need for skilled labor will be crucial for the broader adoption of IPCC in the mining industry.

It is important to highlight that the study of GHG emissions in mining operations is dependent on thorough data gathering and examination. Carvalho et al. highlight the significance of precise CO_2 measurements from mining trucks de [44]. This is further supported by the frameworks developed by Jiskani et al. and Katta et al. for GHG emission calculation and quantification, integrating factors like fuel consumption, energy use, and material handling, and assessing reduction potentials and costs across sectors [45-46]. Additionally, Kecojevic and Komljenovic provide a model for determining fuel consumption and CO_2 emissions under varying conditions, offering insights into the economic impacts of CO_2 legislation [47]. This case study thus presents a comparative analysis based on this scholarly research and expert insights, underscoring the essential need for accurate data when investigating complex issues within the mining industry.

This study introduces a holistic approach to short-term strategic production planning in open-pit mines, prioritizing both economic efficiency and environmental preservation. We enhance an

economic-focused Mixed Integer Linear Programming (MILP) model by integrating the impacts of carbon taxes on mining operations, reflecting the global trend towards eco-friendly mining practices. Utilizing a case study that mirrors a real-world operation, this paper demonstrates the efficacy of the proposed MILP model in formulating production plans that not only ensure economic profitability but also significantly reduce emissions. This dual achievement emphasizes the model's potential as a pivotal tool in the sustainable transformation of the mining industry.

This paper is organized into four sections. Section 2 elaborates on the MILP formulation employed in the study. Section 3 provides a description of the case study, encompassing the basis of the data and context, the approach to the solution, the main findings, and the discussion of the results. Section 4 concludes by summarizing the key findings, contributions, and recommendations for future research.

2. Methodological Framework

The primary challenge addressed in this study is to develop and apply a MILP model for optimizing short-term production scheduling in open-pit mines. Therefore, a comprehensive MILP model was formulated. Employing binary and continuous decision variables, the formulation precisely determines block sequencing, material flows, and resource allocation across processes and destinations. Rigorous constraints enforce precedence relationships, capacities, grade requirements, and stockpile balancing. This robust mathematical framework enables optimized scheduling for operational efficiency and profitability.

In the block sequencing approach, the utilization of side-cut and drop-cut methods during the extraction process from blocks has been considered. For the side-cut method, each block within a bench can be extracted if its adjacent side includes three adjacent blocks in the same direction that have been completely mined beforehand. The drop-cut extraction method is authorized once all nine blocks directly above the target block have been fully extracted. In this overall mining strategy, the drop-cut scenario has been activated along with just two perpendicular side-cut methods (north and east directions). To improve the efficiency of optimization, the mathematical framework of block sequencing that has been proposed to date has been fine-tuned.

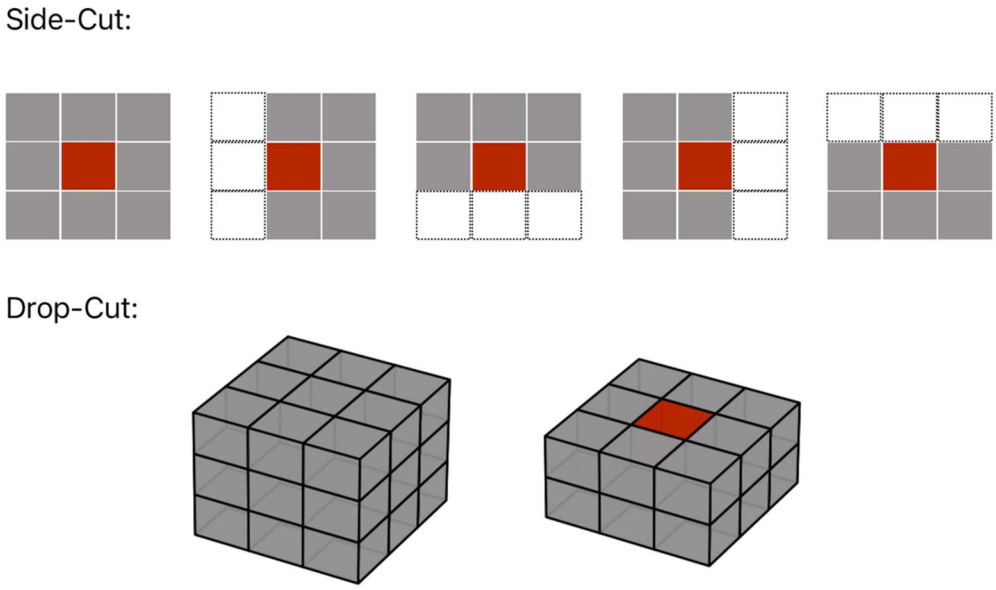

Figure 1. Side-Cut and Drop-Cut Mining Techniques.

2.1. Indices

t Time period (t = 1, 2, . . ., K)

e Element e (e = 1, 2, . . ., E)

p Process p (p = 1, 2, . . ., P)

s Stockpile s (s = 1, 2, . . ., S)

w Waste dump w (w = 1, 2, . . ., W)

r Ramps r (r = 1, 2, . . ., R)

2.2. Parameters

J(n)	Set of blocks that must be extracted during the short-term time horizon (set in long-term planning)
N	Number of blocks in J(n)
ME^t	Minimum fraction of each block that could be extracted in period t
O_n	Tonnage of mineralized zone in block n
R_n	Rock tonnage of block n
$g\,{}^{n}_{e}$	Grade of element e in block n
WPB(n)	Set of blocks that are directly above and adjacent to the west side of block n
SPB(n)	Set of blocks that are directly above and adjacent to the south side of block n
VPB(n)	Set of vertical precedent blocks for block n
$N_{WPB}(n)$	Number of blocks in the set W P B(n)
$N_{SPB}(n)$	Number of blocks in the set SP B(n)
$N_{VPB}(n)$	Number of blocks in the set V P B(n)
R(n)	Set of corresponding ramps to haul extracted materials of block n
P(n)	Set of processes that can receive ore from block n
SP(n)	Set of stockpiles that can receive ore from block n
W(n)	Set of waste dumps that can receive waste material from block n
MC^t	Unit mining cost in period t
$WC\,{}^{t}_{w}$	Unit waste rehabilitation cost in period t for waste dump w
$PR\,{}^{t}_{p}$	Unit processing revenue in period t for process p
$PC\,{}^{t}_{p}$	Unit processing cost in period t for process p (includes both the unit cost of processing by process p and the unit cost of transport of ore to process p)
$RH\,{}^{t,p}_{s}$	Unit re-handling cost for stockpile s sending ore to process p in period t (includes the unit cost of transporting ore from stockpile s to process p)
H^t	Unit haulage cost in period t (includes the unit cost of haulage of material inside the pit to the pit exit)

MU^t	Maximum acceptable tonnage that could be mined based on maximum available mining capacity in period t
ML^t	Minimum acceptable tonnage that could be mined based on minimum available mining capacity in period t
PU_p^t	Maximum acceptable ore tonnage that process p can process based on maximum process p capacity in period t
PL_p^t	Process p minimum ore acceptable tonnage in period t
$gu_p^{t,e}$	Upper bound on acceptable grade of element e for process p in period t
$gl_p^{t,e}$	Lower bound on acceptable grade of element e for process p in period t
$OGSP_s^e$	Grade of element e in the ore which is sent from the stockpile s to processes
$UGSP_s^e$	Upper bound of grade of element e in the stockpile s
$LGSP_s^e$	Lower bound of grade of element e in the stockpile s
CSPs	Maximum storage capacity of stockpile s
IMC_s^e	Initial metal content of element e in stockpile s
dE_n^r	Distance of block n to the exit of the pit
P[SP(s)]	Set of processes that can receive ore from stockpile s (destination of stockpile s)
SP[P(p)]	Set of stockpiles that can send ore to process P (source of process p)

2.3. Variables

u_n^t	Fraction of block n extracted in period t (where n ∈ J(n))
$uw_n^{t,w}$	Fraction of block n extracted in period t and sent to waste dump w (where w ∈ W (n))
$us_n^{t,s}$	Fraction of block n extracted in period t and sent to stockpile s (where s ∈ SP (n))
$up_n^{t,p}$	Fraction of block n extracted in period t and sent to process p (where p ∈ P (n))
x_n^t	Binary variable, if block n is extracted in period t it gets a value of one, otherwise zero
$b_n^{t,r}$	Binary variable, if ramp r is selected for haulage of extracted material from block n in period t, it gets value of one, otherwise zero
$y_s^{t,p}$	Ore tonnage sent from stockpile s to process p in period t (where s ∈ SP |P (p) is the set of stockpiles that send ore to process p)
I_s^t	Inventory of stockpiles at the end of period t

2.4. Objective function

Maximizing Profit in Ore Processing Operations To maximize profit in ore processing operations, the objective function calculates the total revenue generated from processing ore minus the total costs incurred over the planning horizon. The profit maximization problem can be defined as follows:

$$\text{Maximize Profit} = \text{Total Revenue} - \text{Total Costs}$$

where:

- **Total Revenue** is calculated based on the price per tonne of the product processed and the total tonnes processed.
- **Total Costs** include all operational costs associated with mining, processing, waste management, rehandling, and haulage.

The components of Total Revenue and Total Costs are detailed below:

Total Revenue from processed ore is given by the equation (1):

$$\text{Total Revenue} = \underbrace{\sum_{t=1}^{K}\sum_{n=1}^{N}\sum_{p\in P(n)} u_n^{t,p} \times R_n \times PR_p^t + \sum_{t=1}^{K}\sum_{s=1}^{S}\sum_{p\in P(SP(s))} y_s^{t,p} \times PR_p^t}_{\text{Total Revenue from processed ore}} \quad (1)$$

Total Costs encompass various operational expenses and are defined by equation (2):

$$\begin{aligned}\text{Total Costs} = {} & \underbrace{\sum_{t=1}^{K}\sum_{n=1}^{N} R_n \times u_n^t \times MC^t}_{\text{total mining cost}} + \underbrace{\sum_{t=1}^{K}\sum_{n=1}^{N}\sum_{p\in P(n)} u_n^{t,p} \times R_n \times PC_p^t}_{\text{total processing cost}} + \\ & \underbrace{\sum_{t=1}^{K}\sum_{n=1}^{N}\sum_{w\in W(n)} u_n^{t,w} \times R_n \times WC_w^t}_{\text{total waste cost}} + \underbrace{\sum_{t=1}^{K}\sum_{s=1}^{S}\sum_{p\in P(SP(s))} y_s^{t,p} \times RH_{s,p}^t}_{\text{total haulage cost}} + \\ & \underbrace{\sum_{t=1}^{K}\sum_{n=1}^{N}\sum_{r\in R(n)} b_n^{t,r} \times dE_n^r \times H^t}_{total\ haulage\ cost}\end{aligned} \quad (2)$$

When considering the implementation of IPCC instead of the traditional TS system, we use the cost factors detailed in Table 4. This table provides a comparison of the unit costs for various stages of mining operations under both IPCC and TS systems, highlighting the potential cost savings and efficiency improvements with IPCC.

2.5. Constraints

Constraint (3) ensures that all blocks within the mine are mined exactly once during the planning horizon, preserving the unique mining event for each block:

$$\sum_{t=1}^{K} u_n^t = 1, \forall n = 1, \dots, N \quad (3)$$

Constraint (4) guarantees that each block n is allocated to only one destination per time period t, whether it is for processing, stockpiling, or waste:

$$\sum_{p\in P(n)} u_n^{t,p} + \sum_{s\in SP(n)} u_n^{t,s} + \sum_{w\in W(n)} u_n^{t,w} = u_n^t, \forall n = 1, \dots, N, \forall t = 1, \dots, K \quad (4)$$

Constraint (5) asserts that the total amount of ore directed from block n over all periods should equal the ore content available in block n, ensuring full extraction:

$$R_n \times \sum_{t=1}^{K} \left(\sum_{p \in P(n)} u_n^{t,p} + \sum_{s \in SP(n)} u_n^{t,s} \right) = O_n, \forall n = 1, \dots, N \quad (5)$$

Constraint (6) connects the act of mining to the decision process, requiring that a block can only be mined if the decision to mine it has been made:

$$u_n^t \leq b_n^t, \forall n = 1, \dots, N, \forall t = 1, \dots, K \quad (6)$$

Constraint (7) establishes that mining can only take place if the amount extracted meets or exceeds a predefined minimum threshold, promoting efficient use of resources:

$$ME_t \times b_n^t \leq u_n^t, \forall n = 1, \dots, N, \forall t = 1, \dots, K \quad (7)$$

Constraint (8) controls the total amount of ore mined in each period, ensuring it stays within the operational limits set for the mining project:

$$ML^t \leq \sum_{n=1}^{N} R_n \times u_n^t \leq MU^t, \forall t = 1, \dots, K \quad (8)$$

Constraint (9) stipulates that the tonnage targets for all processing plants are met each period, adhering to the upper and lower bounds of their requirements:

$$PL_p^t \leq \sum_{n \in P(n)} R_n \times u_n^{t,p} + \sum_{s \in SP|P(p)} y_s^{t,p} \leq PU_p^t, \forall t = 1, \dots, K, \forall p = 1, \dots, P \quad (9)$$

Constraints (10) to (13) enforce the precedence relationships between blocks, ensuring that mining operations adhere to a logical and safe sequence. This includes the conditions under which mining can proceed based on the status of adjacent blocks and encompasses several specific cases:

Constraint (10) ensures that a block can only be mined if all blocks that are above and adjacent to its west side have been mined, reflecting the activated drop-cut scenario:

$$N_{WPB(n)} \times b_n^t - (1 - y_1^t) \leq \sum_{\tau=1}^{t} \sum_{i \in WPB(n)} u_i^\tau, \forall n = 1, \dots, N, \forall t = 1, \dots, K \quad (10)$$

Constraint (11) dictates that a block can only be mined if all blocks that are above and adjacent to its south side have been mined, representing one of the perpendicular side-cut methods:

$$N_{SPB(n)} \times b_n^t - (1 - y_2^t) \leq \sum_{\tau=1}^{t} \sum_{i \in SPB(n)} u_i^\tau, \forall n = 1, \dots, N, \forall t = 1, \dots, K \quad (11)$$

Constraint (12) states that a block can only be mined if all blocks that are directly above it have been mined, ensuring vertical precedence is maintained:

$$N_{VPB(n)} \times b_n^t - (1 - y_3^t) \leq \sum_{\tau=1}^{t} \sum_{\mathrm{i} \in \mathrm{VPB(n)}} u_i^\tau, \forall n = 1, \dots, N, \forall t = 1, \dots, K \quad (12)$$

This overarching constraint (13) combines the conditions for all three scenarios, affirming that a block's mining is contingent on the completion of mining in all relevant preceding blocks:

$$b_n^t \leq y_1^t + y_2^t + y_3^t \tag{13}$$

Constraint (14) dynamically calculates the grade of stockpiles after changes in their composition, ensuring the material quality stays within specified bounds:

$$gl_{t,p}^e \leq \frac{\sum_{s\in SP|P(p)} y_s^{t,p} \times OGSP_s^e + \sum_{n\in P(n)} u_n^{t,p} \times R_n \times g_n^e}{\sum_{s\in SP|P(p)} y_s^{t,p} + \sum_{n\in P(n)} u_n^{t,p} \times R_n} \leq gu_{t,p}^e, \quad \forall t = 1,\dots,K, \forall p = 1,\dots,P, \forall e = 1,\dots,E \tag{14}$$

Constraint (15) balances the flow of materials, ensuring that the amount reclaimed from a stockpile during a period does not exceed the stockpile's inventory at the end of the previous period:

$$\sum_{n\in SE(SP(n))} R_n \times u_n^{t,s} - \sum_{p\in SP|S(s)} y_s^{t,p} + I_s^{t-1} = I_s^t, \forall t = 1,\dots,K, \forall s = 1,\dots,S \tag{15}$$

Constraint (16) ensures that the reclaimed material from a stockpile does not exceed the accumulated inventory up to that point, effectively managing the stockpile levels:

$$\sum_{p\in SP|S(s)} y_s^{t,p} \leq I_s^{t-1}, \forall t = 1,\dots,K, \forall s = 1,\dots,S \tag{16}$$

Constraint (17) controls the average grade of elements in the material sent to stockpiles, keeping it within acceptable limits to ensure quality control:

$$LGSP_s^e \leq \frac{\sum_{n\in SE(SP(n))} u_n^{t,s} \times R_n \times g_n^e}{\sum_{n\in SE(SP(n))} u_n^{t,s} \times R_n} \leq UGSP_s^e, \forall t = 1,\dots,K, \forall s = 1,\dots,S, \forall e = 1,\dots,E \tag{17}$$

Constraints (18) and (19) manage the flow of materials from stockpiles, ensuring the reclaimed material maintains the required grade for processing.

$$\sum_{p\in SP|S(s)} y_s^{t,p} \leq \frac{N_{e,s}^{t-1} - LGSP_s^e \times I_s^{t-1}}{OGSP_s^e - LGSP_s^e}, \forall t = 1,\dots,K, \forall s = 1,\dots,S, \forall e = 1,\dots,E \tag{18}$$

$$\sum_{\mathrm{p}\in \mathrm{P[SP(s)]}} y_{\mathrm{s}}^{\mathrm{t,p}} \leq \frac{-N_{\mathrm{s}}^{\mathrm{e,t-1}} + UGSP_{\mathrm{s}}^{\mathrm{e}} \times I_{\mathrm{s}}^{\mathrm{t-1}}}{-OGSP_{\mathrm{s}}^{\mathrm{e}} + UGSP_{\mathrm{s}}^{\mathrm{e}}}, \forall t = 1,\dots,K, \forall s = 1,\dots,S, \forall e = 1,\dots,E \tag{19}$$

N_s^e represents the metal content of element e in stockpile s at the end of period t − 1, which is calculated by the equation (20):

$$N_{\mathrm{s}}^{\mathrm{e,t-1}} = \sum_{\tau=1}^{t-1} \sum_{\forall \mathrm{n:s}\in \mathrm{SP(n)}} un_{\mathrm{n}}^{\tau,s} \times R_{\mathrm{n}} \times g_{\mathrm{n}}^{\mathrm{e}} + IMC_{\mathrm{s}}^{\mathrm{e}} - \sum_{\tau=1}^{t-1} \sum_{\mathrm{p}\in \mathrm{P[SP(s)]}} y_{\mathrm{s}}^{\tau,\mathrm{p}} \times OGSP_{\mathrm{s}}^{\mathrm{e}}, \quad \forall e = 1,\dots,E, \forall t = 1,\dots,K, \forall s = 1,\dots,S \tag{20}$$

Constraint (21) determines that each block can only be assigned to one of the available ramps for hauling per period, ensuring exclusive routing for the material:

$$\sum_{r\in R(n)} x_n^{t,r} = R_n \times u_n^t, \forall n = 1,\dots,N, \forall t = 1,\dots,K \tag{21}$$

Constraint (22) ensures that the total material hauled for a block in any given period must match the total material that has been extracted from that block:

$$x_n^{t,r} \le M \times b_n^{t,r}, \forall n = 1,\dots,N, \forall t = 1,\dots,K, \forall r = 1,\dots,R(n) \text{ (} M \text{ is a large number)} \tag{22}$$

Constraint (23) asserts that the binary decision for hauling material from each block is consistent across the periods and ramps:

$$\sum_{r\in R(n)} b_n^{t,r} = b_n^t, \forall n = 1,\dots,N, \forall t = 1,\dots,K \tag{23}$$

Constraints (24) to (29) are domain constraints that set feasible operational ranges for the utilization of blocks, stockpiles, and ramps, ensuring that all variables stay within bounds that reflect realistic mining operations:

$$0 \le u_n^t \le 1, \forall n = 1,\dots,N, \forall t = 1,\dots,K \tag{24}$$

$$0 \le u_n^{t,w} \le 1, \forall n = 1,\dots,N, \forall t = 1,\dots,K, \forall w \in W(n) \tag{25}$$

$$0 \le u_n^{t,p} \le 1, \forall n = 1,\dots,N, \forall t = 1,\dots,K, \forall p \in P(n) \tag{26}$$

$$0 \le u_n^{t,s} \le 1, \forall n = 1,\dots,N, \forall t = 1,\dots,K, \forall s \in SP(n) \tag{27}$$

$$0 \le x_n^{t,r} \le 1, \forall n = 1,\dots,N, \forall t = 1,\dots,K, \forall r \in R(n) \tag{28}$$

$$0 \le y_s^{t,p} \le 1, \forall t = 1,\dots,K, \forall s = 1,\dots,S, \forall p \in SP \mid S(s) \tag{29}$$

Constraint (30) maintains that the inventory of any stockpile cannot exceed its maximum capacity, avoiding overstocking and potential operational inefficiencies:

$$I_s^t \leq CSP_s, \forall t = 1, \dots, K, \forall s = 1, \dots, S \tag{30}$$

Constraint (31) imposes binary conditions on decision variables for block mining and ramp selection, restricting them to be either 0 or 1. This binary nature enforces clear decisions on whether a block is mined or a ramp is used in each period:

$$b_n^t, b_n^{t,r} \in \{0,1\}, \forall n = 1, \dots, N, \forall t = 1, \dots, K, \forall r \in R(n) \tag{31}$$

This MILP model optimizes short-term open pit production schedules through a comprehensive set of decision variables and constraints. Binary variables determine block extraction sequencing and ramp allocations, while continuous variables track material flows to processing plants, stockpiles, and waste dumps. Key constraints ensure precedence relationships are respected, mining and processing capacities are met, stockpile inventories are balanced, and transportation distances are minimized.

3. Case Study

The open-pit mine under consideration comprises 200 mining cuts with varying tonnages, iron grades, and rock types, which need to be extracted and allocated to various destinations. These destinations include two mineral processing plants with capacity limits and grade requirements, two stockpiles for temporary storage and blending, and two waste dumps. The model accounts for routing distances connecting blocks to destinations and incorporates a carbon tax imposed at a fixed rate per tonne of CO_2 emitted based on estimated GHG emissions from mining equipment and activities.

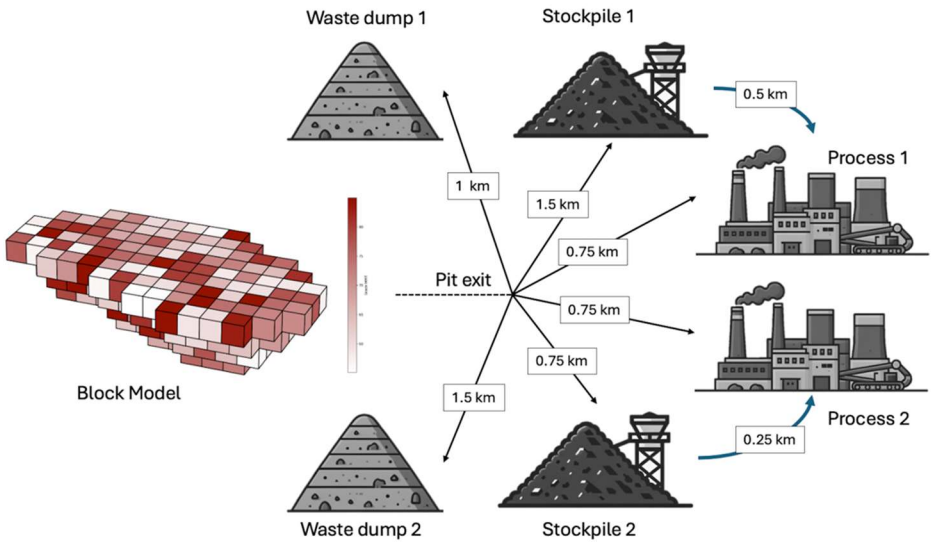

Figure 2. Open Pit Mine Schematic.

A schematic layout of an open-pit mining operation (as depicted in Figure 2) showcases the various components critical to mining logistics and planning. In the center is the block model that represents the mine itself, with pathways leading to different operational sites. On either side, there are two waste dumps where overburden and waste material are stored. Near the mine there are two stockpiles that serve as temporary storage for ore. The two processing plants, labeled Process 1 and Process 2, are where the ore is treated and processed.

3.1. Assumptions and Limitations

The study makes several key assumptions regarding the input data and estimation of GHG emissions. The input data, such as mining cuts and production targets, are derived from long-term planning models. It assumes consistent operational practices and conditions across all mining activities. Additionally, the accuracy of GHG emission estimates relies on available data related to fuel consumption, energy use, and material handling, as well as insights from industry experts. However, there are limitations to consider. The synthetic data was created to resemble the real case to verify the model's functionality. However, without access to actual data, scalability remains a limitation of this research. Actual GHG emissions can vary significantly based on operational practices, site-specific conditions, and equipment efficiency, which may not be fully captured by the assumptions used. The findings are constrained by the availability and accuracy of data on fuel consumption, energy use, and emissions. Inaccuracies or gaps in this data can affect the reliability of the emission estimates. The study focuses on open-pit mining activities and may not be directly applicable to other types of mining operations, such as underground mining, which have different emission profiles and operational characteristics. Economic factors such as fluctuations in energy prices, changes in carbon tax policies, or variations in operational costs are not accounted for, which could impact the economic feasibility of the proposed strategies over time. Additionally, advances in mining technology and equipment efficiency could alter the emission factors used in the study, potentially affecting the relevance of the findings in future scenarios. Furthermore, GHG emissions related to mining activities can be influenced by factors like equipment maintenance, operational downtime, and changes in mining intensity, which may not be fully considered. These assumptions and limitations highlight the need for careful consideration of operational practices, data accuracy, and the specific context of each mining operation when applying the study's findings to real-world scenarios.

3.2. Data Foundation and Context

To enable an exhaustive juxtaposition between IPCC systems and conventional TS systems, a synthetic data set was meticulously assembled. This data set serves as a robust and credible foundation for the rigorous analytical examination.

Figure 2 shows the possible destinations for extracted material, detailing distances and pathways involved. By visually representing these elements, the figure helps understand the scale of distances and different destinations when using IPCC instead of TS systems. The heart of this data set is a theoretical geological block model, made up of 200 blocks cuts. This carefully crafted model outlines the spatial arrangement of these blocks, offering detailed insights into different rock types, grades (like phosphor, sulfur, and iron), and the dimensions and capacity of every single block. Through the synthesis of this data set, the goal is to accurately simulate operational situations, thereby facilitating a thorough investigation of the relative strengths and weaknesses of each transportation approach.

Table 1 presents an overview of the general characteristics of the block model, while Figure 1 offers a visual perspective of the block model as described in the study.

Table 2 presents the specifications of two processes, including the lower and upper grade percentages of the input, as well as the range of capacity for each process, which is measured in millions of tons.

Table 1. General information about the problem.

	Bench No.			
	0	1	2	3
Number of Cuts	93	61	34	12
Ramps no.	1, 2	3, 4	5, 6	7, 8
Number of periods/months	12			
Total number of Cuts	200			
Total rock tonnage/ x 106 t	94.7			

Table 2. Processes' main features.

Process	Grade %		Capacity / x 106 t
	Lower	Upper	Min. – Max.
Process 1	70	85	1 - 2
Process 2	70	85	1 – 1.75

Table 3 provides an overview of the key characteristics of two stocks. It presents information on the acceptable input percentages for lower and upper grades, as well as the output grade percentage.

Table 3. Stockpiles' main features.

Stockpile	Lower grade/%			Upper grade/%			Output grade/%		
	MWT	S	P	MWT	S	P	MWT	S	P
Stockpile 1	55	0	0	65	8	7	60	4	3.5
Stockpile 2	65	0	0	78	8	7		4	3.5

Table 4 presents the unit cost breakdown by mining operation stage and revenue per processed ore for three mining methods - TS, FIPCC, and SMIPCC. The cost components include processing (PC), stockpile to plant haulage (RHI), waste rock handling (WR), mining (MC), haulage per tonne-meter (H), crusher costs (CR) and the revenue per processed ore (PR)

Table 4. Unit Cost Breakdown by Mining Operation Stage and Revenue from Processed Ore [12, 39].

Method	PC ($/t)		RHI ($/t)		WR ($/t)		MC ($/t)	H ($/t-m)	CR ($/t)	PR ($/t)
	P1	P2	SP1 to P1	SP2 to P2	W1	W2				
TS	4	5	0.5	0.25	1.75	1.5	1	1.00×10^{-3}		130
FIPCC								6.50×10^{-4}	2.80×10^{-2}	
SMIPCC								6.90×10^{-4}	4.03×10^{-2}	

Mining operations require a significant amount of energy to power the equipment used in mining. The primary sources of energy for mining operations are typically diesel fuel, electricity, and natural gas, all of which produce GHG emissions. The amount of GHG emissions associated with energy consumption in mining operations can vary widely depending on the type of energy source used and the efficiency of the equipment.

Within the scope of this study on open-pit mining activities, we have made specific assumptions about the machinery used to estimate GHG emission factors. These assumptions include the use of the Caterpillar 793 E truck (rated payload capacity: 218 tonnes) for haulage (with average speed of 40 kph), the 6090 FS Hydraulic Shovel (bucket capacity: 42.6 cubic meters) for mining operations, the MD6290 Rotary Drill for drilling, and standard industrial explosives for blasting. These specific models are chosen to provide a standardized basis for emission estimation, although we acknowledge that actual emissions can vary based on operational practices and site-specific conditions.

Following these assumptions, in Table 5, we present the GHG Emission Factors for each aspect of open-pit mining. This includes emissions from mining, haulage, ancillary and processing which are significant sources in mining operations.

Table 5. GHG Emission Factors for Open Pit Mining Activities [47, 48].

Activity	CO_2-eq (kg)	Unit
Mining	5.37×10^{-1}	per tonne
Processing	6.90×10^{-1}	per tonne
Ancillary Operations	6.86×10^{-2}	per tonne
TS	2.23×10^{-1}	per tonne-m
Crusher	1.61×10^{2}	per hour
Conveyor	1.61×10^{-1}	per hour-m

It must be noted that the calculation of the GHG emissions is assumed as a post-process and is done with the help of the data provided in Table 5 and the results of the model after optimization. As a result, by having the total amount of GHG emissions produced and the carbon tax penalty ($ per tonne of CO_2-equivalent), the carbon tax penalty can be calculated.

3.3. Solution approach

In the field of optimization, particularly in complex domains like mining, the choice of a solver—a software or algorithm designed to find solutions to mathematical problems—is critical. Solvers are valuable for their ability to navigate large solution spaces and avoid entrapment in local optima. They vary in approach and complexity, ranging from exact algorithms for Linear Programming (LP) to heuristic and metaheuristic methods for more intricate problems.

In this research, we utilized the Gurobi Optimizer (version 10.0.1), renowned for its efficiency in handling large-scale MILP problems. Gurobi was selected due to its robustness and advanced capabilities in dealing with the multifaceted requirements of the proposed mining model. The developed model, executed on a system with an Apple M2 CPU (eight physical cores and eight logical processors), with 24GB of RAM, took nine hours to achieve the optimized results.

3.4. Results and Discussion

3.4.1. Model Validation

Figure 3 showcases a range of extraction and dispatch trends. The cumulative extraction tonnage, illustrated by the dotted line, displays a consistently upward trend indicative of a progressive increase in material extraction over time. This trend validates the model's capability to simulate continuous mining operations over the project's lifespan. The total block tonnage, represented by a solid horizontal line, serves as a reference for the total available material, demonstrating the model's static resource estimation component. The steadiness of the total waste and mineral tonnage lines suggests that the model appropriately accounts for the conservation of mass in the system.

Figure 4 presents the results of the model's optimization. This stacked bar chart conveys the monthly planned output for various materials, categorized as products P1 and P2, stockpiles SP1 and SP2, and waste W1 and W2. The color-coded segmentation indicates the model's ability to differentiate and allocate tonnage to various operational categories. The pattern across the months reflects the model's scheduling functionality, highlighting the balance between ore extraction and waste management. The clear distinction between different material types over time indicates the model's sophisticated handling of multiple product streams and its ability to forecast the temporal distribution of mining outputs.

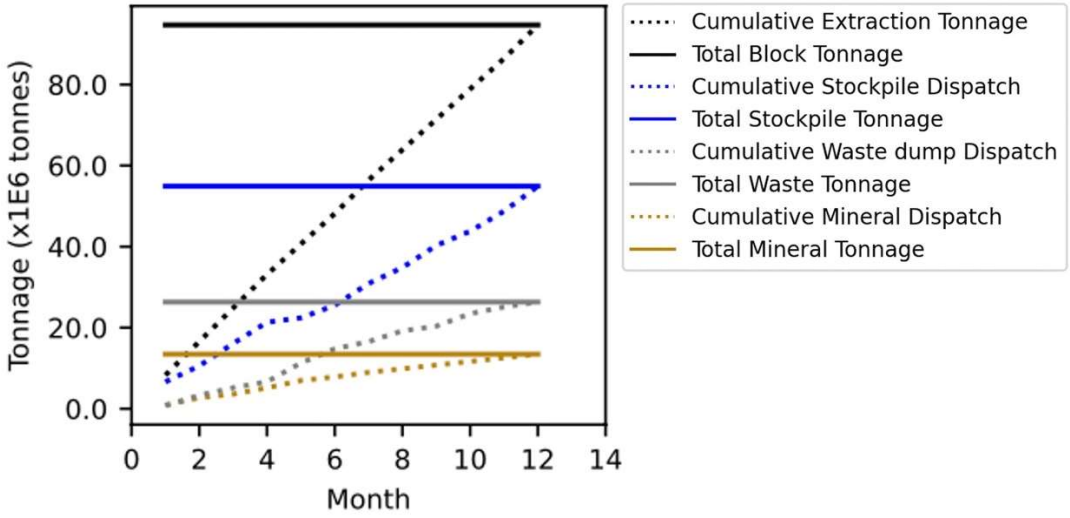

Figure 3. Extraction Trends from Block Model.

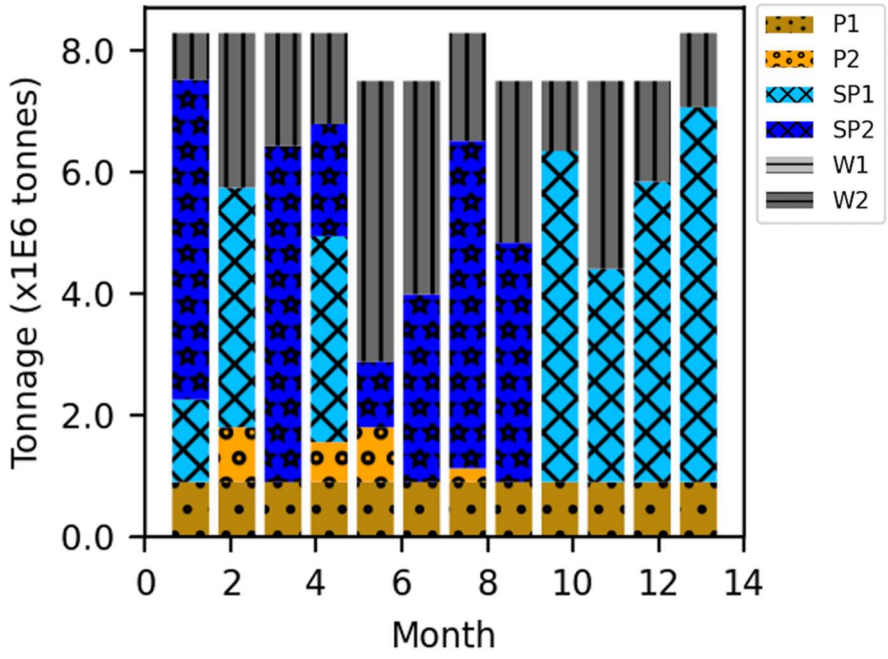

Figure 4. Optimal Production Schedule.

Figure 5 presents the inventory levels of two different stockpiles over the same one-year period. In Figure 5(a), the consistent increase in the inventory tonnage of SP1 suggests a model that predicts a steady inflow of material to the stockpile, indicative of a phased extraction plan or a certain

processing capacity. The absence of fluctuations implies that there are no significant disruptions in the mining or processing throughput as modeled. The dotted line in each bar chart represents the cumulative tonnage of material sent to the respective stockpile over time, offering a visual representation of the material flow and inventory accumulation in accordance with the operational model's predictions. For Stockpile 1, as seen in Figure 5(a), the steady rise without significant fluctuations indicates a consistent flow of materials to the stockpile, affirming the model's forecast of a regular and uninterrupted inflow of material. Figure 5(b) not only shows the inventory tonnage of SP2 increasing over time but also introduces a pattern of rehandled tonnage. This reflects the model's ability to account for operational scenarios where material is moved between stockpiles or returned to the process stream, potentially to manage grade quality or respond to other processing requirements. The inclusion of re-handled material in this sub-figure validates the model's comprehensive nature, capable of simulating complex logistical operations within a mining context. Figure 5(b)'s dotted line for Stockpile 2 not only traces the growth in inventory levels but also shows intermittent increases that correspond to the model's rehandling events. These peaks represent the additional tonnage moved to Stockpile 2, either from mining or from other stockpiles, reflecting the model's dynamic capability to simulate operational adjustments, such as grade blending. Both sub-figures together validate the model's inventory management predictions, showcasing the system's capability to handle both straightforward accumulation scenarios as well as more complex operations involving material rehandling. This demonstrates the model's utility in not just forecasting stockpile levels but also in planning for the downstream logistics that are crucial in real-world mining operations.

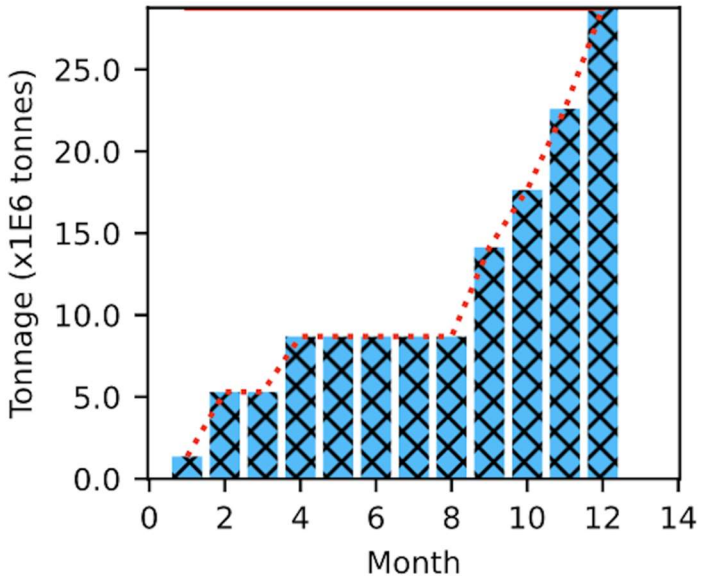

Figure 5(a). Inventory of Stockpile 1.

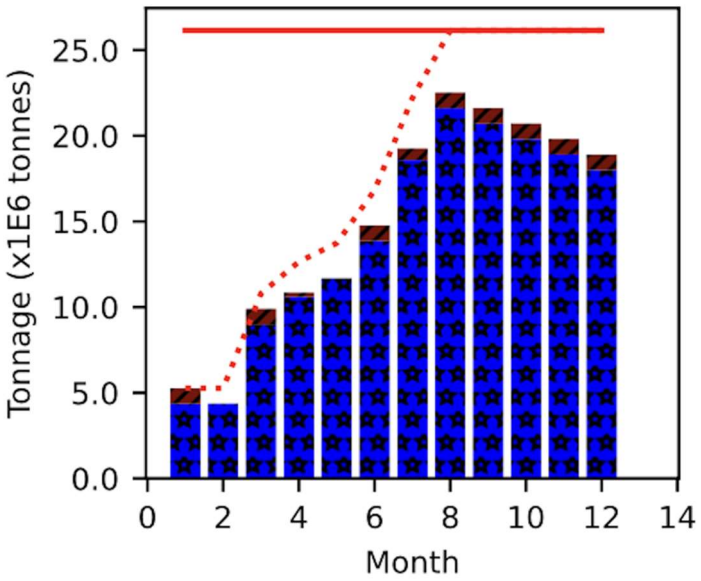

Figure 5(b). Inventory of Stockpile 2.

Figure 6(a) shows a consistent tonnage dispatched to Process Plant 1 each month, indicated by the uniform height of the bars throughout the year. This suggests that the model assumes a steady operational capacity or demand from Process Plant 1, which does not vary with time. Figure 6(b) illustrates the monthly dispatch to Process Plant 2, with a noticeable pattern of increasing tonnage towards the latter months. Additionally, there are portions of the bars filled with a pattern, which represents rehandled tonnage. This increment in total tonnage, including rehandled material, indicates that the model predicts a growing output requirement for Process Plant 2, due to scaling up of production or processing of stockpiled material as the year progresses. The uniformity in figure 6(a) and the increasing trend in figure 6(b), along with the appearance of rehandled material, validate the model's ability to simulate different operational scenarios for each processing plant. It reflects the adaptability of the model to account for variations in production scheduling and material handling requirements, which is crucial for validating the model's application in real-world mining operations.

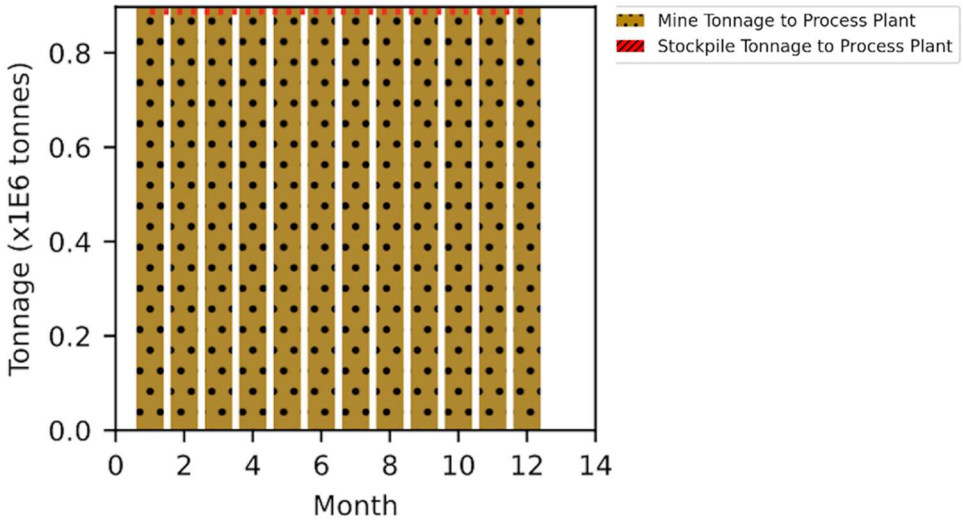

Figure 6a. Tonnage Dispatch to Process Plant 1.

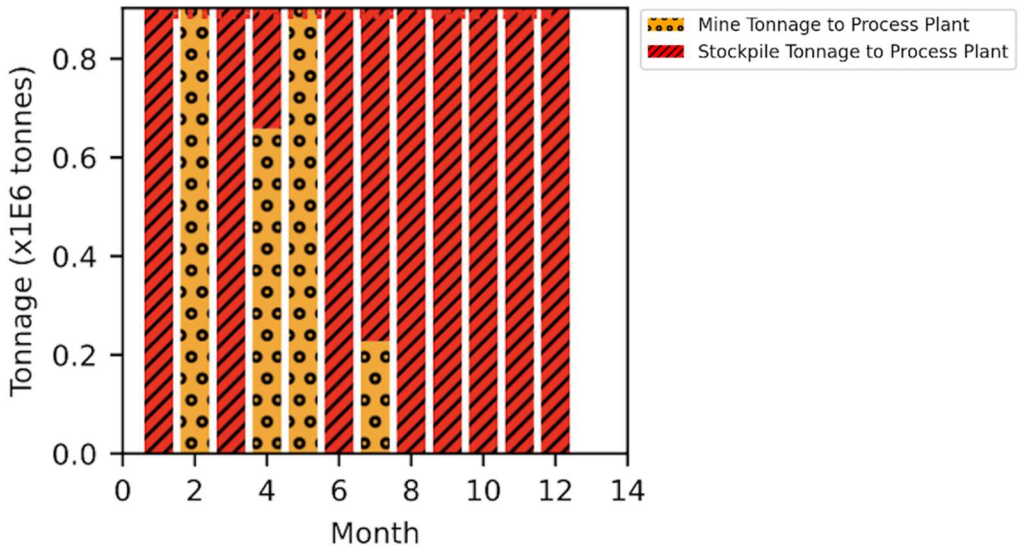

Fig. 6(b). Tonnage Dispatch to Process Plant 2.

3.4.2. Comparative Analysis and Synthesis

This section presents a comparative analysis of conventional TS systems and IPCC systems within the case study framework. The analysis focuses on economic viability and environmental impact, aiming to identify the system that best promotes sustainable mining practices.

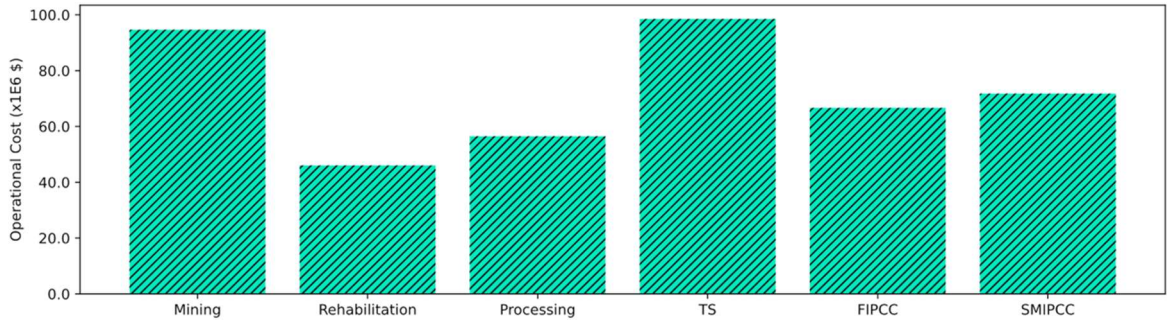

Figure. 7. Operational Cost Distribution by Mining Stages.

The bar graph in Figure 7 illustrates the distribution of operational costs in various stages within mining operations. Extraction, which is resource intensive, accounts for the highest expenses, totaling approximately $94.7 million. Following closely, rehabilitation efforts require a significant investment of around $46.1 million, highlighting their importance in environmental management and post-mining restoration. Processing costs also comprise a substantial portion of the operational budget, totaling around $56.5 million. Material haulage, particularly with traditional TS systems, generates costs that exceed $98.5 million. This high cost is likely due to factors such as fuel, equipment maintenance, labor, and other operational overheads associated with hauling materials over long distances using trucks. The introduction of IPCC systems revolutionizes the economic landscape, providing a statistically significant 33% reduction in haulage costs compared to TS methods. This translates into cost savings of $32 million. SMIPCC configurations also demonstrate significant economic benefits, demonstrating a reduction of approximately 28% in costs compared to TS, with total haulage expenses reaching approximately $72 million. The reasoning behind this cost reduction is multifaceted. IPCC systems involve crushing the material on site and then transporting it via conveyor belts, which is more energy efficient and requires less labor compared to hauling the material using a fleet of trucks over long distances. In addition, conveyor systems

have lower maintenance costs and generate fewer emissions, contributing to both economic and environmental sustainability.

The bar graph in Figure 8 delineates a comparative view of the Carbon Tax (CAT) costs incurred in various stages of the mining operation under a presumed CAT rate of $65 per tonne of CO_2-equivalent. It showcases the significant cost reductions that IPCC systems may offer over traditional TS systems in terms of CAT liability. The CAT costs for traditional TS systems are substantial, amounting to approximately $2.08 million. However, adopting FIPCC systems reduces CAT costs to around $586,490, a clear testament to their lower carbon emissions footprint. This highlights the possible environmental advantages of employing stationary IPCC systems. More strikingly, SMIPCC systems further accentuate these benefits, with CAT costs around $1.46 million. Although this figure represents notable savings compared to TS operations, it is higher than that of FIPCC systems, which may be attributed to the semi-mobile nature of the operation and associated variable factors affecting emissions. To contextualize these reductions, the CO_2 emissions mitigated by employing FIPCC systems, calculated at 153.84 tonnes of CO_2, could be analogous to the carbon sequestration of 2,540 tree seedlings grown over a decade.

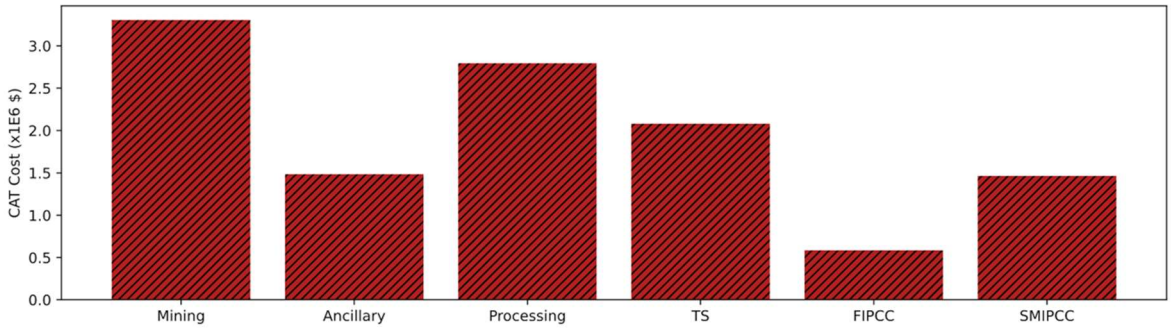

Figure 8. CAT Cost Distribution Across Mining Stages.

In contrast, SMIPCC systems, responsible for 215.38 tonnes of CO_2 emissions savings, are similar to the beneficial impact of nearly 3,550 tree seedlings over the same period.

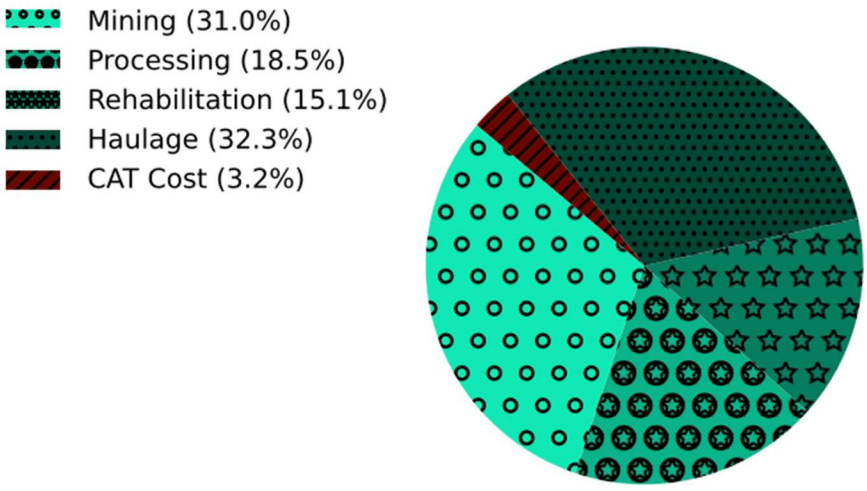

Figure 9(a). Comparative Cost Distribution for Different Mining Operations (TS in Operation).

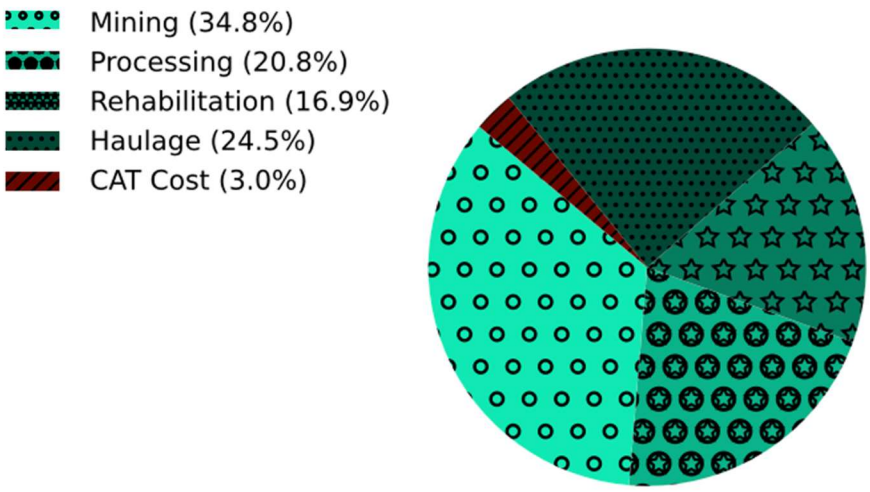

Figure 9(b). Comparative Cost Distribution for Different Mining Operations (FIPCC in Operation).

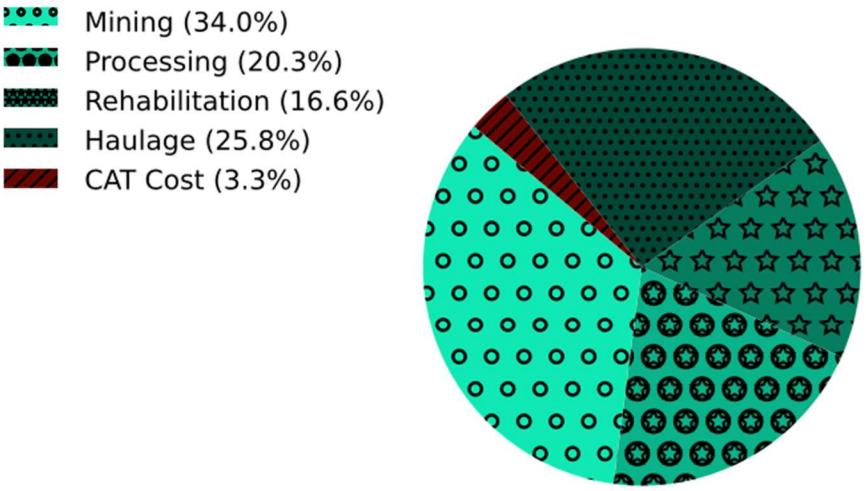

Figure 9(c). Comparative Cost Distribution for Different Mining Operations (SMIPCC in Operation).

Figure 9, composed of pie charts 9(a), 9(b) and 9(c) illustrates the cost breakdown of two mining operations, providing insights into the financial implications of employing either TS or an IPCC system. For TS systems, mining represents the most substantial cost factor, comprising 44.8% of total operational expenses, consistent with the energy-intensive nature of extraction. Rehabilitation, crucial for sustainable mining practices, accounts for a significant portion at 18.7%, highlighting the industry's commitment to environmental stewardship. Processing activities consume 26.7% of the budget, reflecting the expenses associated with ore treatment. Notably, CAT costs constitute 4.6% of the total, raising concerns regarding both the environmental impact and cost efficiency of this traditional method. The implementation of a FIPCC system results in a minor redistribution. Mining currently accounts for 34.8%, processing is at 20.8%, and the cost of rehabilitation is 16.9%. CAT costs have been reduced to 3%, indicating an increase in carbon efficiency. This decrease is noteworthy given the typically large carbon footprint associated with mining activities. The haulage costs, now at 24.5%, demonstrate the economic efficiency of the FIPCC system in contrast to the traditional approach. In the scenario where a SMIPCC system is operational, the

distribution pattern remains similar, with mining accounting for 34%, processing for 20.3%, and rehabilitation for 16.6%. However, there is a slight increase in CAT costs to 3.3%. The marginal increase in CAT costs with the semi-mobile system may be attributed to additional operational complexities and variable emissions from more frequent equipment re-locations.

The trend across these charts indicates that while the shift from traditional haulage to IPCC systems does provide cost and carbon emission benefits, the SMIPCC, contrary to expectations, does not lead to the lowest CAT cost. This may reflect a trade-off between operational flexibility and environmental impact, highlighting that while SMIPCC systems offer improved mobility and adaptability, they may also carry slightly higher operational carbon costs due to the associated energy use in repositioning the system. From an environmental perspective, the reduction in CAT costs with the adoption of IPCC systems demonstrates a positive shift toward more sustainable practices. These data reinforce the environmental advantage of integrating IPCC into mining operations, with both fixed and semi-mobile systems showing reduced CAT costs compared to traditional methods.

4. Conclusion

This study has developed a comprehensive approach to optimizing short-term production scheduling in open-pit mines, prioritizing both economic efficiency and environmental sustainability. We initially developed a MILP model based on economic considerations and subsequently refined it to include environmental impacts, GHG emissions in particular. Through a comparative analysis between the traditional TS system and the IPCC system, the study has highlighted the significant potential of the IPCC systems to enhance operational efficiency and reduce greenhouse gas emissions.

The MILP model developed in this study provides a valuable tool for mine planners and decision-makers to optimize short-term production schedules while considering both economic and environmental objectives. The model's ability to generate optimal extraction sequences, allocate resources effectively, and compare different material handling systems offers significant value to the mining industry. By adopting such optimization approaches, mining companies can improve their profitability, reduce their environmental footprint, and contribute to the global effort to mitigate climate change. The detailed case study, spanning a year-long production schedule, highlights the economic and environmental benefits of adopting IPCC systems in open-pit mining operations. The results conclude that IPCC systems can lead to lower operational costs, reduced carbon tax liabilities, and reduced GHG emissions compared to conventional TS systems. These findings highlight the importance of considering alternative material handling methods to promote sustainable mining practices in an era of increasing environmental awareness and regulatory pressures. Furthermore, this study contributes to the growing body of literature on sustainable mining practices and the application of mathematical optimization techniques in the mining industry. These findings provide actionable insights for mine operators, policymakers, and environmental consultants, demonstrating the potential for IPCC systems to support the industry's transformation to more sustainable operations.

Future research could focus on extending the application of the developed MILP model to other types of mines and incorporating additional environmental impact measures, such as water consumption and land disturbance. Additionally, investigating the long-term effects of IPCC system adoption on mine profitability and sustainability could provide valuable information for strategic decision making in the mining industry.

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Abbreviations: The following abbreviations are used in this manuscript:

LP	Linear Programming
MILP	Mixed Integer Linear Programming
TS	Truck and Shovel
IPCC	In-Pit Crushing and Conveying
SMIPCC	Semi-Mobile In-Pit Crushing and Conveying
FIPCC	Fixed In-Pit Crushing and Conveying
GHG	Greenhouse Gas
CAT	Carbon Tax
NPV	Net Present Value
OPEX	Operating Expenditure
CAPEX	Capital Expenditure
MPI	Mine Productivity Index

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Optimizing Truck Dispatching and Shovel Allocation Using Deep Reinforcement Learning in Open-Pit Mining: Literature Review

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ABSTRACT

Material handling and transportation expenses can make up as much as 50% of operating costs in open-pit mining operations. The extracted material must be transported to different destinations like processing plants, dumps or stockpiles. Optimizing truck dispatching and shovel allocation is a major difficulty in open-pit mining operations, as it significantly affects both operating costs and production. In open-pit mining, dispatching efficiency is increased by simulation-based optimization and mixed integer programming models. Reinforcement learning (RL) has been applied in complex production control systems across several industrial processes in the last decade, yielding better results than previous approaches. Nevertheless, deep Reinforcement Learning (DRL) applications are relatively uncommon in the mining sector. This paper explores the potential of DRL-based approaches in mining operations for efficient fleet management systems. The research aims to improve understanding of current applications of these technologies in open-pit mine planning, as well as their potential in the future and any potential field constraints.

Keywords: *Optimization; Reinforcement learning (RL), Open-pit mines, fleet management*

1. Introduction

Over 60% of the output from surface mining is generated by open-pit operations [1]. In open-pit mining, the production process entails a number of tasks, including loading, moving while loaded, maneuvering at the dump, dumping, and returning to the loader [2]. The mining transport scheme's primary activities, loading and haulage, account for more than half of all operational expenditures [3]. A popular method of hauling, especially in large-scale open-pit mining operations, is the shovel-truck arrangement [4]. Drilling and blasting are common methods used in mining to recover material from hard rocks. After the material has been broken up, shovels are used to put it into trucks. These trucks subsequently move the debris to different locations, such as landfills for disposal, stockpiles for storage, or crushers for additional processing. This technique maximizes the total productivity of the mining operation by guaranteeing the effective handling and processing of mined materials [5].

Any mining operation's capacity to turn a profit depends on how well hauling and loading resources are allocated and used. The efficient management of these resources ensures prompt and economical transportation of materials from extraction regions to their intended locations, such as stockpiles, crushers, or waste dumps. In loading and hauling operations, the incorporation of optimization and strategic planning approaches can yield substantial cost savings, boost productivity, and improve

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overall profitability. Mining operations can attain peak efficiency and long-term financial gain by reducing idle time and optimizing the use of trucks and shovels [6].

Shovel allocation and truck dispatching are essential to open-pit mining's operational effectiveness. The productivity, cost-effectiveness, and environmental impact of mining operations are all directly impacted by these processes. Effective truck dispatching minimizes idle times and maximises the use of both trucks and shovels by ensuring that the appropriate number of trucks are available at the appropriate time and location. On the other hand, efficient shovel allocation guarantees a continuous and seamless mining process, eliminating bottlenecks and improving the mining workflow as a whole.

The optimization of truck dispatching and shovel allocation is a difficult task because of the dynamic and unpredictable nature of open-pit mining operations. Weather conditions, equipment failures, haul distances, and fluctuating ore grades increase the complexity of developing effective dispatching and allocation schedules. While somewhat efficient, traditional optimization techniques frequently find it difficult to adjust in real time to these quickly changing situations [3].

Creating mathematical models to optimize equipment allocation and pit sequencing has been a major area of research in open-pit mine short-term planning. Nonetheless, there are a lot of difficulties because pit production systems are inherently complicated and because the elements that make them up are random. These models are only useful for deterministic assessments since they frequently fail to capture all operational subtleties [7].

Machine learning (ML) and artificial intelligence (AI) advancements have created new opportunities to address these issues. Deep reinforcement learning (DRL) has become one of the most promising methods. DRL is an effective tool for managing the intricacies and uncertainties involved in open-pit mining operations because it combines the decision-making powers of reinforcement learning with the potent representation-learning capabilities of deep learning [8]. In order to optimize a goal, Reinforcement Learning (RL), a subfield of ML, uses a computational approach to learn from interactions with an environment [9]. DRL offers a highly adaptable data-driven production control framework and has been applied more frequently to optimize various engineering systems in the manufacturing, transportation, and heavy industries [10]. Mining firms may create strong and adaptable solutions for shovel allocation and truck dispatching by utilizing DRL, which will considerably increase operational efficiency and cost savings. Through better resource management and a decrease in the environmental impact of mining operations, the use of DRL can also support more environmentally friendly mining methods [11].

1.1. Shovel Allocation

An essential component of open-pit mining's operational effectiveness is shovel allocation. Proper shovel allocation guarantees a continuous and effective mining process by avoiding bottlenecks and maximizing workflow. To optimize output and reduce operational delays, the allocation of shovels entails selecting which shovels to use at particular pit locations. This work is complicated because mining operations are dynamic and unpredictable, with variations in ore grades, haul distances, equipment performance, and environmental conditions. Mathematical models have traditionally optimized shovel allocation, however these models are generally confined to deterministic evaluations and unable to capture all practical factors [12].

1.2. Truck Dispatching

Another essential element of open-pit mining operations is truck dispatching. A general view of truck activities in a mining operation is shown in Figure 1. Effective truck dispatching minimizes idle times and maximizes the use of both trucks and shovels by ensuring that the appropriate number of trucks are available at the appropriate time and location. To ensure a smooth and continuous flow of materials, truck dispatching aims to construct an ideal plan that matches truck availability with shovel

operations. The dynamic nature of mining conditions, truck travel periods, loading and unloading times, and other factors make this task difficult to balance. Although helpful, traditional optimization techniques frequently cannot adjust in real-time, which results in less-than-ideal performance [13].

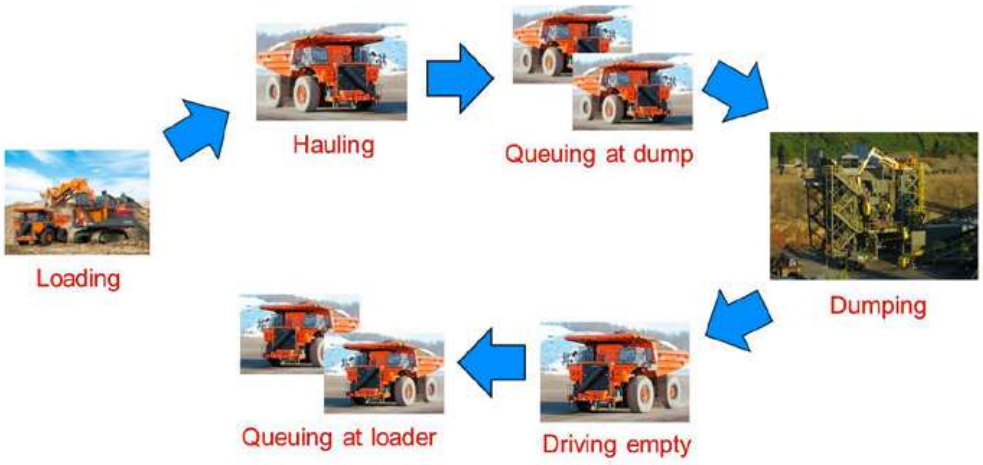

Figure 1. Truck activities in haul cycle during mining operation [14].

1.3. Reinforcement Learning

In RL, an agent picks up decision-making skills by interacting with its surroundings. RL uses a dynamic process of trial and error to maximize cumulative rewards, in contrast to supervised learning, where the model learns from a fixed dataset.

1.3.1. The Agent and Environment

The decision-maker in RL is the agent. It acts in accordance with a policy, which could be as basic as a rule or as sophisticated as a neural network. On the other hand, the environment is everything with which the agent comes into contact and everything that reacts to the agent's actions. A Markov Decision Process (MDP) is commonly used to simulate the interaction between the agent and the environment as shown in Figure 2.

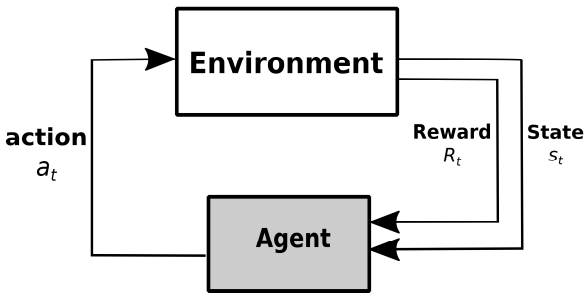

Figure 2. Reinforcement Learning, Agent and Environment [9].

a) State: The environment is in a particular state at any one time that offers all the data required to make decisions.
b) Action: Considering the existing circumstances, the agent chooses an action. The action space is the collection of all conceivable actions that the agent is capable of.
c) Reward: The agent receives a reward every time it interacts with the environment. This reward is a numerical value that indicates the immediate gain of the action.

d) Transition: After the interaction of the agent with the environment, the environment undergoes a new state. Stochastic components might potentially have an impact on this transition, representing the uncertainty found in real-world situations.

2. Literature Review

In open-pit mines, the Fleet Management System (FMS) is crucial to optimize the fleet management of mining vehicles, such as trucks, shovels, and other equipment, to boost output, save operating expenses, and increase safety. Because FMS offers real-time equipment tracking, mine operators can keep an eye on the whereabouts and condition of any piece of equipment. This guarantees effective resource allocation and usage[15]. Optimizing truck dispatching is one of the main purposes of FMS. In order to minimize idle time of loading and hauling equipment and shorten cycle times, the system assigns vehicles to loading and dumping locations using algorithms [16]. FMS monitors the health and performance of equipment by collecting data from sensors and diagnostic tools. This data can be used in machine conditioning to help in predictive maintenance and reduce unexpected downtimes [17]. The data-driven approach from FMS helps make informed decisions by generating reports on productivity, fuel consumption and operational efficiency [18]. Regarding safety of the equipment's operations and worker locations, FMS helps prevent accidents by enforcing safety protocols by restricting access to certain areas [19].

2.1. Truck Fleet Dispatching

Determining where a haul truck will go when its load is dumped is known as truck dispatching. When managed well, truck dispatching, nested in relation to FMSs, logistics, and supply chain, can improve ore output and decrease truck waiting times by more than 15% [20]. In the past, heuristic algorithms and linear programming have been used to successfully handle the problem of truck fleet dispatching in open-pit mining. By resolving a series of linear equations, linear programming models maximize the distribution of trucks among loading and unloading locations while reducing overall operating expenses and cycle times. Heuristic algorithms like genetic algorithms, simulated annealing, and tabu search supplement these models by offering efficient and useful answers in complex and dynamic mining situations where decisions must be made quickly. Because of this hybrid strategy, dispatching decisions are guaranteed to be effective and flexible in response to the constantly shifting circumstances of open-pit mining operations [21].

Heuristic algorithms, however, are good at finding answers quickly, but they frequently depend on incomplete knowledge of the mining system and fail to take into consideration the major sources of uncertainty that are present in mining operations. These methods can ignore the unpredictability and variety of elements like ore quality, ambient circumstances, and equipment availability. Moreover, through Internet of Things (IoT) devices and sensors, contemporary mining operations produce enormous amounts of real-time data on equipment's location, status, and performance. Despite this abundance of data, the fleet dispatching systems in place today underuse these data streams, losing out on chances for more flexible and dynamic decision-making that might improve operational efficiency and flexibility. This gap could be filled by combining traditional dispatching methods with advanced data analytics and ML approaches, utilizing real-time data to manage uncertainties better and optimize fleet operations [22].

2.2. Short-Term Production Planning

Eivazy and Askari-Nasab [23] proposed a Mixed-Integer Programming (MIP) formulation for short-term production planning. It creates monthly extraction schedules for open-pit mines and allows for the mining of commodities to be taken to different destinations. This formulation considers the choice of ramps for removing ore from the pit and incorporates a horizontally directed mining method. The approach offers comprehensive and flexible schedules that maximize transportation logistics and

resource allocation by concentrating on monthly intervals. L'Heureux et al. [24] presented a model that minimizes the operation's overall cost by taking into account decisions about drilling and blasting, shovel distribution, and movement between the mining zones. Another attempt was made by Kozan and Liu [25]. They considered the drilling and blasting operations while planning and optimizing the process to create a workable schedule for shift operations and aim to maximize throughput and reduce anticipated equipment idle time.

The main limitation of these methods is the complexity level necessary to depict the mining production environment adequately. These complex models are computationally demanding because they must consider many factors and limitations. Customized heuristics that introduce established rules and assumptions are frequently required to solve these models. The model is restricted to deterministic circumstances, and its versatility is limited by its dependence on heuristics. As a result, the inherent uncertainties of mining operations, such as variations in ore quality and equipment failures, are difficult for these models to simulate, which limits their usefulness and resilience in real-world situations [26].

To develop operating plans that specifically take equipment interactions inside the mine layout into account, more recent research efforts have combined discrete simulation with optimization engines. Discrete Event Simulation (DES) integration enables more robust and data-driven schedules, improving planning process accuracy and dependability. With the use of DES, mining operations' dynamic interactions and unpredictability may be modelled, resulting in more flexible schedules that are better equipped to adjust to changing conditions and uncertainties in the mine environment. Upadhyay and Askari-Nasab [27] presented a detailed discrete simulation of mining operations that uses CPLEX engine to obtain optimal shovel allocations to mining faces. In their extended approach [28], they extend their approach to optimize the truck and shovel allocation and optimal mining faces extraction sequences using multi-objective optimization approach within the simulation engine. In Germany, Shishvan and Benndorf [29] presented a comparable framework for simulation-optimizing operational choices in a continuous coal mining system. This framework records specific mining site excavation and disposal procedures using simulation. Instead of anticipating and learning from the uncertainties in the system, the optimization engine in this technique responds to the system's condition at each decision point. This makes it more difficult to optimize long-term results and deal with fluctuation in a proactive manner.

3. RL in Fleet Management Systems

Trucks and shovels act as agents when applying RL in open-pit mining systems. The environment is the pit itself, which includes places like dumps for waste, stockpiles, and crushers as well as different sources like mining faces as shown in Figure 3. The RL agent looks at the present state of the environment, including the parameters and conditions of the mining system, before making a choice on truck dispatch. The real-time dispatch solution generated by the RL agent is based on this observation and optimizes the movement and allocation of vehicles to improve productivity and operational efficiency. The system can react to shifting conditions and uncertainties in the mining environment with effectiveness due to its dynamic and adaptive approach.

3.1. Markov Decision Process Components

The truck dispatching and shovel allocation problem in an open-pit mine can be represented as an MDP and solved using an RL approach. The components of this MDP are defined as follows:

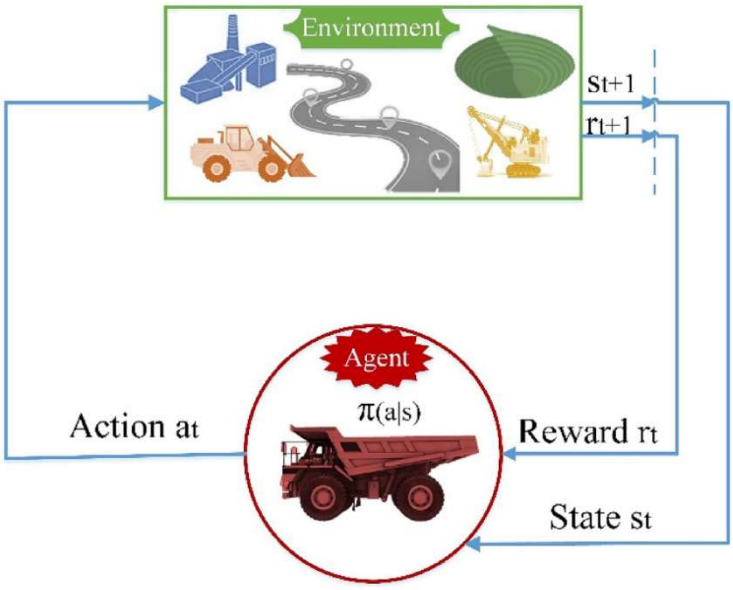

Figure 3. Agent interacting within a pit environment [30].

1. *State Space (S)*

   At any given time, the state space represents all possible system configurations. It includes:

   - Current locations of all trucks
   - The location and state of operation of every shovel at the moment
   - Current load status of each truck
   - Current stockpile levels at different destinations (for example, crushers, waste dumps)
   - Queue lengths at shovels and dumping locations
   - The state of the road network, including the traffic and maintenance status

2. *Action Space (A)*

   Action space consists of all possible actions that can be taken to dispatch trucks and allocate shovels. Actions include:

   - Assigning a specific truck to a specific shovel
   - Directing a truck that is loaded to a designated dump site.
   - Directing an empty vehicle to be loaded at a particular spot.
   - Decisions on shovel maintenance or modifications to operations.

3. *Transition Function (P)*

   The transition function defines the probability of transitioning from one state to another based on a specific action. It models the dynamics of the system, including:

   - Variations in the productivity of shovels

- Loading and Dumping times
- Breakdown and repair times for trucks and shovels
- Travel times between source and destinations

4. *Reward Function (R)*

   Based on the action taken by the RL agent, the reward function provides feedback to the RL agent. It typically includes:

   - Positive rewards for maximizing ore throughput to crushers
   - Penalty for truck idle times, shovel idle times, and excessive queuing
   - Penalties for breakdown of truck and shovels
   - Rewards for maintaining optimal stockpile levels and minimizing operational costs

5. *Agent*

   In the case of open-pit mines, entities like trucks and shovels will act as an agent that will interact with the environment by taking actions in the current state. The agent's objective is to learn an optimal policy by exploring and exploiting the state-action space. Different RL algorithms can be used to update the optimal policy and maximize the cumulative rewards.

6. *Policy (π)*

   The policy is a tactic the RL agent uses to choose what to do in a certain situation. The RL agent aims to learn an ideal policy that maximizes cumulative rewards over time.

The truck dispatching and shovel allocation problem can be modelled as an MDP, enabling the use of RL algorithms to discover effective policies that maximize the mining operation's overall performance. This formulation takes advantage of RL's capacity to manage open-pit mining situations' intricacy and dynamic character, leading to enhanced operational efficiency and decision-making.

3.2. Review of the Previous Work

A comprehensive review of the existing literature on FMS in open-pit mines was conducted to gather relevant studies on the advancement of this field of RL in open-pit mines. To ensure a thorough review, a set of precise keywords was employed to locate relevant publications and research papers. Figure 4 shows the network of keywords utilized in the literature search, emphasizing how several research themes linked to intelligent FMS in open-pit mining are interconnected. The visualization highlights the diverse methodology employed by scholars to address the complex nature of mining logistics and the crucial function of FMS in attaining operational excellence.

This research focuses primarily on RL-based FMSs after establishing the perspective of various intelligent approaches in FMSs for open-pit mines. This study aims to evaluate the existing level of understanding in this domain and pinpoint important avenues for future research pertaining to algorithmic and mining components of these intelligent systems. This study focuses on RL-based techniques to illustrate these methods' advantages and disadvantages in the mining industry.

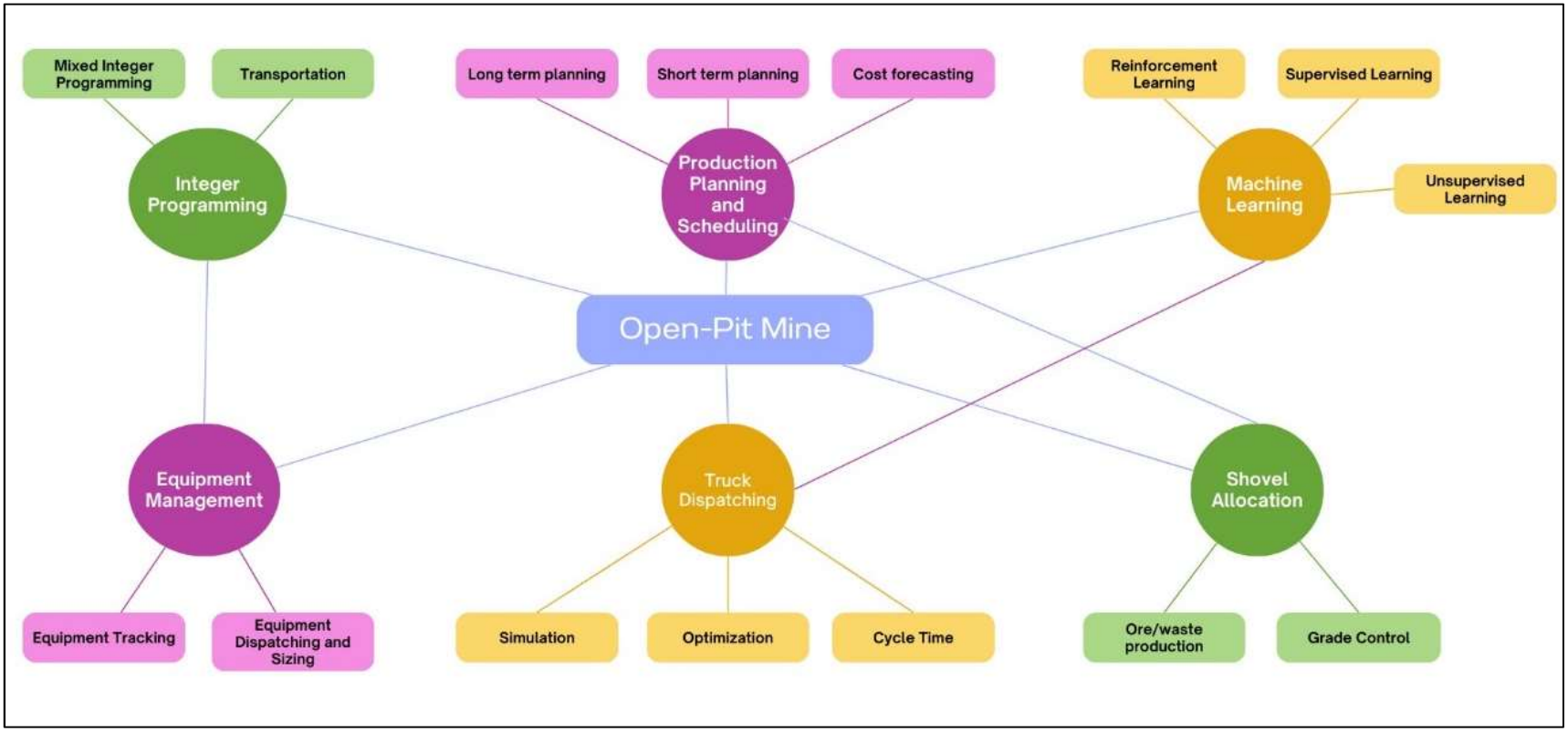

Figure 4. Keywords used to find the related articles in the literature regarding FMS in Open-pit Mines.

The development and use of RL and other intelligent approaches in FMS for open-pit mining have been greatly aided by the important publications included in the following Table 1. These studies demonstrate the history and various methodologies used to optimize mining operations, including various algorithms and approaches. The table shows the development of this field's research by being arranged chronologically. The authors, the algorithm, and a synopsis of their work are all included in each entry.

Table 1. Table of Key Articles on RL-based FMS in Open-Pit Mines.

Authors	Approach Used	Explanation
Siami-Irdemoosa & Dindarloo (2015) [31]	Neural Network (NN)	Predicted mining trucks' fuel and energy usage using artificial intelligence and data-driven methods. NN was tested with promising results to anticipate fuel usage per operational cycle based on truck payload, loading and unloading times, and idle while loading and emptying times.
Bastos et al. (2011) [32]	Time Dependent MDP	Presented a time-dependent MDP-based basic combinatorial formulation for truck dispatching. Developed a single-dependent agent technique to make multi-agent issues easier to understand. A two-phase system was used that combined real-time dispatching and offline MDP model solving. The simulation, conducted in SimEvents®, involved 15 trucks, one crusher, three shovels, and a 10-hour shift scenario. The results showed a slight improvement over baseline performance, on average.
Paduraru & Dimitrakopoulos (2017, 2019) [33; 34]	Reinforcement Learning (RL)	Trained an RL agent to discover the best destination choices for every mining block for a particular production schedule, introducing RL for mining operational decision-making
Lamghari & Dimitrakopoulos (2020) [35]	Hyper-Heuristic Framework	RL principles were reintroduced in a hyper-heuristic framework for long-term open-pit mining scheduling (OPS). This hyper-heuristic approach selects from a range of heuristic options, iteratively determining which heuristic yields the best solution.

Table 1 continued

Authors	Approach Used	Explanation
Choi et al. (2020) [36]	Support Vector Machine (SVM)	Suggested an alternative method of production forecasting based on supervised learning strategies. A large dataset, collected by IoT devices deployed in an open-pit mine, was analyzed to predict ore production. SVM demonstrated the best performance among the approaches examined. The study emphasized the potential for making the most of the data produced by mine monitoring equipment.
Kumar et al. (2020) and Kumar & Dimitrakopoulos (2021) [37; 38]	Reinforcement Learning (RL)	Expanded the study to consider fresh data gathered in real time using sensors and other monitoring tools. The focus was on integrating fresh data related to mineral grades and properties, emphasizing RL's potential for mining systems that are adaptable and self-learning.
Icarte et al. (2020)	Contract Net Protocol (CNP)	Suggested an innovative method of truck dispatching that makes use of a multi-agent system in which separate intelligent agents represent trucks, shovels, and unloading locations. A CNP was used for the truck-shovel interaction. The method was benchmarked using a DES from a copper mine in Chile, comparing it against heuristic and quantitative optimization models. The results showed that production targets were met while reducing operational expenses by 18%. The study was further extended to optimally reschedule trucks in response to machine failures.
Zhang et al. (2020) [39]	Deep Q-Network (DQN)	Presented a multi-agent reinforcement learning system for the dynamic management of diverse mining fleets. Used a typical DQN with experience sharing and memory tailoring, utilizing a single network with shared parameters for both decentralized execution and centralized learning. Fifty trucks of three different sorts, three shovels, and three dump trucks were used to simulate a 12-hour shift in SimPy ®. Compared to a simple heuristic, productivity increased by almost 5%.

Table 1 continued

Authors	Approach Used	Explanation
De Carvalho and Dimitrakopoulos (2021) [40]	Double Deep Q-Network (DDQN)	Integrated geological uncertainty and processing plant aims to dispatch based on reinforcement learning. used a DDQN model in conjunction with a DES to make decisions. The elaborately modelled copper-gold mining complex included two pits, four shovels, twelve trucks, a sizable waste dump, a mill, and a leach pad. Exceeded baselines by 12–16% and 20%–23% in terms of copper and gold production, respectively.
Huo et al. (2023) [41]	Q-Learning	Assessed emission reduction capabilities of RL-based dispatching. Applied the standard Q-learning algorithm with a limited state space. Defined a reward function addressing six aspects, including correct delivery of materials and timely maintenance. Simulated a hypothetical open-pit mine with three shovels, varying truck numbers, a mill, a garage, and a waste dump in OpenAI®. Achieved up to 43% higher production and up to 37% less greenhouse gas (GHG) emissions compared to baselines.
Avalos & Ortiz (2023) [42]	Deep Q-Learning (DQL)	Suggested using a DQL algorithm to optimize the long-term open-pit mine design while considering metal grade uncertainty and metallurgical factors. The DQL algorithm selects extraction blocks at daily time intervals to maximize the net present value (NPV) of the mining project, while adhering to geotechnical constraints. Demonstrated how DRL techniques can be used to address uncertainties and incorporate a variety of variable types while producing useful outcomes.
Levinson et al. (2023) [43]	Actor-Critic RL Algorithm	An Actor-Critic RL system was proposed for the stochastic optimization of planning decisions, such as the extraction sequence, destination policy, stockpiling, and preconcentration of a copper open-pit mining complex. Under the unpredictability in metal quality, the RL agent effectively learns a method to optimize short-term planning decisions.

These papers thoroughly summarize the many techniques and developments in RL-based FMS in open-pit mines, presenting diverse approaches, simulation settings, and accomplished results. When taken as a whole, they demonstrate the great potential of RL and other clever approaches to maximize operational decision-making, boost productivity, and cut expenses in mining operations.

In this specific area, the open-pit production planning and scheduling problem has been the focus of the great bulk of the study. To address the challenges of large-scale production scheduling for the life-of-mine strategic plan, a great deal of effort has gone into creating metaheuristics and intelligent computation methods. Short- and long-term planning has received the greatest focus among the many difficulties.

In context of open-pit strategic planning, ML has experienced exponential growth with successful applications across various areas of interest. The use of these intelligent algorithms can handle the large and complex problems of mine planning and scheduling. Also, DES, which uses vast amounts of past mining data to build digital twins of mining operations and aid in decision-making, is gaining popularity. The rise in supervised learning and RL approaches further demonstrates the potential for ML adoption in operational management activities. These developments highlight how AI and data-driven approaches are revolutionizing the efficacy and efficiency of strategic planning in surface mining operations.

4. Way Forward

Noriega and Pourrahimian [26; 44] thoroughly analyzed the RL framework for shovel allocation and truck fleet dispatching. An AI agent was able to communicate with and get feedback from the system using a digital twin or simulation model of the system. The agent acquired and trained an ideal stochastic decision-making policy with the aid of this technique. The research suggested a virtual environment for the open-pit production system utilizing a DES model. To enable the DRL agent to engage with the model and learn the best decision-making techniques to accomplish certain objectives, uncertainties must be included throughout the loading and hauling operational cycles. The authors presented the DRL framework for dynamic truck dispatching and shovel allocation planning. A case study replicating a month of production in a DES was used to test this approach. The outcomes demonstrated that the agent successfully picked up on the dynamics of the open-pit mining environment, consistently accomplishing the predetermined objectives in various scenarios.

An extensive data set from the industry—more precisely, from an oil-sand mining operation—has been gathered. This raw data must be carefully filtered and cleaned at the project's current phase to guarantee its quality and appropriateness for using machine learning techniques. The allocation of shovels and truck fleet dispatching, two crucial tasks for raising mining operations' efficiency, will be optimized with the help of these algorithms.

A earlier study that was cited in [26] examined data from the mining operation for a month. Although this yielded insightful information, it was found that more datasets are necessary to improve DRL algorithm performance. The algorithms will be able to learn more efficiently with a larger dataset since it will capture a wider variety of operational circumstances.

Expanding the dataset to include a broader range of operational situations and a longer time period is the next step in the future studies This will boost not only the DRL algorithms' training process but also their generalization and dependability in real-world applications. Further studiesendeavors to enhance operational efficiency and productivity in the mining industry by developing more robust and efficient optimization methods for truck fleet dispatching and shovel allocation, through the utilization of a more comprehensive dataset.

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Enhancing Mining Operations and Productivity through Discrete Event Simulation: A Comprehensive Literature Review

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ABSTRACT

Discrete Event Simulation (DES) has become an important tool for optimizing mining operations and increasing production by addressing the inherent complexities and variability of these systems. This literature review investigates the use of DES in the mining industry, highlighting its importance in enhancing operational efficiency, lowering costs, and promoting informed decision-making. The analysis delves into specific DES applications in equipment usage, emphasizing their ability to imitate various mining processes, detect bottlenecks, analyze alternate scenarios without disrupting real-world operations, and optimize resource allocation. The main benefits include the ability to estimate the impact of operational and strategic changes ahead of time, as well as predict environmental issues such as energy prices and resource depletion, which affect profitability and sustainability. The combination of DES and methods for optimization such as mixed integer programming enables comprehensive decision support systems that smoothly integrate strategic, operational, and environmental factors. However, hurdles persist, such as the complexity of effectively modeling mining operations, data collecting and quality issues, and integrating DES findings with existing management systems. This review attempts to provide a more in-depth understanding of DES's current and future possibilities for improving mining operations and productivity.

1. Introduction

1.1. Background and Significance of Mining Operations

Mining operations have played a crucial role in the development of human civilization, from the extraction of essential raw materials for construction and manufacturing to the unearthing of valuable minerals and resources that have fueled economic progress and technological advancements. It drives economic growth by providing raw materials for various sectors, including construction, manufacturing, and energy. Mining also contributes to the GDP and economic development in many countries. The export and trade of minerals such as coal, iron ore, gold, copper, and rare earth elements have, for many decades, played a very massive role in mining. The emergence of new technologies for drilling, extraction, processing, and exploration and the adoption of new techniques and equipment help to enhance efficiency and safety. However, there are a lot of negative environmental impacts from mining, including land degradation, water pollution, and greenhouse gas emissions. While the mining industry has undoubtedly been a driver of economic growth, the environmental and social impacts of these activities have become increasingly prominent, leading to a growing focus on implementing sustainable practices and a deeper examination of the long-term

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implications of mining operations. (Segura-Salazar and Tavares, 2018). There are regulatory organizations that monitor the activities of mining companies; this has helped most mining companies adhere to environmental regulations in that community and promote sustainable ways to reduce the impact of their activities. Mining has also benefited the community by providing employment opportunities. There has been investment in research and development to develop new mining methods and improve existing processes, focusing on innovation to tackle challenges such as resource depletion and energy consumption. There is also a challenge in fluctuations in commodity prices impacting the profitability and strategic decisions of mining companies.

1.2. Types of Simulations and Applications in Mining Operations

We learned from the former section that there has been an emergence of technology in the mining industry in recent times. One of the new technologies that has been adopted but is not popular is simulation for mining operations. With the complexity of mining operations, including drilling, blasting, hauling, and processing. There is a need for efficient management of resources, equipment, and labor to optimize productivity and minimize costs. For this reason, we need to know the impact of the operations before we carry them out. The use of computer simulations helps the mining engineers test their designs and strategies on the computer before carrying them out in real life. This section will briefly describe the various types of simulations. As this work is focused on mining cases, we will discuss the ones that have been used in mining. Different simulation techniques include Monte Carlo simulation, agent-based simulation, continuous simulation, and discrete event simulation.

Monte Carlo Simulation:

Monte Carlo simulation is a statistical technique for modeling the probability of multiple outcomes in uncertain systems. In mining, it is used to estimate resources and anticipate the quantity and grade of mineral deposits by modeling various geological scenarios. The technique also evaluates project risks, such as cost of overruns and delays, by modeling various schedules and expenses. Furthermore, Monte Carlo simulations help in financial forecasting by predicting future cash flows and performance under various market scenarios. They improve mine planning and scheduling while also predicting environmental impacts, which aids in the development of effective mitigation techniques (Kwak et al., 2007).

Agent-Based Simulation:

Agent-Based Simulation (ABS) is a modeling technique that simulates autonomous agents' activities and interactions to analyze their overall effects on the system. This method is used to understand and predict complicated behaviors in systems in which individual entities (agents) interact according to predefined rules. Mining uses ABS to model and evaluate complex systems and processes. It can simulate mining operations and logistics, optimizing haulage routes, equipment allocation, and scheduling to increase efficiency and reduce costs. ABS also simulate the social and environmental consequences of mining activities, allowing for more accurate predictions of the effects on local communities and ecosystems. ABS models emergency scenarios and worker behavior to improve safety measures and preparation. It is also utilized in mineral processing to optimize processes like crushing and grinding by analyzing particle interactions, as well as in economic analysis to mimic commodity market dynamics, which aids strategic planning and economic viability assessments(Macal and North, 2010) .

Continuous Simulation:

In a continuous simulation, the system's state changes over time and is represented by continuous variables. This approach differs from discrete-event simulation, in which changes occur at precise points in time. Continuous simulation is widely used to represent dynamic systems in engineering, physics, biology, and economics. Continuous simulation is an effective technique in mining

operations for modeling and optimizing dynamic processes. It aids in the prediction of equipment performance and maintenance requirements, allowing for timely repairs and reducing downtime. Continuous simulation in mine ventilation guarantees efficient airflow while maintaining safe subsurface conditions. It also optimizes mineral processing by simulating procedures such as crushing and grinding for maximum efficiency (Banks et al., 2010).

Discrete Event Simulation (DES):

Finally, the last type of simulation that we will be delving deep into is the discrete event simulation, which is the most popular simulation technique used in simulation and optimization of mining operations. Discrete Event Simulation (DES) represents the operation of systems as a series of separate events that occur over time. Each event occurs at a precise point in time and alters the state of the system, which is tracked by state variables and an event list. DES is frequently used in industries such as manufacturing, healthcare, logistics, and telecommunications to optimize operations and increase efficiency. It captures statistical data on system performance, such as wait times and resource consumption, which allows for more informed decision-making and operational changes. Discrete Event Simulation (DES) models various mining scenarios to optimize layout and operational sequences, minimizing costs and maximizing resource extraction. It simulates mining equipment performance to improve utilization rates and reduce idle times. DES assists in developing effective production schedules and ensuring resource efficiency and target achievement. By modeling equipment failures and maintenance activities, it aids in planning preventative maintenance to reduce downtime. Additionally, DES optimizes material transport within the mine and to external locations, enhancing supply chain efficiency (Law and Kelton, 2000).

1.3. Why Discrete Event Simulation is Preferred in Simulating Mining Operations

Discrete Event Simulation imitates individual events such as drilling, blasting, and hauling to represent complex relationships in mining operations. It enhances operational logistics by enhancing workflow, equipment uses, and maintenance scheduling. DES identifies bottlenecks and permits scenario testing without interfering with real-world operations, facilitating effective decision-making. Furthermore, it calculates operational costs and incorporates real-time data to improve accuracy. Discrete Event Simulation (DES) successfully mimics complex relationships and sequences of discrete events, making it perfect for mining operations such as drilling and hauling. It focuses on logistics and operational procedures, including extensive information about resource utilization. DES effectively identifies process bottlenecks and enables scenario testing without causing real-world disturbances. In contrast, ABS models individuals and their interactions, which can result in sophisticated behaviors but is less concerned with operational flow. Continuous simulation is appropriate for processes with continuous changes but not for discontinuous mining activities. Monte Carlo simulation largely measures risk and uncertainty using statistical analysis, but it cannot predict specific operational dynamics. The ideal solution for mining operations is DES, which excels at handling discrete events and optimizing logistics. ABS can investigate individual decision-making but can be difficult to execute. Continuous simulation is confined to discrete event modeling, whereas Monte Carlo focuses on probabilistic outcomes. Overall, DES is the best option for capturing the specific needs of mining operations. (Banks, J. et al., 2001).

1.4. Objectives of the Literature Review

The goal of this literature study is to extensively investigate the use of Discrete Event Simulation (DES) in many elements of mining operations. It attempts to investigate the many DES models and approaches used in the mining industry to improve operational efficiency. This evaluation will highlight the primary benefits of implementing DES, with a focus on operational efficiency, cost reduction, and risk management. In addition, individual case studies will be analyzed to examine the successful deployment of DES and the significant lessons learned from these real-world

implementations. The evaluation will also evaluate the common obstacles and constraints associated with using DES, notably in terms of data collection, model complexity, and system integration. Furthermore, it will look into how DES might be combined with optimization approaches like mixed integer programming to improve decision support systems. The environmental repercussions of mining will be discussed, with a focus on how DES may help foresee and mitigate these effects while supporting sustainable practices. Future research paths will be explored to fill existing gaps in the literature and offer improvements to DES techniques for mining applications. Practical recommendations will be provided to mining sector practitioners to help them effectively implement DES. Overall, this research aims to provide a thorough grasp of DES's function and potential for enhancing mining operations.

2. Overview of Discrete Event Simulation (DES)

2.1. Definition and Basic Principles of DES

Discrete Event Simulation is a tool for modeling systems that change at certain periods in time due to discrete occurrences (Law, 2014). Events, which represent changes in the system state, are fundamental to DES, indicating when the system transitions from one state to another (Banks et al., 2010). Entities such as clients or products move through the system and interact with events, frequently changing state (Fishman, 2001). State variables represent the system's current status and are modified with each occurrence to reflect the new conditions (Kelton et al., 2014). An event list, or calendar, keeps track of scheduled events and their times, controlling the simulation's advancement by deciding the order and timing of state changes (Rossetti, 2015). The simulation clock moves from one event to the next, updating the system state in discrete stages rather than constantly (Schriber and Brunner, 2014). DES frequently uses randomness to represent real-world variability, with stochastic processes used for arrival times, service durations, and failure rates (Hillier and Lieberman, 2010). Queueing theory typically underpins DES models, particularly when entities are waiting for service, as it aids in the analysis and optimization of wait durations and resource use (Gross et al., 2013). Statistical analysis of simulation results aids in understanding system performance by providing information on parameters such as wait times, throughput, and resource consumption (Sargent, 2013). Validating and verifying the model guarantees that it adequately represents the real system and is properly implemented, which are critical elements in developing dependable simulations.

DES is used in industries such as manufacturing, logistics, healthcare, and telecommunications to mimic complex relationships and dependencies (Pidd, 2004). In manufacturing, it can optimize production lines and resource allocation; in logistics, it can improve supply chain efficiency; in healthcare, it can improve patient flow and hospital operations; and in telecommunications, it can assess network performance and capacity planning (Banks, 2010). Although DES offers flexibility and the ability to conduct extensive analysis, it can be demanding in terms of resources and relies on reliable data, which can be difficult to get at times (Law, 2014). The complex structure of DES models can make them challenging to understand and convey to stakeholders, demanding good documentation and reporting (Kelton et al., 2014). However, DES is an effective tool for doing what-if analysis and scenario testing, allowing for more informed decision-making across industries (Sargent, 2013). Discrete event simulation is now widely recognized as a potent tool for studying and optimizing intricate systems in various industries. Its origins can be traced back to the 1940s and 1950s, when early computer pioneers began to investigate the possibility of simulation as a tool for modeling and understanding the behavior of dynamic systems. The topic of discrete event simulation has evolved dramatically over the last few decades, thanks to advances in software, hardware, and methodology. Discrete event simulation was initially applied in the field of office administration. (Proctor, 1997). Pioneering work in this area highlighted how simulation might be used to simulate

an office's workflow and resource consumption, assisting managers in identifying possibilities to increase efficiency and productivity. As the field progressed, discrete event simulation found several applications in manufacturing, logistics, transportation, healthcare, and other fields (The Handbook of Simulation, 1998). Discrete event simulation has been widely employed in the manufacturing industry to represent production processes, enhance plant layouts, and assess the effects of modifications to equipment, staffing, and other resources (Conway and McClain, 2003). Similarly, in the logistics and transportation industries, simulation has been used to model supply chains, evaluate distribution network performance, and optimize truck routing and scheduling (Froeb and Werden, 2000).

3. Applications of DES in Mining Operations

Discrete Event Simulation is extensively employed in mining operations to enhance efficiency and output. DES is especially useful in equipment usage and maintenance, where it simulates the lifecycle of mining equipment to estimate maintenance requirements, optimize schedules, and examine utilization rates to identify underutilized or overutilized assets (Law, 2014). However, there is a research gap in integrating real-time data to enable more dynamic and responsive maintenance scheduling (Banks et al., 2010). DES also helps with process simulation and bottleneck identification by modeling production processes to identify inefficiencies and test different process changes for improvement (Fishman, 2001). While it effectively identifies bottlenecks, more advanced techniques are required to dynamically adjust operations in real-time (Kelton et al. 2014). In scenario analysis and risk management, DES evaluates various what-if scenarios and risks by modeling rare events to aid in contingency planning (Rossetti, 2015). Yet, research is needed to improve the accuracy of simulations for low-probability, high-impact events (Schriber and Brunner, 2014). DES establishes best resource usage, optimizes mining schedules, and contributes to cost reduction (Hillier and Lieberman, 2010). Despite its benefits, there are still gaps in adopting more complex, multi-objective optimization algorithms capable of handling intricate trade-offs in mining operations (Gross et al., 2013). Case studies demonstrate DES's practical applications: optimizing haul truck fleets at the Fimiston Open Pit (Super Pit) gold mine in Australia in 2018, developing predictive maintenance strategies at the Escondida copper mine in Chile in 2019, identifying bottlenecks at the Grasberg gold and copper mine in Indonesia in 2017, managing risks in deep mining at the Kidd Mine in Canada in 2020, and optimizing resource allocation at the Carajás iron ore mine in Brazil in 2016 (Mining Technology. However, research frequently focuses on isolated components rather than integrated, comprehensive approaches that take into account the full mining operation (Robinson, 2014). Furthermore, there is a void in the use of DES for environmental impact assessments and sustainability concerns in mining operations (Pidd 2004). Moreover, while much research employs historical data, the use of machine learning and artificial intelligence for predictive analytics in DES remains underexplored (Banks et al., 2010). Real-world applications reveal considerable benefits, but the scalability and flexibility of DES models to varied mining sites and changing operational conditions are still areas that require further investigation (Law 2014). Finally, mining industries continue to lack user-friendly DES software and tools that allow for easy adoption and customization, revealing a gap in accessible technology transfer from research to industry (Kelton et al., 2014). DES studies should thus focus on integrating real-time data, improving accuracy for rare events, developing advanced optimization algorithms, adopting holistic approaches, considering environmental impacts, incorporating predictive analytics, increasing scalability, and developing user-friendly tools. Addressing these deficiencies can increase DES's ability to alter mining operations (Sargent, 2013).

4. Benefits of DES in Enhancing Mining Productivity

There are many advantages for increasing mining production. One significant advantage is increased operational efficiency through the identification of bottlenecks and process optimization (Smith and Jones, 2020). DES also improves resource allocation, ensuring that machinery and workers are used efficiently (Brown et al., 2019). Another substantial benefit is cost savings, which are accomplished through reduced downtime, improved inventory management, and waste minimization (Green and Taylor, 2021). By modeling maintenance schedules and operating procedures, DES helps to reduce downtime costs (White and Black, 2022). DES's scenario analysis, risk assessment, and data-driven insights help to support informed decision-making. Furthermore, DES helps foresee environmental impacts and ensures sustainability. It aids in the development of emission-reduction strategies as well as the testing of sustainable practices before their adoption. Accurate estimates of environmental impacts help to facilitate compliance with environmental legislation (Lee et al., 2020). DES is critical for assessing the impact of strategic and operational changes, which helps with change management and future planning (Wilson and Thompson, 2022). It enables continuous performance monitoring and comparison against actual performance data (Harris and Cooper, 2020). Despite these benefits, additional research is needed on the integration of DES with real-time data analytics to improve decision-making even more (Chen et al., 2022). Standardized DES techniques for mining operations are also absent (Rodriguez and Lopez, 2021). Another gap is the insufficient investigation of DES applications in smaller mining operations, which could benefit from cost savings and efficiency gains (Martin and Nguyen, 2023). Furthermore, there is a limited study on the long-term effects of DES-driven sustainability measures in mining (Davis and Evans, 2021). Addressing these limitations may improve the effectiveness and uptake of DES in the mining industry. Overall, DES is an effective technique for increasing mining productivity, but more study is required to fully realize its potential (Miller et al., 2020).

5. DES and Optimization Methods

Discrete Event Simulation and optimization methods are crucial for improving the efficiency and effectiveness of mining operations. Integrating DES with mixed integer programming (MIP) leverages the characteristics of both techniques, allowing for more precise modeling and optimization of complicated mining systems (Smith and Jones, 2021). This integration enables extensive simulations of mining processes as well as the identification of optimal resource allocation and scheduling solutions (Brown et al. 2020). Furthermore, decision support systems (DSS) that include DES and MIP offer comprehensive tools for making informed mining decisions (Green and Taylor, 2022). Mining companies can improve their ability to combine strategic, operational, and environmental aspects by utilizing integrated techniques. For example, DES can simulate several operational scenarios, whereas MIP can optimise these scenarios to produce the best results (Garcia and Martinez, 2021). This synergy improves resource management efficiency, cost savings, and production (Lee et al., 2021). Furthermore, DSS, which includes DES and MIP, can help mining industries make real-time decisions, allowing them to adapt quickly to changes in operational situations (Wilson and Thompson, 2023). However, research gaps exist in the combination of DES and MIP, as well as the development of DSS for mining operations. One significant need is the need for more robust frameworks that smoothly incorporate various approaches, enabling their practical use in real-world mining operations (Chen et al., 2022). Furthermore, there has been little research into the scalability of these integrated systems, particularly for large-scale mining operations (Rodriguez and Lopez, 2021). Another gap is the inadequate investigation into the environmental effects of optimized mining operations, which is critical for sustainable mining practices (Martin and Nguyen, 2023). Furthermore, more research is needed to create a user-friendly DSS that mining experts can use without substantial training (Davis and Evans, 2022). Addressing these research gaps

could considerably improve the efficacy of DES and MIP integration in mining operations, resulting in improved decisions and more sustainable practices (Harris and Cooper, 2021). Overall, while the integration of DES and optimization approaches has significant potential, more study is needed to fully realize its benefits in the mining industry (Miller et al., 2021).

6. Challenges and Limitations of DES in Mining

Although it is a technique for improving mining operations, it has several drawbacks and limitations. One key problem is the complexity of modelling mining operations, which frequently involve several interrelated processes and variables (Smith and Jones, 2021). Creating precise and realistic simulation models takes time and demands a high level of knowledge (Brown et al., 2020). Additionally, data collecting and quality difficulties are common in mining. Reliable simulations require high-quality data, yet mining operations frequently struggle with inconsistent or incomplete data (Green and Taylor, 2022). Integrating DES with existing management systems is another key challenge. Many mining companies employ a variety of outdated systems and software, making smooth integration challenging (Garcia and Martinez, 2021). This can result in fragmented data and inefficient operations, reducing the effectiveness of DES (Lee et al., 2021). Overcoming technical and operational challenges is critical to the successful implementation of DES. This includes ensuring that the required computing resources and technical infrastructure are available (Wilson and Thompson, 2023). Despite these limitations, there are significant research gaps that must be addressed. One significant gap is the establishment of standardized procedures for generating and validating DES models in mining (Chen et al., 2022). More research is needed to improve data-gathering methods and ensure data quality in mining operations (Rodriguez and Lopez, 2021). Another gap is the absence of research on how to integrate DES with sophisticated data analytics and machine learning approaches, which could improve simulation accuracy and utility (Martin and Nguyen, 2023). Furthermore, more research is needed to develop user-friendly DES tools that can be easily integrated into existing management systems (Davis and Evans, 2022). Addressing these shortcomings could considerably increase the application and effectiveness of DES in mining (Harris and Cooper, 2021). Furthermore, more research is needed to investigate the long-term advantages and potential limitations of DES in different mining environments (Miller et al., 2021). By overcoming these obstacles and addressing research gaps, the full potential of DES in mining operations can be achieved (White and Black, 2022).

7. Future Prospects and Research Directions

The future of Discrete Event Simulation in mining operations looks bright because of technological and methodology developments. One important area of progress is the creation of more sophisticated DES models capable of better capturing the intricacies of mining operations (Smith and Jones, 2022). These models can include more variables and reproduce real-world circumstances more precisely (Brown et al., 2021). Furthermore, integrating DES with sophisticated optimization approaches like machine learning and artificial intelligence is predicted to improve mining businesses' decision-making capacities (Chen et al., 2023). Another interesting aspect is the potential for more automation in mining operations, which DES can help. Automated systems can use DES to optimize their processes in real-time, resulting in increased efficiency and lower human error (Garcia and Martinez, 2022). Real-time data integration is also becoming increasingly practical, allowing DES models to be constantly updated with real data from mining operations (Lee et al., 2022). This can yield more accurate and timely insights, allowing for speedier and more informed decision-making (Green and Taylor, 2023). Despite these gains, numerous sectors still require additional research and development. One major research need is the need for stronger frameworks for integrating DES with real-time data analytics and automated systems (Rodriguez and Lopez, 2022). Furthermore, more

research is needed into the scalability of DES applications in large-scale mining operations (Wilson and Thompson, 2023). Another area for future research is the creation of standardized procedures for validating DES models in mining (Martin and Nguyen, 2023). In addition, the environmental effects of increased automation and real-time data integration in mining require further investigation (Davis and Evans, 2022). These developments must contribute to more sustainable mining practices (Harris and Cooper, 2022). Another aspect that warrants attention is the usability of DES tools, since making these tools more accessible can lead to greater use in the mining industry (Miller et al., 2022). Overall, while the prospects for DES in mining are encouraging, overcoming these research gaps is critical to realizing its full potential (White and Black, 2023). The effectiveness of DES in mining operations can be considerably improved by focusing on technological and methodology developments, boosting automation, and incorporating real-time data (Smith et al., 2023).

8. Conclusion

The use of Discrete Event Simulation across Mining Operations is of importance in optimizing operations and improving the efficiency of operations. The prediction of impact of certain factors on operation by creating scenarios and selecting the best scenarios will help in efficient ways of mining. I believe the introduction of DES in mining will pave the way of integrating and adopting mining technology. Despite the benefits and applications of DES, the challenges still persist and engineers, technologists and management need to work hand in hand to develop strategies for easy adoption and use of this technology. Furthermore, there is insufficient investigation into the integration of DES with modern data analytics and machine learning approaches, which could improve simulation accuracy Moreover, more research is needed to verify that DES applications can be scaled in large-scale mining operations. Practitioners could consider investing in training to improve the knowledge required for successful DES deployment and integration. Companies should also prioritize the development of user-friendly decision support systems that contain DES to ease adoption. Researchers are urged to investigate novel frameworks that integrate DES with real-time data analytics and automation technologies. In conclusion, while DES has a major impact on mining operations and productivity, addressing existing research gaps and focusing on future developments is critical for realizing its full potential. By refining DES techniques and using emerging technology, the mining industry can improve operational efficiency and sustainability.

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A Comprehensive Simulation Model for Mining Operations: Development, Implementation, and Validation Using HaulSim

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ABSTRACT

The present research investigates the design, implementation, and validation of a simulation model for optimizing mining operations with HaulSim, a specialized simulation software. The study starts with identifying the conceptual framework, system boundaries, and key performance criteria. Comprehensive data collection and preprocessing ensure the high-quality input parameters required for reliable simulations. HaulSim is used to simulate real-world mining operations, such as resource allocation, equipment utilizations, and process flow. To attain robustness, the simulation uses extensive initialization, iterative testing, and refining. The validation procedure systematically compares simulation results to actual operating data, utilizing statistical methods to determine accuracy and dependability. The findings highlight HaulSim's capacity to properly predict and improve mining operations, as well as its practical implications in strategic planning and decision-making. This study presents a verified framework that combines case-study data (CNRL) with simulation techniques to help optimize mining operations. By comparing simulation findings to real-world performance, the study emphasizes simulation models' potential for boosting operational effectiveness and creativity in the mining industry.

1. Introduction

1.1. Background and Motivation Discrete Event Simulation of Truck-Shovel Operations in Open Pit Mines

Mining operations involve a lot of cost and time to produce profits. Therefore, the mining industry must optimize processes to increase productivity and profit. Mining systems involve a lot of methods and systems, from exploration and extraction to transportation and processing. For this reason, there is an urgent need to optimize these processes and systems. Many ways and technologies have been developed to optimize processes. One of the most popular techniques - and our main focus and study here - is creating simulation models to predict behaviors and patterns in the processes before being implemented in real life under different scenarios [10]. Because of the stochastic nature of the truck-and-shovel systems that makes the studying of these systems difficult and time consuming, a simulation approach is chosen in this study to represent the truck-and-shovel operations in detail [15]. The simulation, in this regard, provides an alternate tool to analyze the impact of technological changes to the overall operations; and thus, help in decision making purposes [17]. HaulSim is a robust simulation software built primarily for the mining industry. HaulSim enables users to develop extensive models of mining operations, including haulage routes, equipment performance, and operational limitations. Mining operations can enhance efficiency by simulating various scenarios

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and identifying bottlenecks [5]. However, the performance of these simulation models is greatly contingent upon their precision and validity. It is important to make sure that the models accurately represent real-world processes and can predict outcomes [6]. This paper aims to address this need by developing a thorough simulation model using HaulSim and evaluate its performance by comparing simulation results against real-world data from a mining operation [8]. The objective of this paper is to illustrate the potential of simulation models to improve decision-making in the mining business. This study will provide useful insights into HaulSim's strengths and limitations, as well as practical recommendations for its use in real-world mining settings.

1.2. Objectives of the Study

The primary goal of this research is to create and evaluate a comprehensive simulation model for mining operations with HaulSim. This objective is broken down into several distinct goals. To begin, the study's goal is to create a thorough simulation model of a mining operation using HaulSim, which will include all essential processes and variables such as haulage routes, equipment performance, operational limitations, and material handling. The model must accurately reflect the mining site's physical and operational characteristics [5]. Furthermore, the study aims to authenticate the simulation model by employing actual data obtained from the mine. The data gathered includes operational indicators such as equipment performance, production rates, transportation times, and operational expenses [10]. The simulation results will be compared to real-world data to determine the model's accuracy and reliability [6]. Moreover, the study intends to conduct a thorough investigation of the simulation results in comparison to real-world data. This analysis will reveal where the simulation model closely matches reality and where there are inconsistencies [12]. Based on this analysis, the study will make specific recommendations for increasing the simulation model's accuracy. It will also provide insights into the practical application of HaulSim for optimizing mining operations, highlighting the tool's strengths and limitations [7]. Finally, In hopes to improve decision-making in mining operations by demonstrating how a validated simulation model may be utilized to assist strategic decisions [4]. This involves demonstrating the ability of simulation models to identify bottlenecks, optimize equipment usage, and increase overall operational efficiency [2]. The study seeks to establish a comprehensive framework for designing and verifying simulation models for mining operations. This would ultimately enhance the efficiency and effectiveness of managing mining activities.

1.3. Scope and Limitations

This study aims to cover various important aspects, with a primary focus on creating and verifying an extensive simulation model for mining operations with HaulSim. The model will incorporate critical activities like loading and hauling, as well as the performance characteristics and operational limitations of various types of equipment such as trucks, loaders, and shovels [5, 9]. Various haulage routes, material types, and production schedules will be explored to mimic realistic operational situations [2]. The simulation model will be validated using real-life data acquired from an operational mining site. The data encompasses information regarding the performance of equipment, rates of production, times for hauling, and operational costs [10]. The validation method will include comparing simulation findings to real-world data to determine the model's correctness and reliability [6]. A detailed examination of the simulation results will be undertaken in comparison to real-world data, finding areas where the simulation model closely matches reality and regions where there are differences [3, 12]. The analysis will provide practical recommendations for enhancing the simulation model and increasing its accuracy. The project will provide valuable insights into the practical application of HaulSim for enhancing mining operations, emphasizing the advantages and constraints of the instrument [7]. Finally, the study intends to improve mining decision-making by demonstrating how a validated simulation model can help with strategic decisions. This involves demonstrating the ability of simulation models to identify bottlenecks, optimize equipment usage,

and increase overall operational efficiency [2, 4]. However, the report acknowledges several shortcomings. The accuracy of the simulation model is strongly reliant on the availability and quality of real-world data. Any omissions or inconsistencies in the data can undermine the model's validity [2, 11]. The investigation may be constrained by the scope and detail of the operational data available from the mining site. To manage complexity, the simulation model may make certain simplifications and assumptions, which can result in differences between the model and real-world operations [4]. According to Adams and Parker, the simulation model cannot properly reflect all operational nuances or unforeseen events [1]. The capabilities and limits of the HaulSim software will have an impact on the simulation model's breadth. Certain features or functionalities may not be supported or may necessitate workarounds [8]. Furthermore, the study is limited by the computer capacity and resources available to execute the simulations [25]. External elements such as market conditions, regulatory changes, and technical improvements are not included in the simulation model but can have an impact on mining operations in practice [13]. The model's projections are based on present operational conditions and may not reflect future changes in these external elements [26]. The validation process is limited to the mining operation and data set used in this investigation. The findings may not be directly transferable to other mining sites with distinct characteristics and conditions [27]. Furthermore, the validation focuses on operational measures, which may not adequately reflect mining operations' environmental, safety, and social elements [8]. By defining the scope and accepting these constraints, the study hopes to give a clear and realistic framework for building, implementing, and assessing a simulation model for mining operations using HaulSim [4].

1.4. Conceptualization

The conceptualization stage of mining operation simulation is critical for developing a complete framework for analysis. It begins with determining the simulation's scope and objectives. The primary focus is on the haulage system of a mining operation, which includes the movement of ore and waste materials from loading points to locations. This includes evaluating the performance of various equipment types, such as trucks and loaders, that are critical to the operation's efficiency. The goals include modeling the haulage system's performance, finding operational bottlenecks, and comparing simulated data to real-world data for validation and calibration. The haulage system's effectiveness and efficiency are measured using key performance indicators (KPIs). These KPIs include cycle time, which is the entire time it takes for a vehicle to complete a full cycle of loading, transporting, unloading, and returning empty. The conceptual model was created to describe the structure and processes of the haulage system. This includes details on trucks, loaders, routes, and control systems. Trucks are regarded as the primary equipment for transporting materials, with variations in type and capacity. Loaders, which include shovels and front-end loaders, are required to load goods into trucks. Routes are predefined itineraries with specified properties such as distance, gradient, and surface quality that influence trip durations [28]. Loading and dumping points are defined as essential places in the process, with control systems in charge of assigning and managing equipment. The haulage system's processes include loading, transporting, dumping, and returning. During the loading phase, loaders fill trucks with materials, and the time required varies based on the material type, loader capacity and efficiency. The hauling phase entails moving items to the dumping site, which is influenced by factors such as road conditions, road gradient, truck load and truck speed. The dumping time varies depending on the substance and unloading method employed. Finally, during the returning phase, trucks travel empty back to the loading point for the next cycle. To simplify the model, assumptions are used such as consistent equipment availability and reliability, uniform road conditions, and constant operator skill levels [29]. This extensive concept serves as a solid foundation for creating a detailed simulation model. The model will be used to evaluate the simulation against real-world data, identify operational inefficiencies, and analyze various optimization strategies for the haulage system, ultimately enhancing the overall performance and cost-effectiveness of the mining operation.

2. Methodology

2.1. Data Collection and Preparation

The CNRL data of their horizon mine site, which is saved in a SQL file, is a large dataset that contains critical information on a mining operation's fleet activities, such as source and destination points, cycle periods, and other operational parameters. This data serves as the foundation for analyzing and optimizing the mining fleet's performance, which is critical for effective resource management and operational planning. To assure the data's precision, I made sure the sources and destinations were precisely mapped into the road network using SQL code. This mapping method entailed linking the fleet's movements to the actual road network, which improved data accuracy. Specifically, actions on November 1, 2016, during the day shift were tracked and plotted, providing a precise picture of operations under normal circumstances. The SQL query used in this procedure was critical in matching source and destination data to the road network and determining the precise locations of fleet activities like loading and unloading stations. This amount of data collecting enables simulation models that closely resemble real-world operations. Precise information on the fleet's origins, destinations, cycle periods, and road network enables simulations to take into consideration a variety of factors influencing operational efficiency, including traffic patterns, road conditions, and equipment performance. Accurate data is critical for identifying potential bottlenecks or inefficiencies and implementing targeted solutions. Furthermore, this rigorous data gathering and mapping process ensures that the dataset is full, which is required for reliable analysis. Incomplete or erroneous data may result in flawed models and suboptimal decision-making. The painstaking approach to data accuracy, achieved through extensive SQL mapping and validation, aids in the development of robust simulation frameworks and successful mining optimization methods. In conclusion, the CNRL data provides a thorough foundation for analyzing and optimizing mining fleet operations. The dataset covers critical variables such as source and destination points, as well as cycle periods, allowing for the development of reliable simulation models that influence strategic decisions and improve operational efficiency.

2.2. Model Development

2.2.1. Features

The simulation model's features were derived from the CNRL topography, which was imported as a Digital Terrain Model (DTM) file. This file contained topographic data for the area, including dump locations. The DTM served as the fundamental surface for mapping the road network and conducting simulations. The accurate terrain representation was critical for realistic simulation of mining operations, notably in terms of vehicle mobility and topography's impact on haulage.

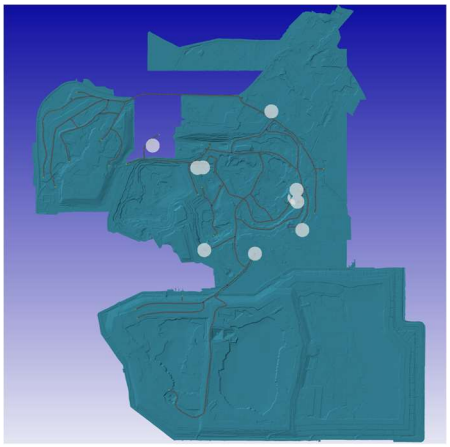

Figure 1. Topography of the mine site.

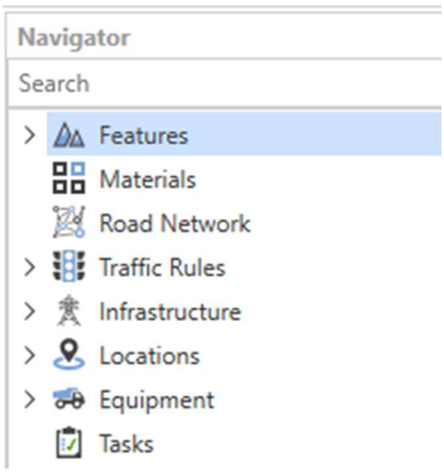

Figure 2. Feature button on the Navigator bar.

2.2.2. Materials

The type of material carried is critical for model analysis and simulation. According to the data, there are several types of materials. However, the most interesting item is ore and waste. Because it is oil sands, the material is loose sand, and material properties such as in-situ bank density, ability to be excavated, swell factors and loose density, loader bucket fill factor, and load and haul or load carry times should be considered. The values of the material's attributes will be entered by right-clicking on the material tab in the navigation pane shown in figure 3, selecting configure, and making the following changes to material attributes in the material pop-up panel. You click on the plus sign at the top left corner shown in figure 4 to add material, select any material, and then study the information on the material dialog box. This information will provide you with the material's numerous properties, such as the swell factor, in-situ density, struck and heaped capacity. You close the window and save the project. In the simulation, the materials that were selected were "Mud-Wet Compactly Dry" and "Sand-Dry". This material was chosen because it resembles the oil sands material used in CNRL operations. The in-situ bank density was 3.25 t/m³ and 1.9 t/m³ respectively, indicating modest compactness. The material has a swell factor of 1.2 t/m³ and 1.1 t/m³ and a loose density of 2.71 t/m³ and 1.73 t/m³ respectively. These features were critical for precisely modeling the handling and movement of material throughout the mining operation, including factors such as load capacity, transit efficiency, and material handling during dumping.

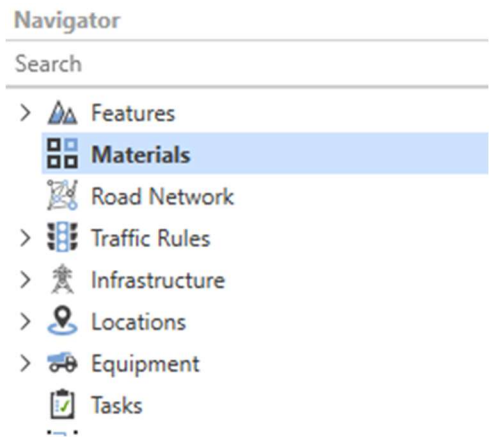

Figure 3. Materials button on the Navigator bar.

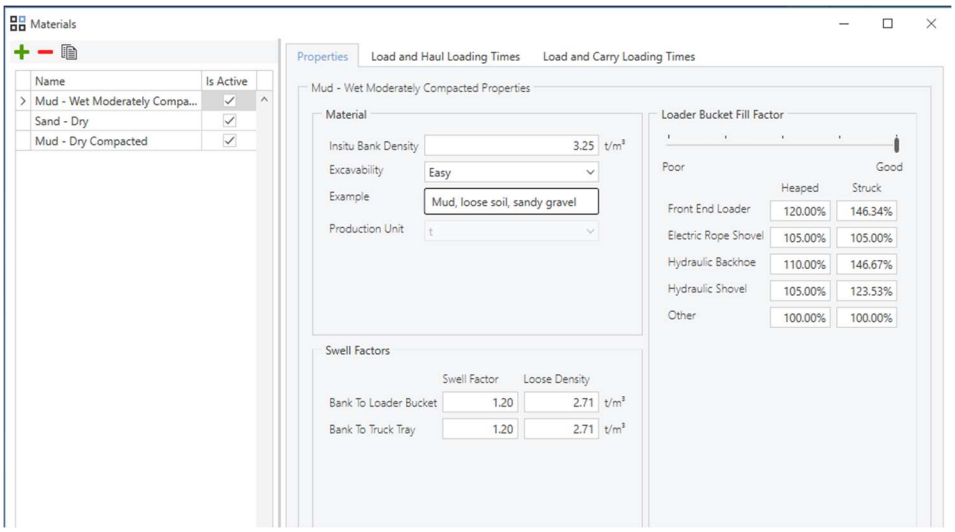

Figure 4. Materials menu dialog box.

2.2.3. Road network

The road network in HaulSim is imported via a string file named deswik_road, which specifies the paths for equipment movement in the simulation. This road network is critical for correct modeling since it influences the speed and efficiency of equipment travel. The file, which is part of the CNRL dataset and topography, must have a String ID that represents the grouping of nodes on the same road, as well as the X, Y and Z coordinates for each X, Y, and Z node, each listed on its own line. The road network representation employs several colors to represent distinct features: gray for waypoints, blue for intersections, and yellow for termination points. These indicators are critical for route analysis and equipment simulation. To import the road network, left-click the road network option in the navigation panel, then import the file and save your changes. You can also display road grades using the legend button on the toolbar and configure cutting planes by modifying the elevation in the Build toolbar, which allows you to see the road's measurements from top down.

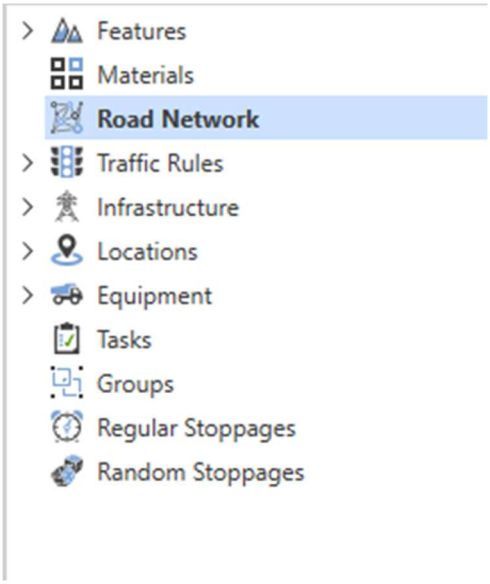

Figure 5. Road Network button on the Navigator bar,

2.2.4. Location

The CNRL data is an SQL file containing information about the mining fleet's sources, destinations, cycle time, and various other details. The sources and destination were mapped on the road for accuracy by using an SQL code to map the sources and destination on a day on a particular shift (day shift) on the road for accuracy. The day that was chosen was the 1st day of the 11th month of the year 2016 during the day shift of the two tables [*Shell_Productivity].[dbo].[EFHtable]* and *[Shell_Productivity].[dbo].[road_network]* were used in extracting the data we need for the sources as well as the destinations for that particular shift.

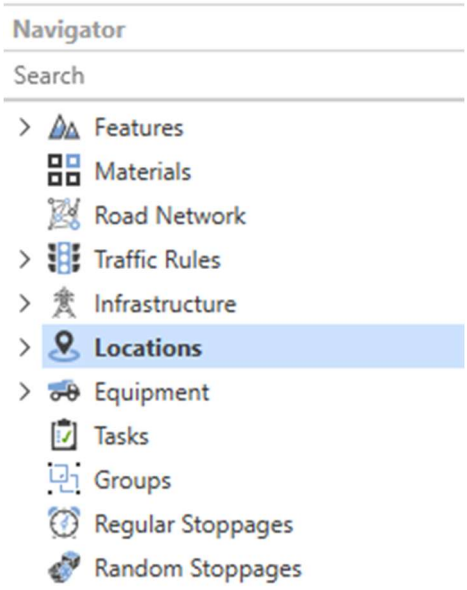

Figure 6. Location button on the Navigator bar.

2.2.5. Sources

In haulage simulation modeling, material is moved from the source (Load and Carry or Load and Haul) to the destination (dump, stockpile, crusher, Haul Load point, or Ore Pass In). In this situation, the material is carried from the digging site and stockpiled at the destination. The material is taken from the Load and Haul unit and either dumped or stockpiled at the oil sand mine. To import the source file, click on the location in the navigation pane, then choose sources, open the file, and import. The next step is to customize and modify the methodology to single or double-sided, then save the file. The next step is to move about the grids. To accomplish this, click in the navigation pane, expand the location tab, and pick source, then right-click on the source tab and select configure. Click the filter button to pick and filter your desired source. Close the pop-up window and save the project. The data's pit sites served as their sources. The data was collected for the year 2016, the 1st day of the eleventh month. Consider looking at the simulation for a day to ensure accuracy. We extracted pit areas for one day during the day shift. The pit sites during that period are listed below: PIT-300-S007, PIT-265-S009, PIT-305-S2503, PIT-BORROW3-S2504, PIT-310-S806, PIT-301-S807, PRJ-CLN-IPD2-2889, ST_SAND_EAST_CR, ST_REJECTS_JPM, PRJ-CLN-IPD2-2900, and ST_SAND_EAST_CR.

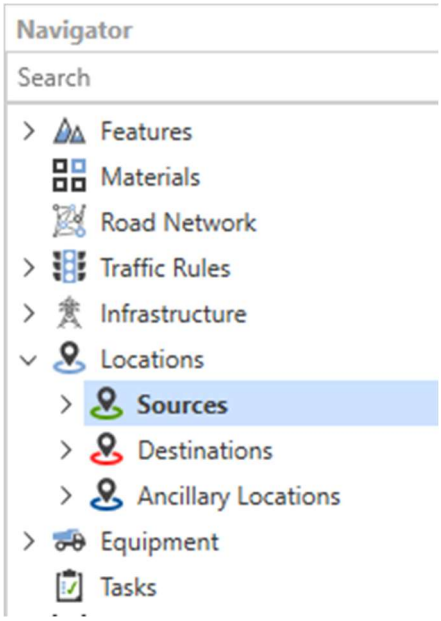

Figure 7. Source button under the Location Menu.

2.2.6. Destination

The destination in HAULSIM is the location where the truck will deposit the material collected from the source. It marks the end of the road network. The data shows the following destinations: dump, crusher, and stockpile. The destination file is either imported or manually added, just like the source file. In this model, we will deal with three different destinations: dump, stockpile, and crusher. To import the destination file, click on the location in the navigation pane, then select the destination, click on import, and finally select the file to import. The details about the file will appear in the import destination pop-up window; click next to import. The details about the file will appear in the import destination pop-up window; click next to import. The next step is to customize and make changes to the destination pop-up window, which allows the user to adjust the layout, crush rate, initial quantity, material, and capacity of the three destinations indicated above, before saving the

project. The destinations are the various dumps and stockpile locations found in the data. The destinations were extracted just like the sources for one day during the day shift. These were the various destinations: CR2_JPM_REJ, DY_INPIT_D2_SHELL_553, DY_INPIT_D2_SANDCHIMNEY, IN_ROADS_JPM, DU_WODA_N_SHELL, DU_WODA_NORTH_SLOP, CR2_JPM, DY_INPIT_D2_SHELL_539, DY_INPIT_D2_CORE and DU_WODA_N_OVB.

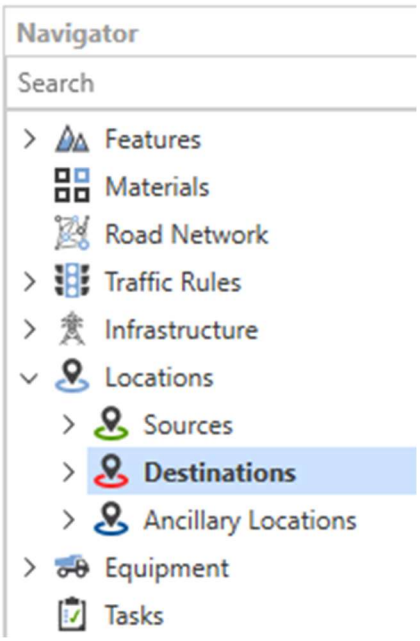

Figure 8. Destination button under the Location Menu.

2.2.7. Ancillary locations

The ancillary location is where the trucks will come from before they move to the assigned locations. The ancillary location was created on the southeast side of the CNRL topography. These are the list of the ancillary locations: 1) Fuel bay: equipment move to this location to refill their tank with fuel, 2) Lunch room; where the operators take a break for their lunch, 3) Truck Bay; the location where the trucks travel from, and 4) Workshop; where the equipment move to if there is a breakdown. These locations were added to mimic the real-life situation in a mining operation. There was no data provided for this, so it was randomly added at locations close to the pit.

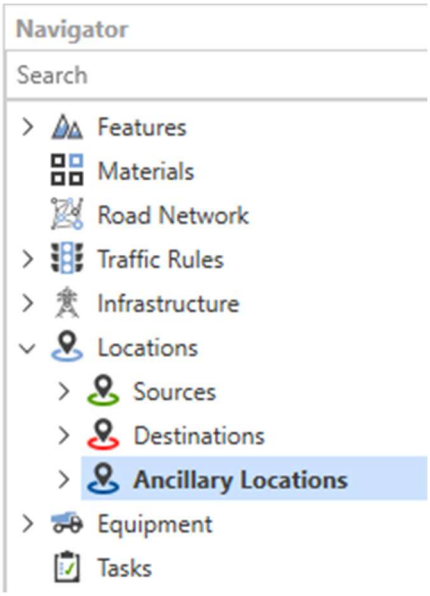

Figure 9. Ancillary Locations button under the Location Menu.

2.2.8. Equipment

After establishing the material, road, sources, and destinations, adding equipment is a critical step in finishing and validating the simulation model. The simulation uses a variety of equipment to accurately mimic the mining operation. Loading units, such as shovels, are stationed at source locations to haul trucks, which transport material to dumps, stockpiles, or facilities. Load and carry units are utilized for material transport, while ancillary units, such as graders and dozers, ease the loading and hauling operation. For the simulation, the equipment consisted of haul trucks and shovels. The shovels used were nine in total, from five different brands: Bucyrus-495B (BE 495B2), Hitachi-EX 2500-6(HIT 2500), Hitachi-EX 8000-6(HIT 8000), Hitachi- EX850-3 (Hit ZX850), and Hitachi-ZX 870LC-5A (Hit ZX870). The truck fleet included 23 trucks of two types: Caterpillar-797B (CAT 797B) and Caterpillar-797B (CAT 797). The CAT 797B has a payload capacity of 349.02t with a maximum speed of 66.22km/h and the CAT 785 has a payload of 99.67t with a speed of 55.68km/h. Both the shovels and trucks were extracted for a single day during the day shift. The table below shows the name of the loaders, the loader type and the start location. Among the 22 haulers 16 were Caterpillar-797B and 8 were Caterpillar-785.

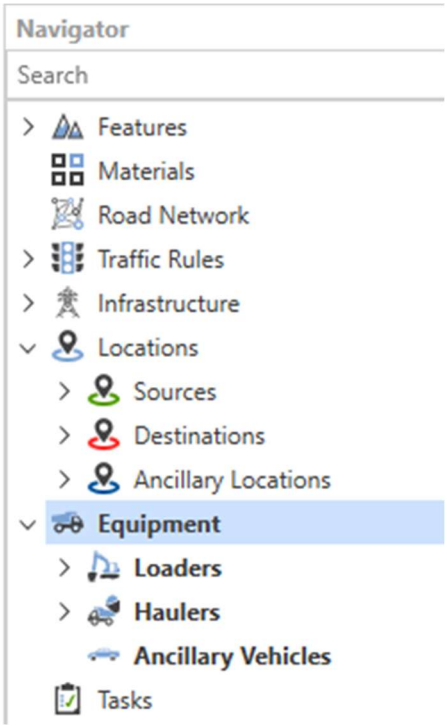

Figure 10. Location button on the Navigator bar.

Table 1. Name, loader type and location of the Loaders.

Name	Loader Type	Start Location
S007	Bucyrus-495B	PIT-265-S009
S009	Bucyrus-495B	PIT-300-S007
S2504	Hitachi-EX 2500-6	PIT-305-S2503
S2504	Hitachi-EX 2500-6	PIT-305-S806
S806	Hitachi-EX 8000-6	PIT-305-S807
S807	Hitachi-EX 8000-6	PIT-BORROW3-S2504
S2889	Hitachi- EX850-3	ST_SAND_EAST_CR
S2899	Hitachi-ZX 870LC-5A	PRJ_CLN_IPD2_2900
S2900	Hitachi-ZX 870LC-5A	ST_REJECTS_JPM

2.2.9. Tasks

The tasks panel is used to assign the loaders to the destination. Right-click on the task button and select configure, and a pop-up window opens where it contains a table. In the table, add load and haul groups. The load and haul groups should contain the number of loaders that are used for the simulation. The load and haul groups are created, each loader is assigned to it, the pit locations of the loader, and the various destinations to which the truck will move from the source to the destination. There are other columns such as the material, task cycle, and tonnages, but those are optional.

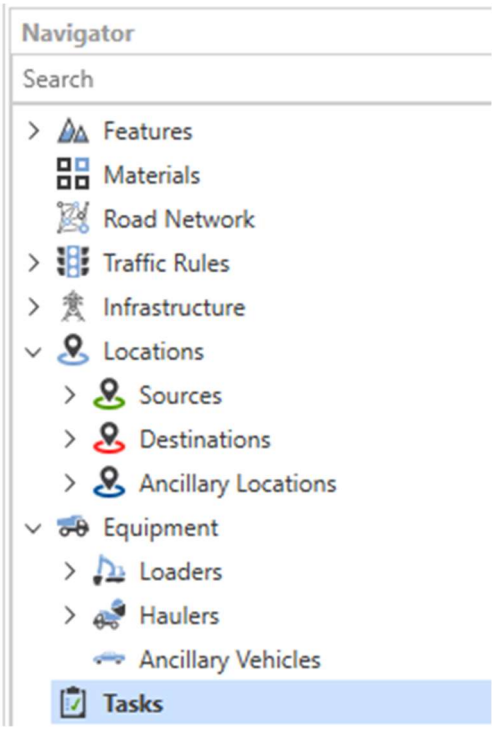

Figure 11. Tasks button on the Navigator bar.

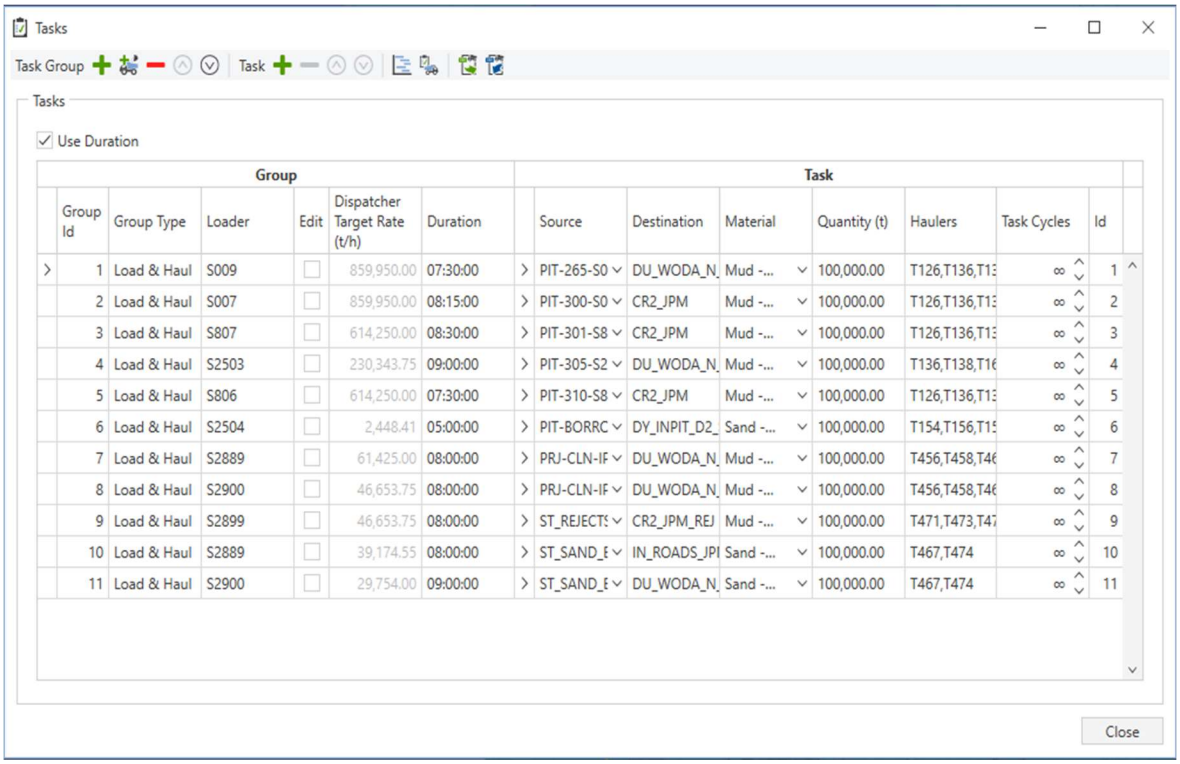

Figure 12. Pop-up window of the tasks button.

2.2.10. Verification

After all, the necessary information has been added to the model. We will verify whether the simulation can run by checking whether any parameters are highlighted in red, as a sign of any errors or inconsistency. If any of the parameters are highlighted in red, we will make the necessary changes to make the model work.

2.2.11. Run simulation

On the Run menu, under the toolbar select the run button to finally run the simulation. The simulation was run for 11 hours, taking account of the 12-hour shift of a mine with 1 hour for the operational and non-operational delays that could reduce the operating hours of the equipment. After the simulation is run, the results from the reports button are obtained on the Run menu bar and imported in an excel format for further analysis.

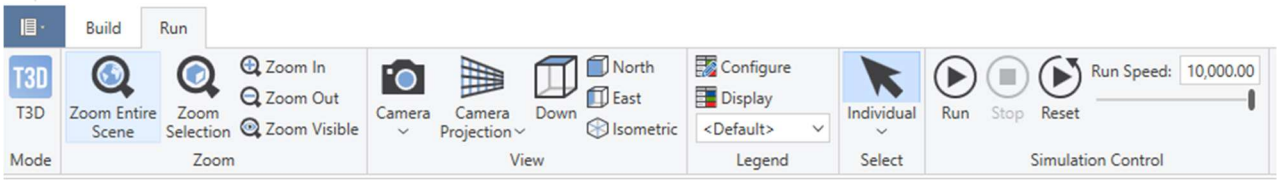

Figure 13. Run button under the Run Menu bar.

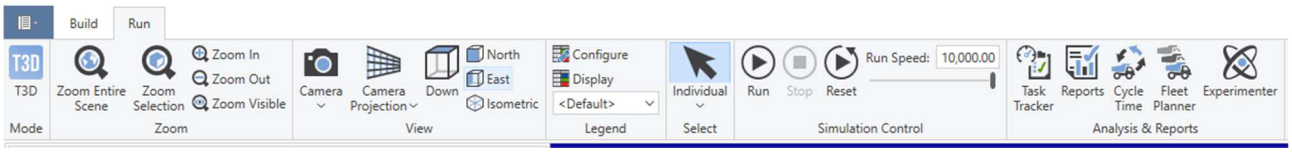

Figure 14. Reports button under the Run Menu bar.

2.3. Validation

After the model was built, it should be analyzed for accuracy and validated by checking how the simulated values are close to historically recorded values. The real-life data was extracted and imported as an excel file taking into consideration a particular shift in a specific day to mimic real world mining operation. The simulation data was extracted in a table form for the comparison. The tonnage from each location was extracted from the simulation results; and the real-life data, the total tonnages for each pit was extracted using SQL. These are the following results obtained after the data was analyzed with python:

3. Results

Once the simulation data was compared to the real-life data, these were the following results that were obtained through tables and graphs. The total tonnages of the pit locations and the dump locations were collected The simulation data and the real life data are summarized in the tables below:

Table 2. Comparisson of the tonnages for pit locations, Simulation vs. Real values.

Pit Locations	Simulation Data (tonne)	Real-Life data (tonne)
PIT-265-S009	34354.70	33631.52
PIT-300-S007	44698.97	45715.32
PIT-301-S807	34037.22	31202.52

PIT-305-S2503	14787.06	11868.55
PIT-310-S806	28839.61	26848.68
PIT-BORROW3-S2504	7403.92	3314.43
PRJ-CLN-IPD2-2889	3584.26	1489.80
PRJ-CLN-IPD2-2900	3584.26	1411.70
ST_REJECTS_JPM	5926.79	9871.80
ST_SAND_EAST_CR	797.89	266

From the table below that is from Table 2, we can spot some differences between the simulation data and the real-life data, the pit locations where there is a significant amount of difference is the "PIT-BORROW3-S2504", "PRJ-CLN-IPD2-2889", "PRJ-CLN-IPD2-2900" and "ST_REJECTS_JPM", "ST_REJECTS_JPM". The percentage difference of the total tonnages between the simulation values and the Real-life values is 7%. This small difference between the total tonnages between both data indicates the closeness of the simulation data to the real-life data. Even though individual pits showed vast differences due to the inflexibility of assigning information to the software, these are some of the limitations of the HaulSim software and the difficulties in getting accurate results for simulations. The most important thing is to work on the simulation and get close or similar results.

Table 3. Comparisson of the tonnages for dump locations, Simulation vs. Real values.

Dump Locations	Simulation Data (tonne)	Real-Life data (tonne)
CR2_JPM	107575.80	103403.70
CR2_JPM_REJ	5926.79	9871.80
DU_WODA_N_OVB	53306.97	33038.88
DY_INPIT_D2_CORE	3801.21	10235.68
DY_INPIT_D2_SANDCHIMNEY	7403.92	3176.33
IN_ROADS_JPM	0	3677.49
DU_WODA_NORTH_SLOP	0	1122.50
DY_INPIT_D2_SHELL_553	0	365.56

We can also see from Table 3, that there is some empty data for the simulation data, this is for the same reason above due to the inflexibility of assigning information to the software. From table 3, we can see from the last three pits that the simulation values are empty, so I represented it with zero, even though the real-life values show that the material was sent to the sump. From the CNRL data, the major places where the ore material was taken to be the "CR2_JPM" and "CR2_JPM_REJ". These are the major crushers where the ore was taken to, the rest are dump locations. Most of the values from the simulation were significantly higher than the real-life data. The percentage difference for the total tonnage at the dumps between the simulation data and real-life data is 8%. This indicates the closeness of the simulation to real life scenario.

We will examine some graphs and make some analysis on the data for the tonnages for the pit locations and the dump locations respectively.

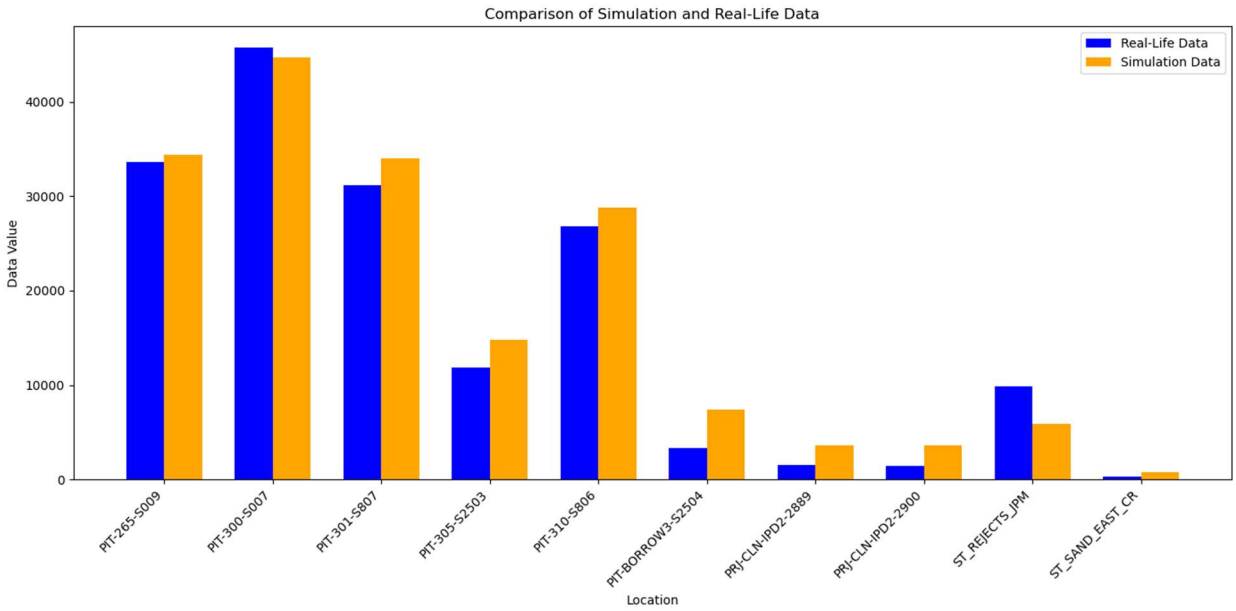

Figure 15. Bar plots representation of tonnages for each pit.

This is a bar graph for the tonnages for each of the pit locations; the blue indicates the real-life data and the yellow the simulation data. We can see from most of the bars that the simulation values for most pits were higher than the real-life data. This is just the graphical representation of Table 2.

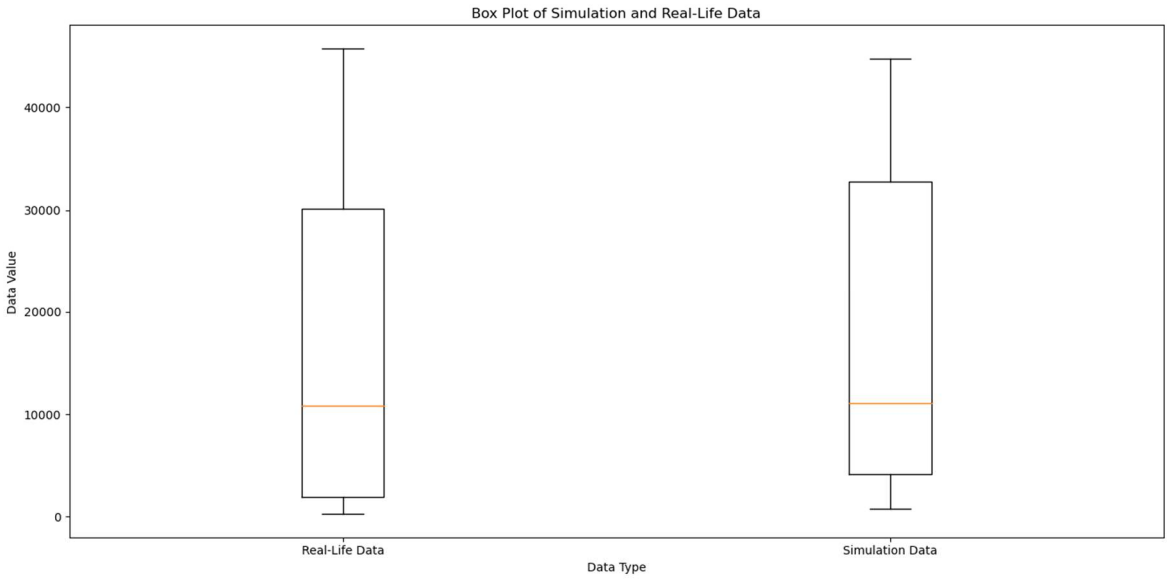

Figure 16. Box plot of Simulation and Real-life Data for the pit locations.

The box plot provides a comparison of the distribution of values between simulated data and real-life data, highlighting significant disparities in their dispersion and central tendency. Both datasets exhibit a comparable median, situated slightly below 10,000, suggesting similar center values. Nevertheless, the real-life data demonstrates reduced variability with a narrower interquartile range (IQR) in comparison to the simulated data, indicating more uniform outcomes. The simulation data, on the other hand, has a larger IQR, indicating more unpredictability and a broader range of probable outcomes. Both datasets exhibit some right skewness, with longer whiskers on the upper end, ranging from near zero to slightly more than 40,000. This comparison indicates that, while the core tendencies

are consistent, the simulation data is less exact or more varied, likely simulating a broader range of scenarios, necessitating additional research to refine the model or identify the source of this variability.

The Pearson Correlation Coefficient is 0.99, which is very near to one. This demonstrates a strong positive linear relationship between simulated values and real-life values. Essentially, when real-life values grow, so do the anticipated values. This substantial correlation suggests that the model is quite good at detecting the underlying patterns in the data.

Moreover, the other measures were used such as the Root Mean Square error and the Mean Absolute Error was calculated to better understand the relationship between both data, and these were the results:

The Mean Absolute Error (MAE) is 2231.71, indicating that the model's predictions depart from actual data by around 2232 units. This metric provides insight into the average magnitude of the errors without considering their direction, offering an overall idea of how inaccurate the predictions are. The Root Mean Square Error (RMSE) is reported at 2524.87, which is slightly greater than the MAE. RMSE is more sensitive to larger mistakes because it squares the differences before average, giving greater weight to significant discrepancies. The fact that the RMSE is not much bigger than the MAE shows that the forecasts contain minimal extreme errors, indicating that the model's performance is rather consistent.

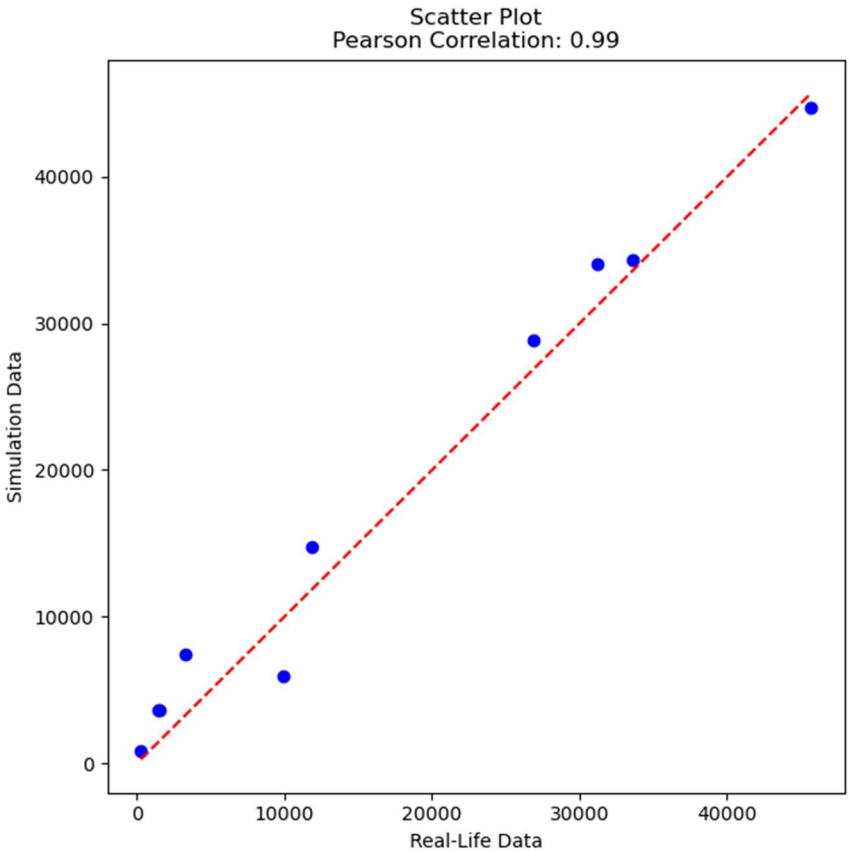

Figure 17. Scatter plot of Simulation and Real-life Data for the extracted tonnage at pit locations.

We will now examine the charts for the dump locations and make some analyses on them:

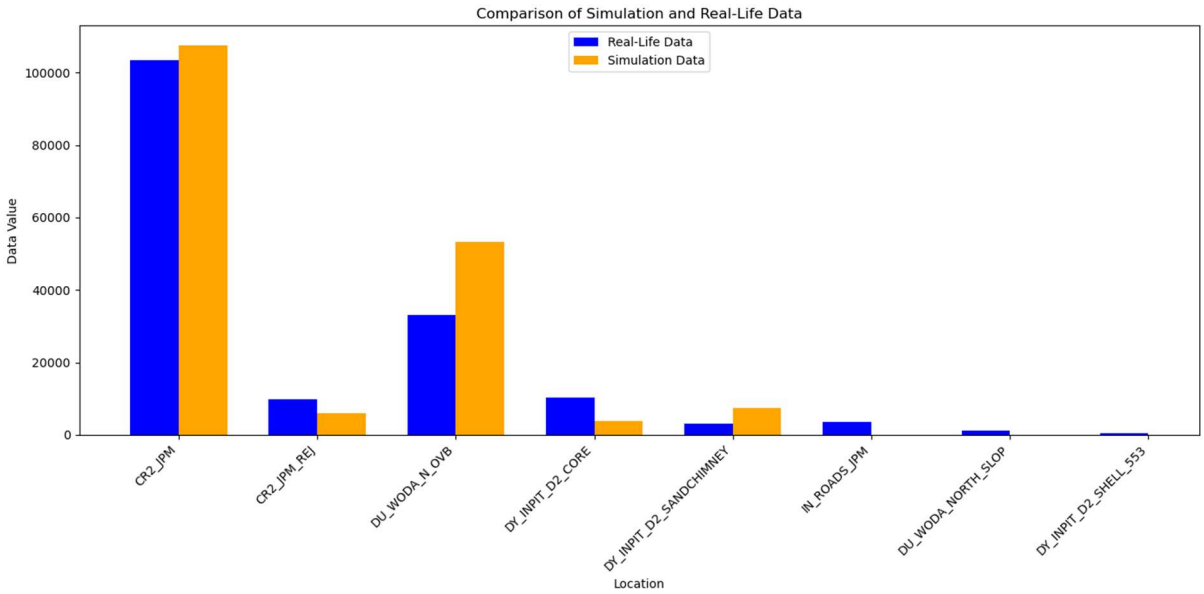

Figure 18. Bar plots representation of tonnages for each dump location.

This is a bar graph for the tonnages for each of the dump locations; the blue indicates the real-life data and the yellow the simulation data. We can see from most of the bars that the simulation values for most pits were higher than the real-life data. This is just the graphical representation of Table 3.

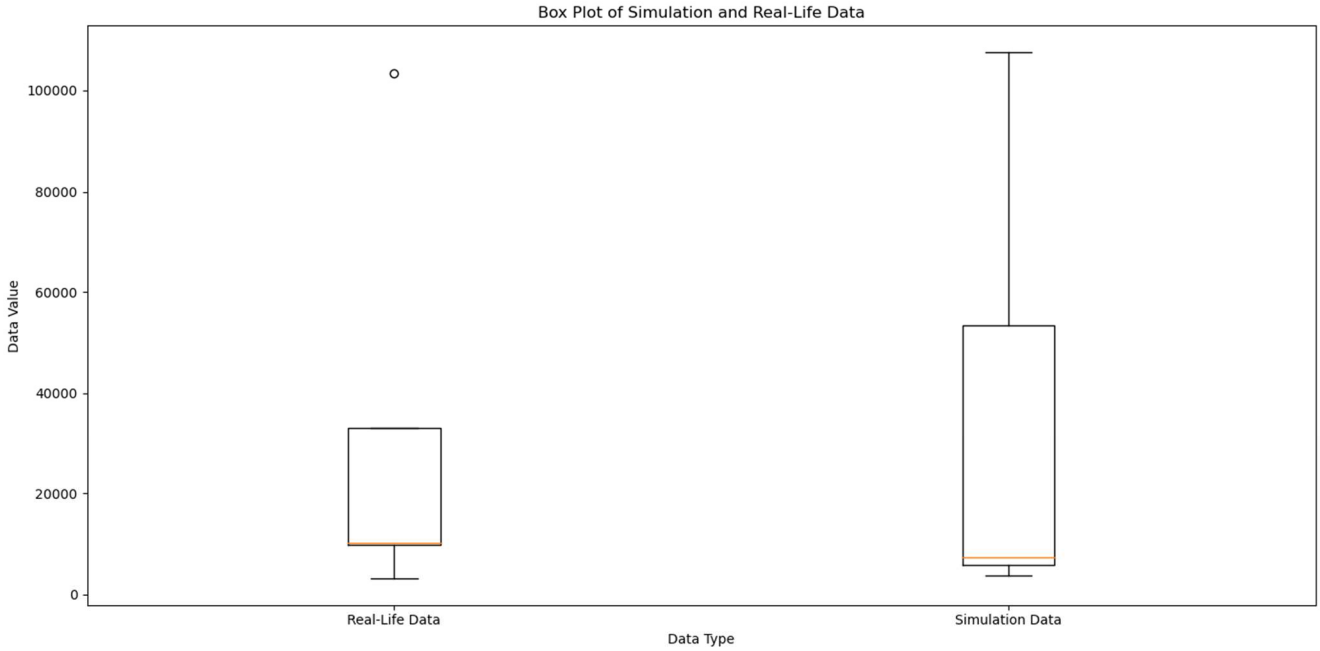

Figure 19. Box plot of Simulation and Real-life Data for the dumped tonnage at dump locations.

The real-life data has a shorter interquartile range compared to the simulation data; this shows reduced variability compared to the real-life data. The simulation data, on the other hand, has a larger IQR, indicating more unpredictability and a broader range of probable outcomes. The simulation data exhibits right skewness, from 0 to 100,000. the real-life data has just a lower tailed whiskers, meaning there is less or almost no variability of the real-life data as compared to the simulation data,

there is an outlier that is visible on the real-life data on the 100000 unit, the same level that the right whiskers of the simulation data extend to, from table 3 we can see the first dump location has more 100000 tonnes of material for each data. The median is on the same level as the interquartile range; this suggests that a larger portion of the data is concentrated in the upper range, with a tail extending towards lower values. This indicates that there are relatively smaller values in the dataset compared to larger values.

The Figure 18 shows a strong correlation between the real-life data and the simulated values. The Pearson Correlation Coefficient of 0.975 shows a very strong positive linear relationship between predicted and actual dump locations, showing that the model adequately reflects the data's accuracy.

The performance metrics for the dump locations provide a complex picture of the model's success. With a Mean Absolute Error (MAE) of 7809.45, the model's predictions are around 7809.45 units off. This represents the average magnitude of prediction mistakes, without regard for their direction. However, the Root Mean Square Error (RMSE) is substantially greater at 10030.35, indicating that there are some significant inconsistencies in the forecasts, since RMSE is more sensitive to outliers.

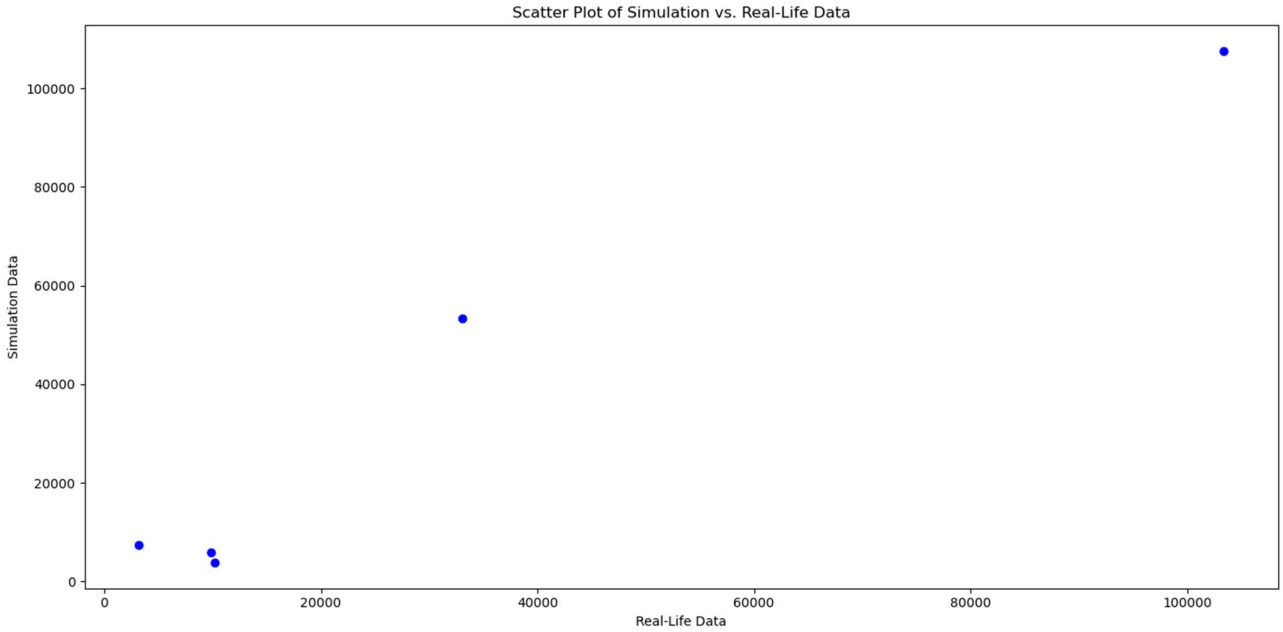

Figure 20. Scatter plot of Simulation and Real-life Data of the dump locations.

4. Discussion

Using comprehensive data on material properties, road networks, equipment, and operational factors, a simulation model of the mining operation was created to mimic the real-life system. The main goal was to evaluate the correctness of the model by contrasting the simulation output with real operational data from the CNRL operations. This comparison helps pinpoint areas for improvement by illuminating the model's advantages and disadvantages.

The simulation considered crucial aspects such as material qualities (e.g., in-situ bank density, swell factor, loose density), road network characteristics, and equipment requirements. The road network, which is critical for calculating equipment movement and speed, was meticulously mapped using a precise string file, assuring accuracy in depicting the mine's design. Equipment data, such as the types and number of shovels and trucks, were retrieved for a single day to provide a snapshot of the operation's capacity and workflow. The simulation model was analyzed by comparing total material

tonnage from simulation and real-life operations. The histogram and box plot representations demonstrated substantial differences between the two data sets. The tables below show the total tonnages that were gathered from collecting data from a single day in a single shift to depict a real-life scenario of the mine. As described in the former chapter the values between both data were not similar because of the limitations of Haulsim and its inflexibility to adjust information to depict real life data. The tables and the bar graphs showed the representation of both data and their discrepancies. Despite all this the total tonnage from the pit and dump as compared to the simulation data showed a percentage difference of 7% and 8%, which is a laudable and acceptable difference between both data. The box plot for the pit and dump location describes the data for each of them respectively. The box plots of the pit location show similarities between the real-life data and the simulation data. It showed that both data were similar with the simulation data having a slightly higher variability. The dump locations were slightly different; this could be attributed to the missing values in the simulation data. However, the simulation data for the dump locations shows variability in both lower and upper values. The real-life data also showed more variability in the lower values but not as much with the higher values as compared to the simulation values. The Pearson correlation matrix between the pit locations and the dump locations were 0.99 and 0.97 respectively. This shows a stronger correlation for the pit locations, though the dump locations showed a lower correlation compared to the pit locations. This as I stated earlier could be due to the missing values of the dump locations. The MAE and RMSE further indicated that the simulation values and the real-life values were similar and the simulation was able to replicate the real-life data really well. Furthermore, the calibration of the model's parameters may require adjustment. Fine-tuning parameters such as equipment cycle durations, haul road conditions, and loading efficiencies may increase the model's accuracy. Incorporating a broader range of real-world data from different days and operational settings would give a more solid foundation for testing the model.

5. Conclusion

The simulation model is a useful tool for analyzing and projecting mining operations, as it provides insights into prospective improvements and efficiencies. However, the current validation procedure indicates considerable disparities between the simulated and actual data, identifying areas for improvement in the model's accuracy. By resolving these constraints and fine-tuning the model's parameters and assumptions, the simulation can become a more trustworthy predictor of real-world performance, enabling more effective decision-making in mining operations. The findings highlight the significance of continual model validation and calibration against actual operating data to ensure simulation relevance and accuracy. The software HaulSim can be further used for comparing different scenarios and selecting the best one. There are also some features for optimizing distances between roads there by enhancing the operations. Short term schedules can be imported from XPAC; a scheduling software to HaulSim and we can create a simulation model from that schedule. I believe HaulSim can be more exploited and used effectively especially with the conjunction of other softwares.

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AI-Enhanced Decision Support for Optimal Fleet Assignment in Open-Pit Mining

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ABSTRACT

Optimal fleet assignment is crucial for the efficiency and cost-effectiveness of open-pit mining operations. Traditional simulation-based or mathematical models often fall short when dealing with the complexities of resource assignment, such as fleet diversity, multiple dig and dump points, and process uncertainties, due to their high computational time and costs. This study addresses this gap by employing a hybrid Discrete Event Simulation-Genetic Algorithm (DES-GA) approach to develop an AI-driven Decision Support System (DSS) for optimal fleet assignment. Graph Neural Networks (GNNs), an AI-based approach, are utilized to enhance resource assignment decisions, a potential that has been overlooked in previous research. The hybrid DES-GA model generates the necessary dataset for GNN training, ensuring assignment optimality while addressing the uncertainties inherent in the mining process. Key features for GNN training include the road network, available fleet, dig and dump points, their adjacency distances, and shovel-to-dig point and truck-to-shovel allocations obtained from DES-GA. The results demonstrate that this approach significantly enhances real-time dispatching, reduces costs, and minimizes environmental impacts by determining the optimal shovel for each dig point and the appropriate truck types and quantities for each shovel. This study provides valuable insights and practical solutions for the mining industry.

Keywords: *Discrete Event Simulation, Genetic Algorithm, Decision Support System, Graph Neural Networks, optimal fleet assignment, real-time dispatching, open-pit mining, mining operations.*

1. Introduction

An optimal fleet assignment is a pivotal factor in the efficiency and cost-effectiveness of open-pit mining operations [1]. The complex nature of resource assignment in mining, characterized by fleet diversity, multiple dig and dump points, and process uncertainties, presents significant challenges. Traditional simulation-based or mathematical models often fail to address these complexities due to their high computational time and costs [2].

Efficient fleet assignment ensures mining operations run smoothly, reducing downtime and operational costs. It also minimizes environmental impacts by optimizing resource utilization and reducing unnecessary machinery movement. Given the scale and financial investment involved in open-pit mining, even marginal improvements in fleet assignment can lead to substantial economic benefits [3].

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Traditional models, while helpful, are often limited by their inability to adapt to the dynamic and uncertain nature of mining operations. These models require extensive computational resources and time, making real-time decision-making impractical. Moreover, they may not fully capture the interdependencies and interactions between different elements of the mining process [4].

GNNs, an AI-based approach, are utilized to enhance resource assignment decisions. GNNs can capture the complex relationships between different elements in the mining process, providing a more accurate and efficient DSS. This study leverages the potential of GNNs to address the uncertainties inherent in the mining process, which have been overlooked in previous research.

This study proposes a hybrid DES-GA approach to overcome these limitations. DES is employed to model the dynamic nature of mining operations, while GA is used to optimize the fleet assignment. The hybrid DES-GA model generates the necessary dataset for training a GNN, further enhancing the decision-making process. The primary objective of this study is to develop an AI-driven DSS for optimal fleet assignment in open-pit mining. The critical features considered for GNN training include the road network, available fleet, dig and dump points, their adjacency distances, and shovel-to-dig point and truck-to-shovel allocations obtained from the DES-GA model. The study aims to demonstrate that this approach can significantly enhance real-time dispatching, reduce costs, and minimize environmental impacts.

This paper is structured to thoroughly examine mining fleet assignment methods. It begins with a comprehensive literature review of existing approaches in this field. Following this, the methodology section delves into the details of the hybrid DES-GA approach and discusses the role of GNNs in enhancing these methods. The subsequent section presents an initial data analysis, including a dataset description and preliminary findings. Finally, the paper outlines the future steps required to complete the research, along with the anticipated outcomes.

2. Literature Review

2.1. Existing Methods and Models for Fleet Assignment in Mining

Fleet assignment in open-pit mining has evolved through various methodologies, including linear programming, DES, heuristic and metaheuristic algorithms, and multi-agent systems. Intelligent Fleet Management Systems have recently been introduced to enhance efficiency and productivity.

Linear programming is used extensively for optimizing the allocation of trucks and shovels in mining operations, aiming to minimize costs and maximize productivity by optimizing objective functions such as profit maximization and cost minimization. For instance, Zhang and Xia developed an integer programming approach for truck-shovel dispatching, resulting in significant cost savings and improved operational efficiency [4].

DES simulates the sequence of mining operations, capturing these processes' dynamic and stochastic nature. Meneses and Sepúlveda demonstrated how DES can model the temporary deterioration of mining roads, impacting productivity and fuel consumption [5]. Additionally, Awuah-Offei et al. evaluated truck-shovel energy efficiency using DES, showing the potential benefits of optimizing fuel efficiency [6]. Ben-Awuah et al. developed a hierarchical mine production scheduling model using DES to link long-term predictive mine plans with short-term production schedules, accounting for constraints and uncertainties in mining and processing capacities [7].

Heuristic algorithms, such as GA and Simulated Annealing, are widely used for fleet assignments. These algorithms explore vast search spaces to find near-optimal solutions efficiently. Alexandre et al. discussed the flexibility of multi-objective evolutionary algorithms in adapting to changing conditions in mining operations [8].

Multi-agent systems simulate interactions between autonomous agents representing different components of the mining operation. These systems model the complex interactions and coordination required for efficient fleet management. Multi-agent systems enhance decision-making by allowing for decentralized control and adaptive responses to dynamic operational changes [9].

Recent studies have introduced innovative models for fleet assignment in mining. Mirzaei-Nasirabad et al. presented a multi-stage optimization model focusing on real-time truck dispatching, which minimizes waiting times and deviations from production requirements [10]. Noriega et al. proposed a Deep Reinforcement Learning system for real-time truck dispatching, significantly outperforming traditional heuristic methods [11]. Upadhyay et al. introduced a simulation-based algorithm addressing equipment selection under uncertainty, providing robust estimations of fleet productivity [12]. Mohtasham et al. introduced a multi-objective optimization model for fleet allocation scheduling, focusing on maximizing production and minimizing fuel consumption [13].

Intelligent Fleet Management Systems leveraging advanced technologies can optimize the efficiency and productivity of mining operations across various planning horizons. Hazrathosseini and Afrapoli discussed the transformative potential of intelligent Fleet Management Systems in mining [14]. Bnouachir et al. proposed an intelligent distributed Fleet Management Systems architecture for open-pit mines, enhancing real-time control and decision-making through AI and IoT technologies [15].

2.2. GNNs and Their Potential in Resource Assignment

GNNs represent a class of machine learning algorithms operating on graph structures, capturing the relationships and dependencies between entities. In mining, GNNs can model interactions between components like trucks, shovels, and dig points, optimizing resource allocation by considering the dynamic nature of mining operations.

GNNs offer significant potential for improving resource assignment in mining by providing real-time, adaptive decision-making capabilities. Wang et al. demonstrated the potential of GNN-enhanced models in real-time fleet dispatching, significantly reducing operational costs [16]. Additional studies have explored various applications of GNNs in resource allocation.

Wang et al. discussed decentralized resource allocation in wireless networks using Aggregation GNNs, showcasing their permutation equivariance property and training with an unsupervised method [17]. Lima et al. applied GNNs for resource allocation in large-scale wireless control systems, enhancing efficiency and scalability [18]. Cranmer et al. proposed the use of GNNs for unsupervised resource allocation and learning reward structures for near-optimal allocation policies based on interactions between allocation targets [19]. Eramo et al. utilized neural graph-based models to predict processing capacities in Virtual Network Function Instances, capturing spatial and temporal correlations efficiently [20]. Theodoropoulos et al. demonstrated the application of GNNs in resource allocation for multiplayer mobile gaming, improving performance and management compared to traditional approaches [21].

2.3. Gaps in Current Research

Despite the advancements in simulation-based and optimization models, there are still significant gaps in the current research on fleet assignment in open-pit mining. Traditional models often struggle to scale up to large and complex mining operations. As the size and complexity of mining operations increase, models' computational requirements and complexity also grow, making it challenging to maintain efficiency and accuracy. Existing models typically are not designed for real-time decision support, limiting their applicability in dynamic environments. Making timely decisions is crucial in mining operations, where conditions can change rapidly, and unexpected events can occur. Additionally, the potential of AI techniques, such as GNNs, in enhancing fleet assignment decisions

has not been fully explored. While initial studies have shown promise, more research is needed to fully understand and harness the capabilities of AI in this context. Furthermore, models need to consider the environmental impact of fleet assignment decisions, cost, and productivity. Sustainable mining practices are becoming increasingly important, and optimizing fleet assignments to minimize environmental impact is a critical area of research.

This literature review highlights the various methods and models used for fleet assignment in mining, the applications of DES and GA, the potential of GNNs, and the gaps in current research. Addressing these gaps and leveraging advanced techniques such as GNNs can significantly improve fleet assignment efficiency, cost-effectiveness, and sustainability in open-pit mining.

3. Methodology

A systematic and multifaceted methodology is required to effectively address the complexities of optimal fleet assignment in open-pit mining. This methodology encompasses several critical steps, starting with collecting and analyzing detailed operational data and then integrating advanced simulation and optimization techniques. The following subsections outline the processes and techniques, including data collection and road network mapping. To provide a visual summary of the methodology, the flowchart in Figure 1 illustrates the key steps involved:

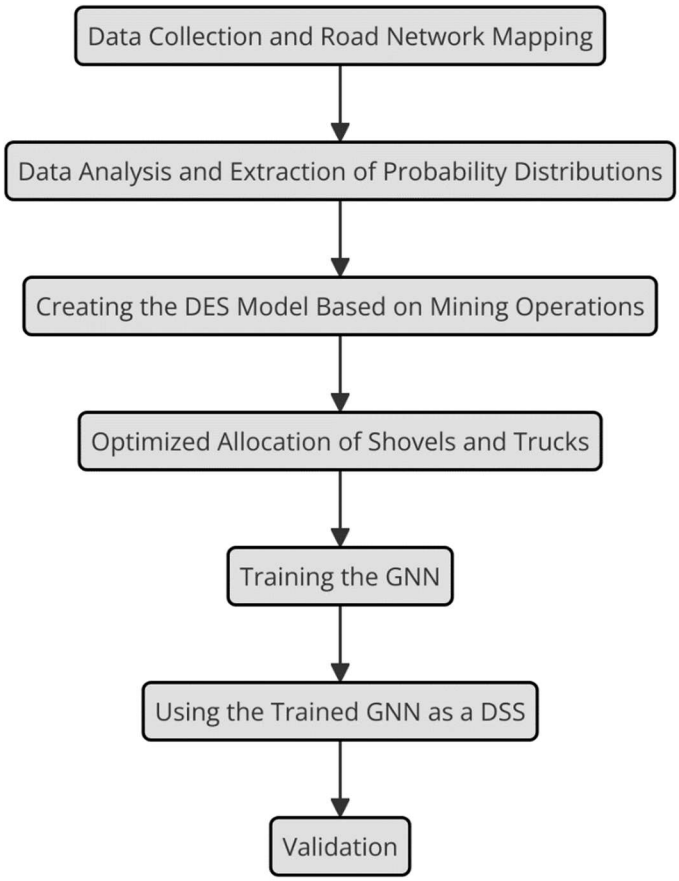

Figure 1. Flowchart of the methodology

3.1. Data Collection and Road Network Mapping

Data collection is the foundational step in developing the hybrid DES-GA model for optimal fleet assignment in open-pit mining. This involves gathering comprehensive data on various aspects of

the mining operation, including the road network, fleet characteristics, and operational parameters. The road network data encompasses the layout of the mining site, distances between nodes (such as dig and dump points), and the topology of the routes used by the mining fleet. Accurate road network mapping is crucial as it directly impacts the simulation and optimization processes. This data is collected from the mine's topography map for each month, ensuring that the model reflects the most current operational conditions.

In addition to the road network, detailed information about the mining fleet is collected. This includes the types of trucks and shovels, their capacities, and performance metrics under different conditions. Operational parameters such as loading and dumping times, weather conditions, and the types of loads carried are also gathered. This data collection phase ensures the simulation model is based on realistic and comprehensive input, which is essential for generating accurate and reliable results. Furthermore, historical operational data and maintenance records are collected to enhance the model's ability to predict equipment performance and maintenance needs.

Qualitative insights from mining operation experts are also gathered to complement the quantitative data. These insights provide contextual understanding and practical considerations that may not be captured in numerical data alone. Interviews and questionnaires with site managers, equipment operators, and maintenance personnel help to identify potential bottlenecks, inefficiencies, and areas for improvement in the current fleet assignment practices. This holistic approach to data collection ensures that the model is grounded in empirical data and practical operational knowledge.

3.2. Data Analysis and Extraction of Probability Distributions

Once the data is collected, it is analyzed to extract meaningful insights and distributions. This involves statistical data analysis to determine the average velocities of different types of trucks under various conditions. For instance, a truck's velocity may vary depending on whether it is empty or full, its load, and the prevailing weather conditions. Such distributions are critical for modeling the dynamic and stochastic nature of mining operations.

Additionally, the analysis includes determining the loading and dumping times for different equipment and under various conditions. These times are influenced by factors such as the type of material being handled, the efficiency of the loading and dumping equipment, and external conditions like weather. By extracting these distributions, we can accurately simulate the real-world behavior of the mining fleet, which is essential for optimizing fleet assignments and improving operational efficiency.

The data analysis process further includes identifying patterns and trends in equipment usage and maintenance needs. This involves analyzing historical data to predict future equipment performance and maintenance requirements. By understanding these patterns, the model can incorporate maintenance schedules and potential downtimes into the simulation, ensuring a more realistic representation of the mining operations. This analysis is based on fitting the data to intervals and durations of maintenance, ensuring accurate predictions and efficient scheduling, thereby enhancing the overall reliability and performance of the mining fleet.

3.3. Creating the DES Model Based on the Mining Operations

Developing a DES model tailored to the mine's specific environment is crucial in optimizing fleet assignments. The first step in creating the DES model is to define its objectives and scope, which includes identifying key performance indicators (KPIs) such as equipment utilization, cycle time, and overall productivity. The scope encompasses the processes to be modeled, including loading, hauling, and dumping operations, as well as interactions between different types of equipment.

Accurately modeling the mine layout and road network is essential. This involves mapping the dig and dump points, haul routes, and significant locations within the mine. The collected road network data is integrated into the model to ensure realistic simulations, with topology details such as gradients and distances being crucial for determining travel times and fuel consumption. Additionally, detailed information about the mining equipment, including trucks and shovels, is incorporated into the DES model. Each piece of equipment is modeled based on its capacities, performance metrics, and operational parameters derived from the earlier data analysis phase, such as loading and dumping times.

The core of the DES model involves simulating the operational processes and interactions within the mine, including loading material by shovels, hauling loads by trucks, and dumping material at designated points. The model accounts for stochastic elements like equipment breakdowns, maintenance activities, and varying loading and dumping times, providing a realistic representation of the mining operations. To ensure the accuracy and reliability of the DES model, it undergoes a rigorous validation and calibration process. This involves comparing simulation outputs with historical operational data and adjusting model parameters to minimize discrepancies, ensuring the DES model accurately reflects the real-world behavior of the mining fleet.

3.4. Optimized Allocation of Shovels and Trucks

The GA is implemented in two stages to optimize shovel and truck allocation:

3.4.1. Stage 1: Shovel Allocation

The first stage of the GA focuses on assigning shovels to dig points based on shovel capacity and dig point tonnage. The objective function aims to maximize the sum of the product of shovel capacity and assigned dig point tonnage, ensuring high-capacity shovels are assigned to high-tonnage dig points. The fitness function is formulated as Eq (1):

$$Goal\ Function = \sum (SC \times ADT) \tag{1}$$

Where:

- SC is the shovel capacity.
- ADT is the assigned dig point tonnage.

This function ensures that resources are allocated efficiently to maximize productivity.

3.4.2. Stage 2: Truck Allocation

In the second stage, the GA randomly assigns trucks to shovels. This allocation is evaluated through a simulation run in the DES model. The fitness function in this stage aims to maximize the average utilization of shovels and trucks. Utilization is calculated by the ratio of active operational time to total available time for each piece of equipment. The final objective is to maximize this average utilization across all shovels and trucks, ensuring optimal resource usage.

The flowchart in Figure 2 illustrates the GA process for optimizing shovel and truck allocation:

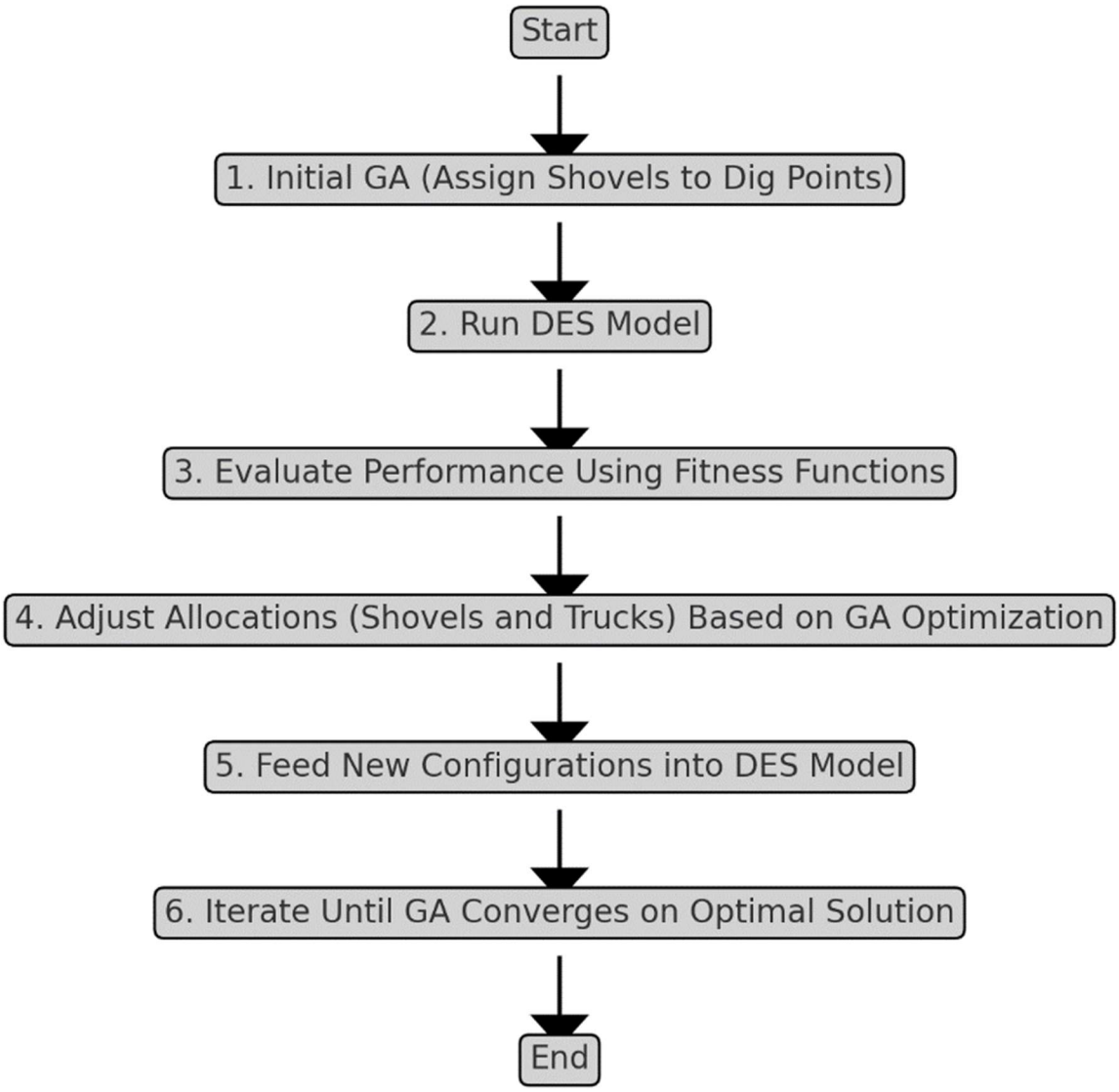

Figure 2. Flowchart of the Integration Process between DES and GA for Optimizing Mining Operations.

3.5. Training the GNN

Once the optimal fleet assignments are identified using the DES-GA approach, the next step is to train a GNN. The GNN is trained on the dataset generated by the DES-GA simulations, which includes detailed information about the road network, fleet characteristics, and optimal assignments. The GNN includes two layers: the first layer represents the fleet, and the second layer represents the road network. Nodes in the first layer represent components of the mining fleet (e.g., trucks, shovels), while nodes in the second layer represent the nodes in the road network (e.g., dig and dump points). Edges represent the interactions and assignments between these components.

Training the GNN involves feeding it with input features such as adjacency distances, fleet capacities, performance metrics, and target outputs, which are the optimal fleet assignments from the DES-GA model. The GNN learns to predict optimal assignments by minimizing errors between its predictions and outputs. This training process enhances the GNN's ability to make accurate and efficient fleet assignment decisions, leveraging the complex relationships within the mining operation data.

The training process includes multiple stages, including selecting appropriate GNN architectures and hyperparameters. The training dataset is divided into training, validation, and test sets to ensure the model's generalizability and robustness. During training, the GNN undergoes iterative updates through backpropagation, adjusting its weights to improve prediction accuracy. Regularization techniques and cross-validation prevent overfitting and ensure the model performs well on unseen data.

Once trained, the GNN is evaluated on the test set to assess its performance and accuracy in predicting optimal fleet assignments. Metrics such as mean squared error (MSE), mean absolute error (MAE), and R-squared (R^2) are used to quantify the model's predictive performance. The trained GNN is a powerful tool for real-time decision support, capable of adapting to new data and providing accurate fleet assignment recommendations.

3.6. Using the Trained GNN as a DSS

The trained GNN is then integrated into the DSS to assist in real-time fleet assignment decisions. The DSS leverages the GNN's predictive capabilities to provide adaptive and efficient decision support under varying operational conditions. When new data or scenarios arise, the GNN uses its trained model to predict optimal fleet assignments, enhancing the mining operation's responsiveness and adaptability.

The use of GNN in DSS allows for real-time updates and refinements to fleet assignments based on ongoing operations and new data inputs. This real-time decision-making capability is a significant advantage over traditional models, which often struggle to adapt quickly to dynamic changes in the mining environment. By continuously learning from new data, the GNN-enhanced DSS ensures that the mining fleet is always optimally utilized, improving operational efficiency, and reducing costs.

In addition to real-time decision support, the DSS provides a user-friendly interface for operators and managers to interact with the system. Visualizations and dashboards display key performance indicators, fleet assignments, and predictive insights, enabling informed decision-making. The DSS also includes features for scenario analysis, allowing users to simulate different operational strategies and assess their potential impacts before implementation. This comprehensive DSS enhances mining operations' overall management and optimization.

3.7. Validation

Validation is a crucial step to ensure the reliability and accuracy of the proposed methodology. This involves testing the performance of the integrated DES-GA and GNN model against real-world data from mining operations. The validation process will include comparing the predicted fleet assignments with actual assignments and evaluating the outcomes based on performance metrics such as cost savings and productivity improvements.

Several key aspects should be considered during the validation process. Inputs such as truck cycle times, loading times, travel distances, equipment availability, and the volume of transported material will be integral to the validation model. The results should be assessed against historical data to ensure accuracy. Key performance indicators (KPIs) like equipment utilization rates, production output, and the amount of material transported will be analyzed to measure the model's effectiveness. For instance, the model's predictions on fleet allocation and scheduling should be compared with actual operations to identify discrepancies and refine the methodology. The performance metrics of cost savings, productivity improvements, and transported material will be crucial in assessing the benefits of the proposed system.

While detailed results from our model validation process are not yet available, they will be included in future studies to maintain transparency and rigor. Successful validation will confirm the

methodology's effectiveness and potential to enhance fleet management in open-pit mining, providing a robust tool for industry decision-makers.

4. Analysis Section

4.1. Analyzing Data

The data analysis focused on evaluating the performance of the mining fleet under various operational conditions. To maintain confidentiality, all data were standardized using Z-scores, which allowed for effective comparison and analysis while maintaining the privacy of the raw data.

The fleet comprises 164 trucks of varying capacities and thirty-five shovels of varied sizes. The distribution of these trucks and shovels is as shown in Table 1 and Table 2:

Table 1. Fleet composition.

Truck Type	Number of Trucks	Capacity (tons)
Type 1	22	135
Type 2	93	100
Type 3	33	60
Type 4	16	35

Table 2. Shovel Composition.

Shovel Type	Number of Shovels	Bucket capacity (tons)
Large Shovel	5	12.5
Medium Shovel	23	8
Small Shovel	7	4.5

The initial descriptive statistics provided critical insights into the mining fleet's operational metrics. Key variables were carefully analyzed, including truck and shovel capacities, loading, and dumping times, and travel distances. Using Z-scores ensured that the data was presented in a manner that facilitated clear and accurate interpretation. This approach helped identify performance variations and highlighted areas where operational efficiency could be improved.

Table 3 represents a sample of the descriptive statistics for key variables. It is important to note that these values are only a subset of the entire dataset used in this study.

Table 3. Sample Descriptive Statistics of Key Variables.

Description	**Mean** ($\times \mathbf{10^{-16}}$)
Loading time for truck Type 1 with large shovels (waste)	-0.12
Loading time for truck Type 2 with large shovels (waste)	1.80
Loading time for truck Type 2 with large shovels (ore)	0.18
Full Haul velocity for truck Type 1	-12.1
Full Haul velocity for truck Type 2	-6.53
Dumping time at waste dump 1 for truck Type 1	-2.06
Dumping time at waste dump 1 for truck Type 2	0.23
Dumping time at waste dump 2 for truck Type 2	-0.36
Dumping time at crusher for truck Type 2	-1.45
Empty Haul velocity for truck Type 1	4.26
Empty Haul velocity for truck Type 2	3.82

The data presented in Table 3 is extracted from a comprehensive dataset collected during the study. This sample helps illustrate the variability and central tendencies of critical operational metrics in the fleet. Each variable's mean and standard deviation values highlight typical performance measures and deviations from the mean under different operational conditions. The standardization using Z-scores allows for an objective assessment of performance across different metrics and facilitates the identification of outliers and areas needing improvement. This method provides a clear framework for analyzing the performance and efficiency of the mining fleet, serving as a basis for further optimization efforts.

Due to data security concerns, the original data cannot be displayed. Instead, a sample of the data was standardized to demonstrate accuracy and validity. Using Z-scores, the mean is near zero, and the standard deviation is near one, indicating proper standardization. After this process, the data does not have units.

4.2. Optimizing Fleet Assignments

The optimization process was conducted in two primary steps to enhance the efficiency of fleet assignments. Initially, shovels were assigned to dig points, followed by trucks allocated to these optimized shovel-dig point pairs.

4.2.1. First Optimization Step: Shovel to Dig Point Assignment

In the first step, shovels were assigned to dig points using a GA to maximize productivity and efficiency. The fitness evolution during this process is depicted in the Figure 3:

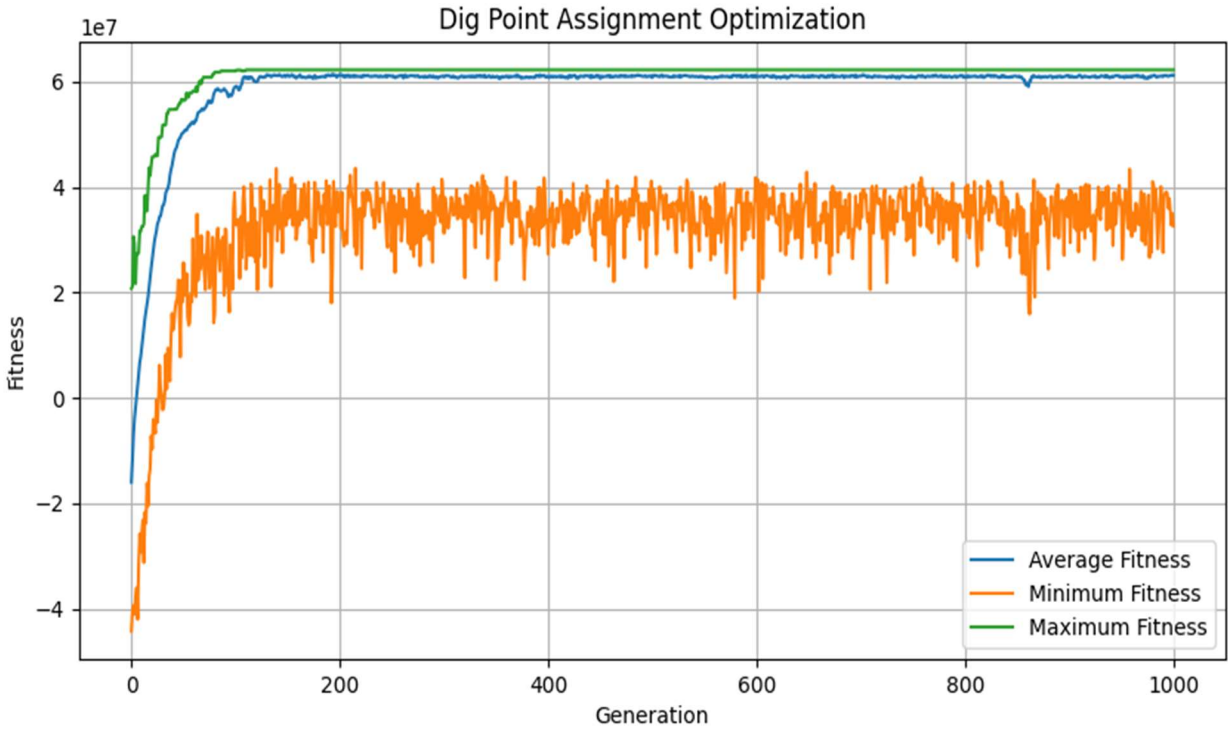

Figure 3. Fitness evolution during shovel assignment optimization.

This graph shows the optimization process for dig point assignments using a GA. The x-axis represents the number of generations, while the y-axis indicates the fitness value. The chart tracks the average fitness (blue line), minimum fitness (orange line), and maximum fitness (green line) over one thousand generations. The fitness values are in units 10^7, highlighting the optimization's progression and stability over time. The fitness values improved significantly during the initial generations, indicating rapid convergence toward optimal solutions. As the generations progressed, the fitness values stabilized, demonstrating that the algorithm effectively identified near-optimal assignments for the shovels to dig points.

4.2.2. Second Optimization Step: Truck Allocation

Following the optimal assignment of shovels to dig points, the second step focused on allocating trucks to these shovel-dig point pairs. The goal was to maximize the fleet's average utilization rate, leading to more efficient use of available resources. The optimization process substantially improved the average utilization rate, increasing from 56% to 58.52%.

Table 4. Optimization Results.

Metric	Before Second Optimization	After Second Optimization	Improvement (%)
Average Utilization Rate	56%	58.52%	2.52%

The second optimization step builds upon the initial improvements, demonstrating the iterative nature of the optimization process. The GA achieved higher efficiency and resource utilization levels by continuously refining the strategies and allocations, contributing to the mining operations' overall effectiveness.

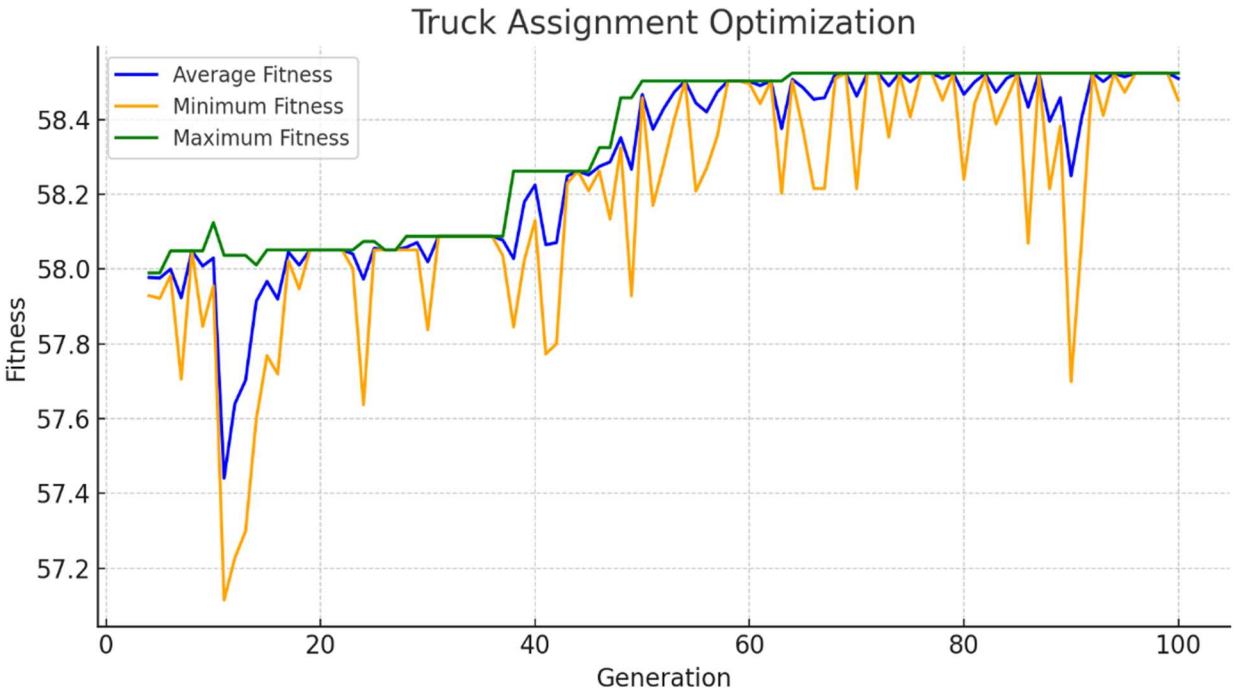

Figure 4. Fitness evolution during truck assignment optimization.

This graph in Figure 4 displays the optimization process for truck assignments using a GA. The x-axis represents the number of generations, while the y-axis indicates the fitness value. The chart tracks the average fitness (blue line), minimum fitness (orange line), and maximum fitness (green line) over one hundred generations. The fitness values show the gradual improvement and stabilization of the truck assignment optimization process. The graph indicates that the fitness values show significant fluctuations during the initial generations, gradually improving and stabilizing over time. The results suggest that while the algorithm optimizes truck assignments, further refinements and iterations may be required to achieve more stable and optimal solutions.

5. Discussion

Analyzing and optimizing mining fleet assignments has revealed considerable potential for enhancing operational efficiency and reducing costs. The initial steps, which involved assigning

shovels to specific dig points and allocating trucks to these shovel-dig point pairs, demonstrated promising results. These optimizations led to significant improvements in utilization rates and overall operational efficiency. Specifically, the optimization process resulted in a substantial increase in the average utilization rates of the fleet, achieved by meticulously assigning shovels to the most suitable dig points and optimizing truck allocations. This strategic allocation enhanced operational efficiency and led to notable cost savings and environmental benefits. Reduced idle times, optimized travel routes, and improved resource utilization contributed to lower operational costs, decreased fuel consumption, and reduced emissions.

The application of GAs proved particularly effective in tackling the complex optimization challenges associated with fleet assignments. The fitness evolution graphs indicated a rapid convergence towards optimal solutions, underscoring the robustness of this approach. However, the success of these optimizations hinges on the quality and standardization of the input data. Ensuring consistent and high-quality data collection practices is crucial for future optimizations. Additionally, mining operations are subject to dynamic and often unpredictable conditions, necessitating the development of algorithms capable of adapting in real-time to maintain and improve operational efficiency. While the optimization techniques have shown promising results in controlled environments, scaling these solutions to real-world operations requires careful planning and implementation. Ensuring the scalability and flexibility of the algorithms will be critical for their successful deployment and realizing the full potential of these advancements in mining fleet management.

6. Conclusions

The optimization and data analysis conducted thus far has laid a solid foundation for enhancing the efficiency and sustainability of mining operations. However, several key areas require further research and development to fully realize the potential benefits of these optimizations. The next step involves training GNNs using the standardized datasets generated from the current optimization processes. GNNs can leverage the complex relationships within mining operation data to provide more precise and adaptive fleet assignments, focusing on capturing intricate patterns and dependencies to enhance decision-making capabilities.

Once the GNNs are trained, the subsequent phase will integrate these advanced AI models with existing DSS. This integration will facilitate real-time, data-driven decision-making processes, allowing for dynamic adjustments to fleet assignments based on current operational conditions. The goal is to create a seamless interface between GNNs and DSS, ensuring enhanced decision-making capabilities are effectively utilized in daily operations.

The final step involves rigorous validation and testing of the integrated system. This includes conducting pilot tests in real-world mining environments to assess the performance and reliability of the GNN-enhanced DSS. Validation metrics will focus on evaluating the system's accuracy, efficiency, and scalability, with feedback from these tests used to fine-tune the models and ensure robust performance under various operational scenarios.

Future research will continue to explore integrating advanced AI techniques, such as GNNs and developing real-time data integration systems. Enhancing environmental impact analysis and predictive maintenance capabilities will also be key focus areas, contributing to more sustainable and efficient mining operations. In conclusion, the initial optimization efforts have demonstrated significant potential for improvements in mining fleet management. By refining and expanding these techniques, there is a strong potential to achieve even greater efficiencies and sustainability in mining

operations, with ongoing and future research playing a pivotal role in advancing the field of mining optimization.

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Quality Prediction in Process of Flotation Plant with Gradient Boosting and Long Short-Term Memory Model

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ABSTRACT

Machine learning has demonstrated its efficacy in various database domains, indicating interest in its application in mining processes. Popular models, such as support vector machines, and random forests, deep learning models, including convolutional neural networks (CNN), recurrent neural networks (RNN), and generative adversarial networks (GAN), are emerging as optimal tools for handling large-scale datasets. Predicting the output quality in mining processes, such as flotation plants, is crucial for optimization. This paper employs two powerful methods, the Extreme Gradient Boost Regressor (XGBR) and Long Short-Term Memory (LSTM) networks, to predict the concentration purities for iron and waste silica. For this purpose, 23 variables reflecting a floatation plant were monitored and collected every two minutes over a half-year span. This data is then processed, split and restructured for the model use. The solved problem demonstrates the effectiveness of XGBR and LSTM in predicting ore concentrate quality and waste. Compared with LSTM, XGBR exhibits better predictive capabilities for iron and silica on test and validation datasets. This leads to the foundation for realizing automation control of the floatation plant, and this study should encourage traditional machine learning as well as deep learning in mineral processing engineering.

1. Introduction

In mineral processing, froth floatation is an extensively used physiochemical separation phenomenon for valuable and unwanted minerals. Froth floatation employs the physiochemical surface characteristics of the materials, either hydrophilic or hydrophobic [1, 2]. Since they are critical to process management and optimization, processing engineers must promptly and effectively monitor concentrate grade and recovery in froth flotation plants. Implementing online monitoring systems typically requires costly and sophisticated equipment. In order to estimate concentrate grade and recovery using processing parameters, predictive models must be created. Conventional knowledge-based models, which usually rely on explicit calculations for the flotation process, are less feasible to develop due to issues like the difficulty of formulating and solving mathematical equations for a dynamic boundary (the interface between the collection and froth zone), and the limited understanding of the physicochemical principles governing flotation subprocesses [3, 4]

Machine learning (ML), serving as a key component of data-driven strategies, has proven its effectiveness in various data-intensive domains like spam filtering, machine translation, and natural language processing. Consequently, it has sparked the curiosity of engineers involved in mineral processing [5]. Several machine learning models, such as multilayer perception [6], support vector

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machine [7], and random forest [8] have been developed to model flotation processes. These models have shown success in modelling laboratory flotation processes, which typically involve limited and straightforward process data. However, when faced with tasks encompassing extensive and complex data structures, such as high-dimensional, autocorrelated, and temporal data, shallow machine learning models or statistical learning models have proven ineffective. This implies that the previously mentioned shallow machine learning models are not suitable for effectively modelling engineering flotation processes.

In contrast, deep learning models, exemplified by the convolutional neural network (CNN), the recurrent neural network (RNN), and the generative adversarial network (GAN), have emerged as optimal tools for handling large-scale and intricate datasets due to their deep, intricate, and adaptable architectures [10]. Presently, there are only a limited number of reported successful cases involving the application of deep learning in mineral processing, with a particular scarcity of instances pertaining to manufacturing froth flotation [11]. Technical background and database details

In froth floatation, reverse cationic floatation is the most commonly used process to separate the iron particles from undesired particles, such as silica, the dominant gangue mineral in iron ores. During this process, silica particles cling to air bubbles and float to the surface, while iron minerals stay in the water and produce sediment with a high concentration of iron.

The data used in this paper is from a real manufacturing floatation plant, where silica is separated from the iron particles using revere cationic floatation [12]. The flowsheet for the iron ore flotation process is shown in Figure 1 with a zoom on a single flotation cell in our target flotation plant. This flotation facility feeds iron pulp into three parallel-operating flotation cells (flotation cells 1, 2, and 3 in Figure 1) at a rate of approximately 400 t/h. Silica-rich froth is continuously removed from the surface. The process is repeated in the subsequent cell (flotation cell 4, 5, 6 in Figure 1) as depressed sediment with high iron content flows into it. The last flotation (flotation cell 7 in Figure 1) receives an input stream from the output streams of flotation cells 4, 5, and 6.

Data from the real manufacturing plant, collected every 20 seconds for a span of almost half year, was aggregated to a two-minute interval for analysis. Each data sample has 23 measurable values that fall into one of four categories: environment variables (rows 3 to 7), process variables (rows 8 to 21), processed materials (rows 22 to 23), and raw materials (rows 1 to 2), which relate to the purities of iron and silica fed into the plant. Our objective in this paper is to forecast, based on the measurable values, the purity of processed materials at time t (2 minutes) as presented in Table 1.

1.1. Data Processing

Data collected from the database is raw data. The data is then analyzed and further structured to meet the model's requirement. Outliers in the collected data are identified and removed using an outlier detection formula in which IQR is Inter Quartile range, Q1 is the first quartile and Q3 is the third quartile

$$IQR = Q3 - Q1 \tag{1}$$

$$lower_{bound} = Q1 - 1.5 * IQR \tag{2}$$

$$upper_{bound} = Q3 + 1.5 * IQR \tag{3}$$

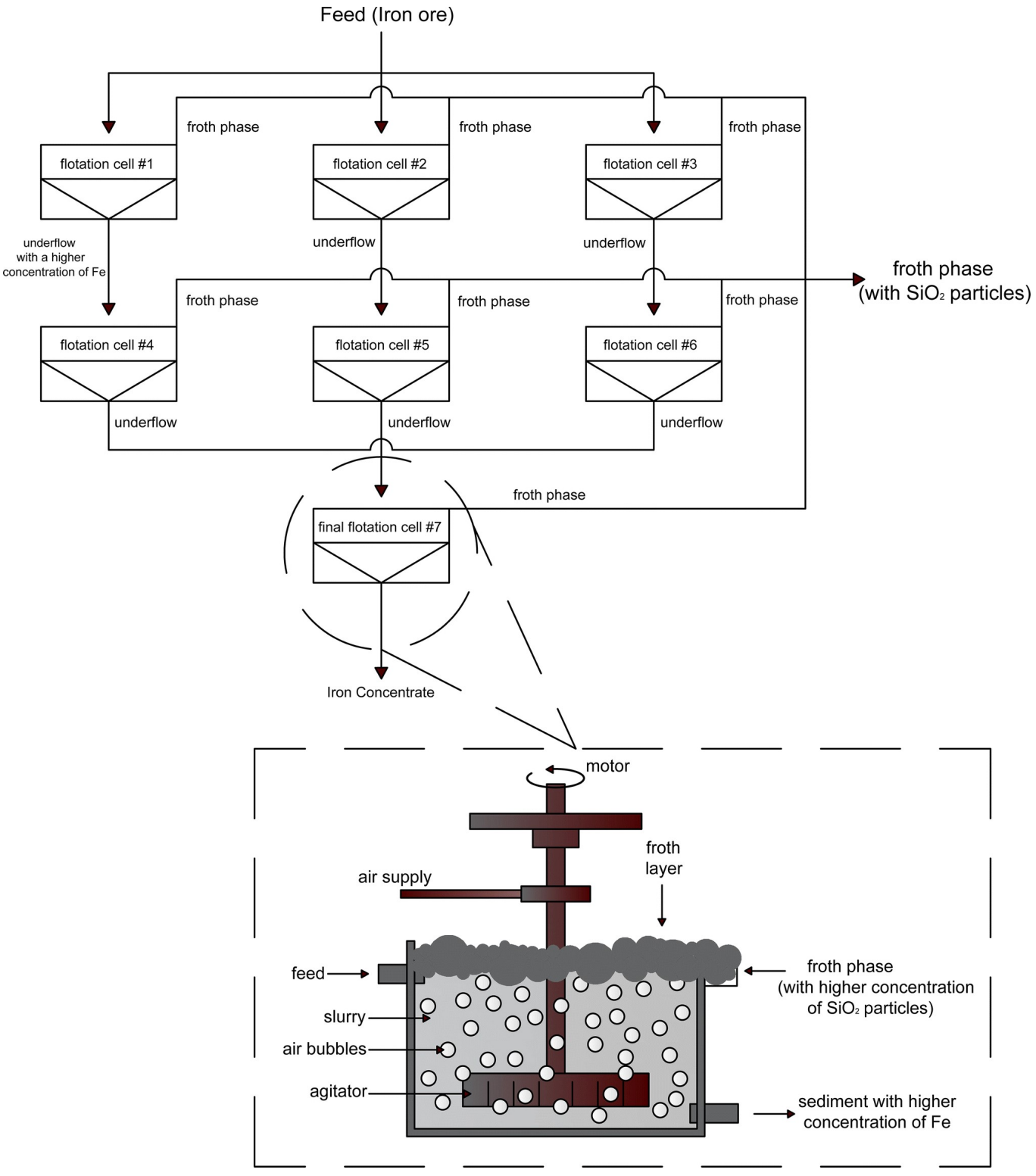

Figure 1. Iron ore flotation process flowsheet featuring a single flotation cell magnified [9].

Table 1. A brief overview of the gathered engineering database.

Timestamp	**3/10/2017 12:00:00 AM**	**3/10/2017 00:02:00 AM**	**3/10/2017 00:04:00 AM**	**3/10/2017 00:06:00 AM**	**3/10/2017 00:08:00 AM**
percent_iron_feed	55.2	55.2	55.2	55.2	55.2
percent_silica_feed	16.98	16.98	16.98	16.98	16.98
starch_flow	3079.1	3150.39	3784.96	3523.24	3570.12
amina_flow	564.697	558.472	557.983	563.416	571.533
ore_pulp_flow	396.533	397.852	394.834	394.453	401.572
ore_pulp_ph	10.0705	10.0755	10.0804	10.0854	10.0936
ore_pulp_density	1.74	1.74	1.74	1.74	1.74
flotation_column_01_air_flow	250.73	249.17	250.049	250.181	250.291
flotation_column_02_air_flow	248.906	249.829	246.533	247.456	251.653
flotation_column_03_air_flow	249.521	251.147	249.829	249.324	251.279
flotation_column_04_air_flow	295.096	295.096	295.096	295.096	295.096
flotation_column_05_air_flow	306.4	306.4	306.4	306.4	306.4
flotation_column_06_air_flow	250.356	250.928	250.378	249.434	252.114
flotation_column_07_air_flow	251.873	246.533	248.643	248.181	250.115
flotation_column_01_level	444.384	461.45	451.991	453.542	448.438
flotation_column_02_level	443.269	421.41	426.335	500.023	425.826
flotation_column_03_level	460.449	467.79	443.024	454.624	461.59
flotation_column_04_level	439.92	458.59	429.998	458.008	485.898
flotation_column_05_level	451.588	453.84	452.629	414.796	482.759
flotation_column_06_level	433.539	448.05	440.77	460.818	466.418
flotation_column_07_level	425.458	451.34	463.421	403.059	479.645
percent_iron_concentrate	66.91	66.91	66.91	66.91	66.91
percent_silica_concentrate	1.31	1.31	1.31	1.31	1.31

After removing outliers, the data is then plotted as a correlation heatmap to check the correlation between different features, as shown in Figure 2. After analyzing the heatmap, it was observed that some of the features have a high correlation (either positive or negative). To check the distribution of our target variables, which are percent_silica_concentrate and percent_iron_concentrate, histograms are plotted. The distribution explains these variables' characteristics, which can help with data preprocessing, model selection, and decision-making. The first target variable shows a positively skewed distribution, while the second target variable shows a slightly negatively skewed distribution, as shown in Figure 3.

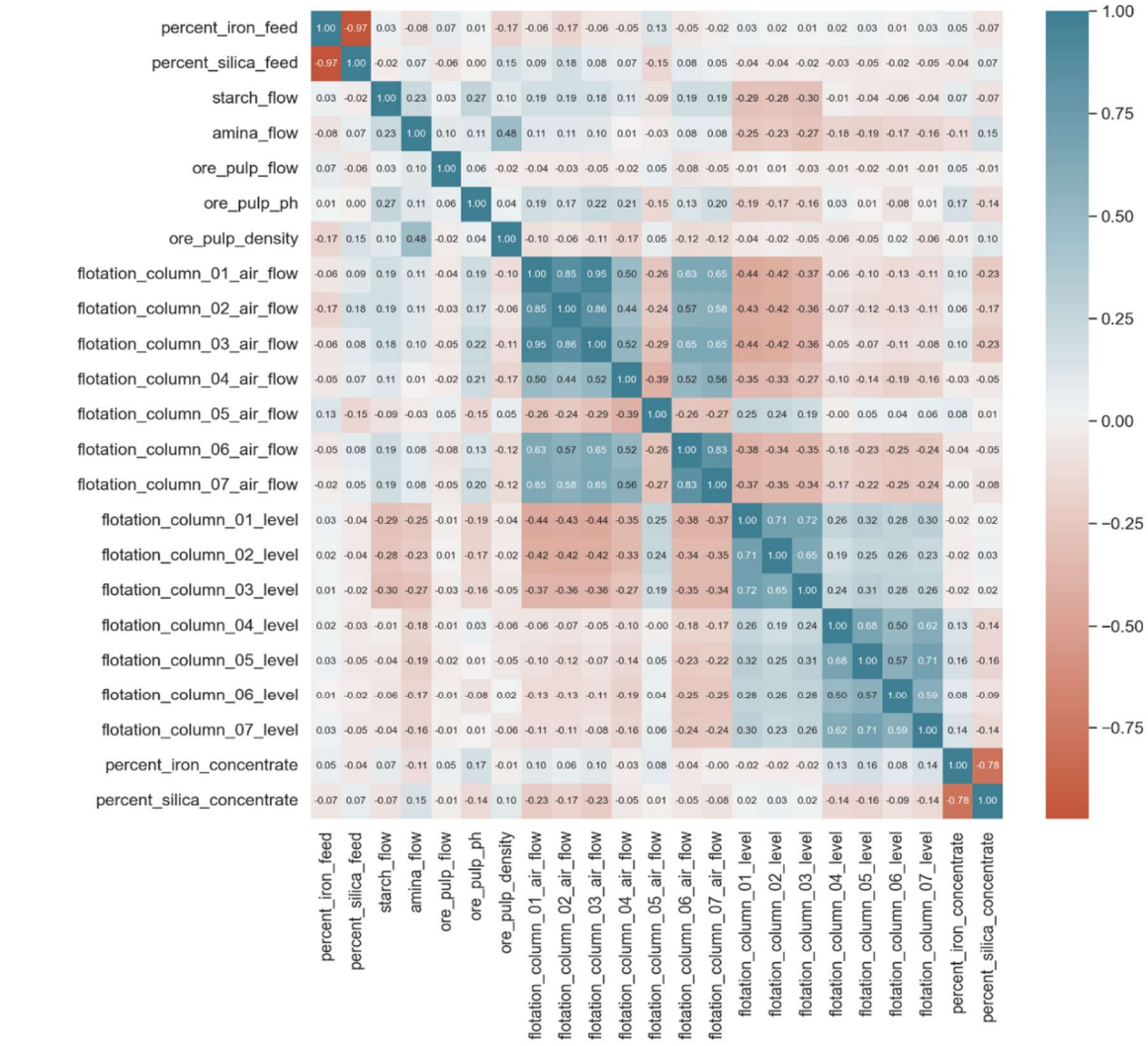

Figure 2. Correlation heatmap of the collected data.

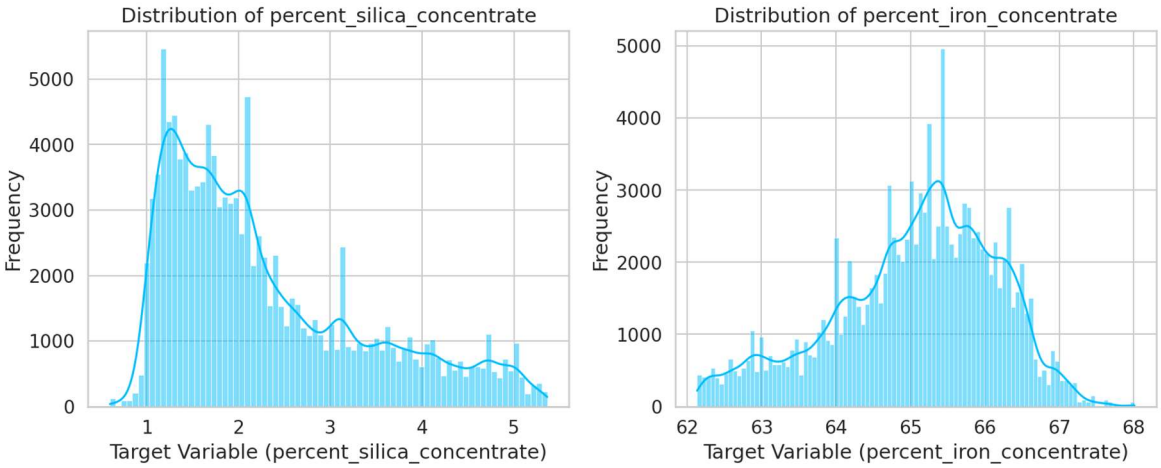

Figure 3. Distributions of the target variables.

As mentioned above, the correlation heatmap shows some highly correlated features. The highly correlated features are averaged to minimize the number of features, and a new data set is created.

1.2. Seasonality

Periodic fluctuations that repeat at certain intervals over time are referred to as seasonality in data. Many datasets, especially those pertaining to time series, exhibit this recognizable pattern. Seasonal elements like the season, month, week, or even day influence this pattern. Seasonality is an important factor to consider and examine in various fields, including retail, finance, environmental studies, and more. The current data set also has a time series relation with the output, so the seasonality in the data set was checked for months, days and hours. Seasonality can be accounted for addressed by various statistical and ML models, such as deep learning's LSTM (Long Short-Term Memory) networks and statistics' ARIMA (Auto-Regressive Integrated Moving Average). This paper employs LSTM and extreme gradient boosting techniques necessitating feature engineering to account for seasonality. After incorporating the seasonality, the correlation heatmap is plotted to check the collinearity of the data, as shown in Figure 4.

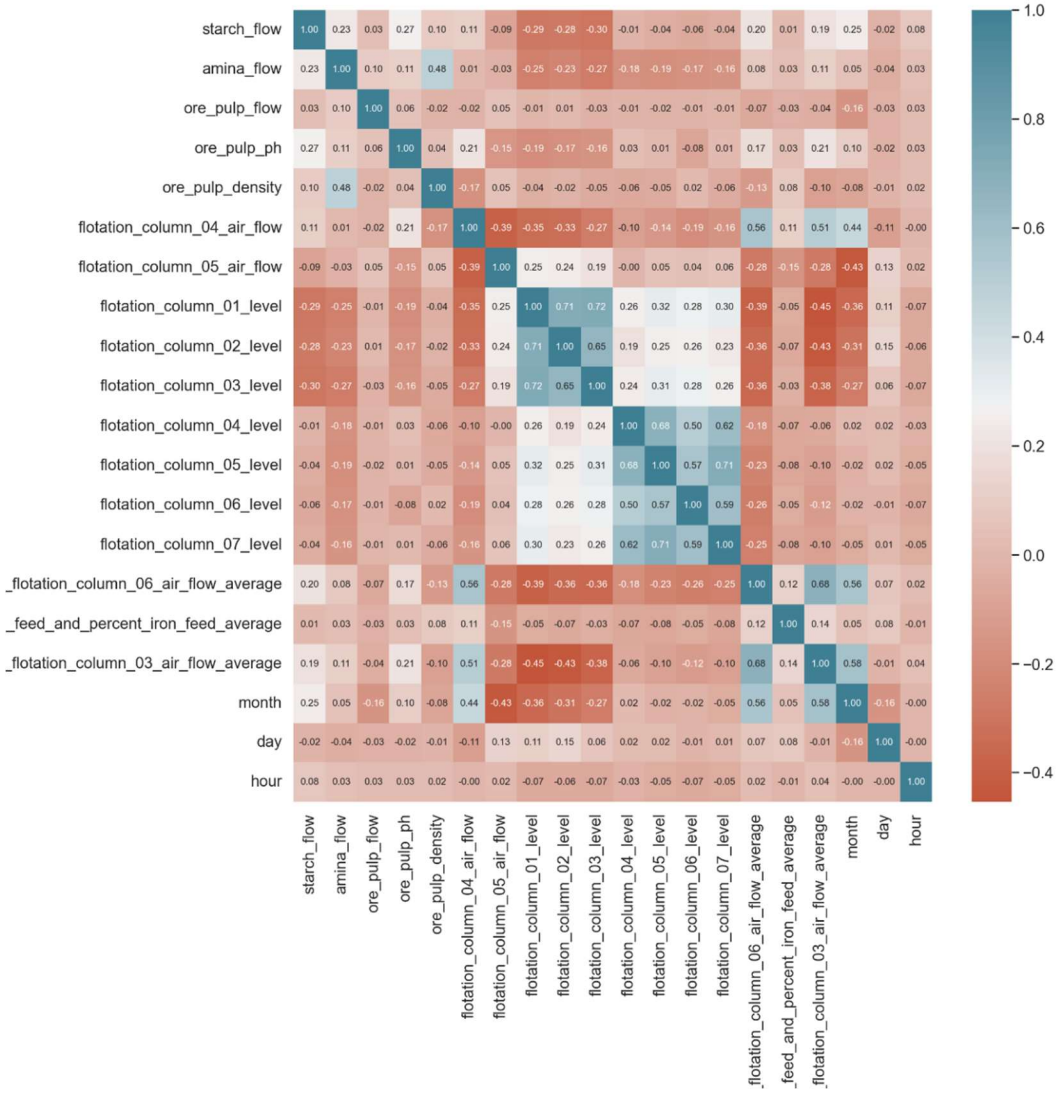

Figure 4. Correlation map of the data after incorporating seasonality.

2. XGB Regressor Model Construction

2.1. Introduction to eXtreme Gradient Boosting Regressor (XGBR)

Gradient boosting, a popular machine learning algorithm, has a highly effective and scalable implementation known as XGBR, or eXtreme Gradient Boosting. The remarkable performance of XGBR regression on a variety of predictive tasks has garnered a lot of attention. It is especially well-known for its speed and accuracy in handling complicated and sizable datasets. XGBR is designed to maximize memory consumption and computational efficiency. It is able to efficiently handle large datasets thanks to its tree construction algorithms and system optimization. XGBR's objective function is a combination of a loss function and a regularization term:

$$Obj(\Theta)=L(\Theta)+\Omega(\Theta) \quad (4)$$

Where, Θ represents the parameters of the models, $L(\Theta)$ is the loss function that measures how well the model's predictions match the actual data, and $\Omega(\Theta)$ is the regularization term that penalizes the complexity of the model to avoid overfitting.

2.2. Training Data Preparation for XGBR

XGBR predicts one target variable at a time because it is a single-output model by design. Nevertheless, XGBR can still be used for multi-output regression tasks, whichinvolve predicting multiple continuous target variables. One XGBR model is trained internally for each target by the wrapper using scikit-learn's 'MultiOutputRegressor'. The wrapper abstracts away the process, enabling a more efficient implementation, but the formula for each target would remain the same as with the independent model's approach.

The data is split down to training and testing sets, with 70% allocated for training and 30% for testing. The test data is further divided into test data and validation data, each comprising 15% of the total data. After splitting, the data were scaled in the range [0,1] using Eq. (5):

$$z = \frac{x-\mu}{\sigma} \quad (5)$$

Where, z is the standardized value, x is the original feature value, μ is the mean of the feature across all data points, and σ is standard deviation of the feature across all data points.

2.3. Model Building and Training for XGB Regressor

XGBR model building and training entails careful data preparation, model type selection, parameter tuning, and assessment. Table 2 shows the parameters, their description and the values used to train this model. The depth of each tree is 20, and the learning rate used in the model training is 0.01. Different values for these parameters were analyzed for tuning purposes to check the model's accuracy, and the optimized values are presented in Table 2.

Table 2. Parameters for XGB Regressor.

Parameter	Value	Description
n_estimators	250	Number of boosting rounds (trees).
max_depth	20	Maximum depth of each tree.
learning_rate	0.01	Step size shrinkage used to prevent overfitting.
random_state	21	Seed for random number generator for reproducibility.
verbosity	0	Verbosity of output messages (0 means silent).
tree_method	hist	Tree construction algorithm (histogram-based).
gpu	cuda	Suggests GPU usage for acceleration (use 'gpu_hist' for actual GPU acceleration).

3. LSTM Model Construction

3.1. Introduction to Long-Short Term Memory Model (LSTM)

A particular kind of recurrent neural network (RNN) called a Long Short-Term Memory (LSTM) network was created to get around conventional RNNs' drawbacks in identifying long-range dependencies and learning from data sequences. LSTMs were first presented by Sepp Hochreiter and Jürgen Schmidhuber in 1997 [13]. Since then, they have been used extensively in many applications, including time series analysis, speech recognition, natural language processing, and more. The following are the main attributes of LSTMs:

Memory Cell: LSTMs have a memory cell that can store information over long sequences. The cell state can be seen as a conveyor belt that runs through the entire sequence, allowing information to be added or removed.

Three Gates: LSTMs have three gates, as shown in Figure 5.

- Forget Gate: Decides what information from the cell state should be thrown away.
- Input Gate: Updates the cell state with new information.
- Output Gate: Produces the output based on the updated cell state

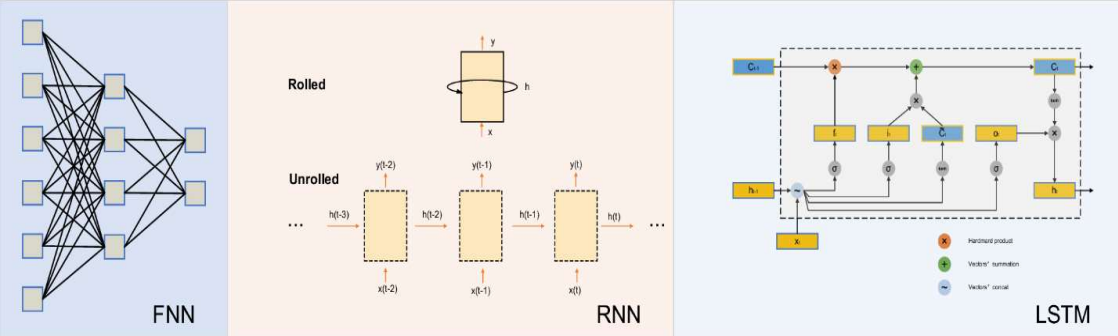

Figure 5. Basic architectures for FNN, RNN and LSTM [9].

Sigmoid and Tanh Activation Functions: Sigmoid activation functions are used in the gates to control the flow of information, with values ranging between 0 and 1. Tanh activation functions are used to regulate the values in the cell state, mapping them between -1 and 1.

3.2. Model Building and Training for LSTM

Forget Gate (f_t):

$$f_t = \sigma\left(W_f \,.\, [h_{t-1}\,, x_t] + b_f\right) \tag{6}$$

Where, σ is sigmoid function, W_f is weight matrix for the forget gate, $[h_{t-1}\,, x_t]$ is concatenation of the previous hidden state and the current input, and b_f is bias state.

Input Gate i_t and candidate Cell state $\widetilde{C_t}$:

$$i_t = \sigma(W_i \,.\, [h_{t-1}\,, x_t] + b_i) \tag{7}$$

$$\widetilde{C_t} = \tanh(W_c.[h_{t-1}, x_t] + b_c)$$

Where W_i and W_c are the weight matrices for the input gate and candidate cell state respectively, $b_i and\ b_c$ are the biases and tanh is the hyperbolic tangent activation function.

Cell State Update (C_t):

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t} \quad (8)$$

LSTM model and training parameters are presented in

Table 3.

Table 3. LSTM Model Configuration and Training Parameters.

Parameter/Step	Description / Value
Data Preprocessing	
Data Resampling	Median over each group of 6 entries
Feature Selection	Dropped '% Iron Concentrate', used '% Silica Concentrate'
Data Split	70% training, 30% testing
Further Data Split	Further split training into 85% training, 15% validation
Scaling	MinMaxScaler applied to features
Model Architecture	
Input Shape	(1, number of features)
First LSTM Layer	50 units, returns sequences
Second LSTM Layer	50 units
Output Layer	1 unit (Dense layer)
Training Parameters	
Optimizer	Adam
Loss Function	Mean Squared Error
Epochs	100
Batch Size	32
Validation Data	Used during training
Model Evaluation	
Test Data	Used to evaluate the model after training

4. Results and Discussion

4.1. For XGBR Regression

XGBR is trained on the parameters mentioned in the Table 2. The model is trained on 86,036 samples, comprising 70% of the data. The remaining 30% of data is divided into a test set and validation set comprising 9218 samples for each. After training the model, the feature importance plot is generated, as shown in Figure 6. Feature importance plot.

. The feature importance plot shows the importance of each feature in the modified data. The most essential feature in this plot is the ‘month’ feature, followed by the ‘day’ feature.

The 'month' feature's high significance indicates a significant seasonal component in the data. This indicates that the time of year significantly impacts the predicted target variables (iron concentrate and silica concentrate). In our data, different months are probably linked to different patterns or trends. The model is picking up on variations that occur in different months. This could be because the feed's percentage of iron and silica changes with time. In addition, the scatter plot was produced to investigate the predicted results further. Figure 7 shows the scatter plot for iron concentrate on the test data set. It shows a strong correlation between the true and predicted values, with an R-square value of 0.9. This suggests that the model fits the test data very well on the first target variable, iron concentrate.

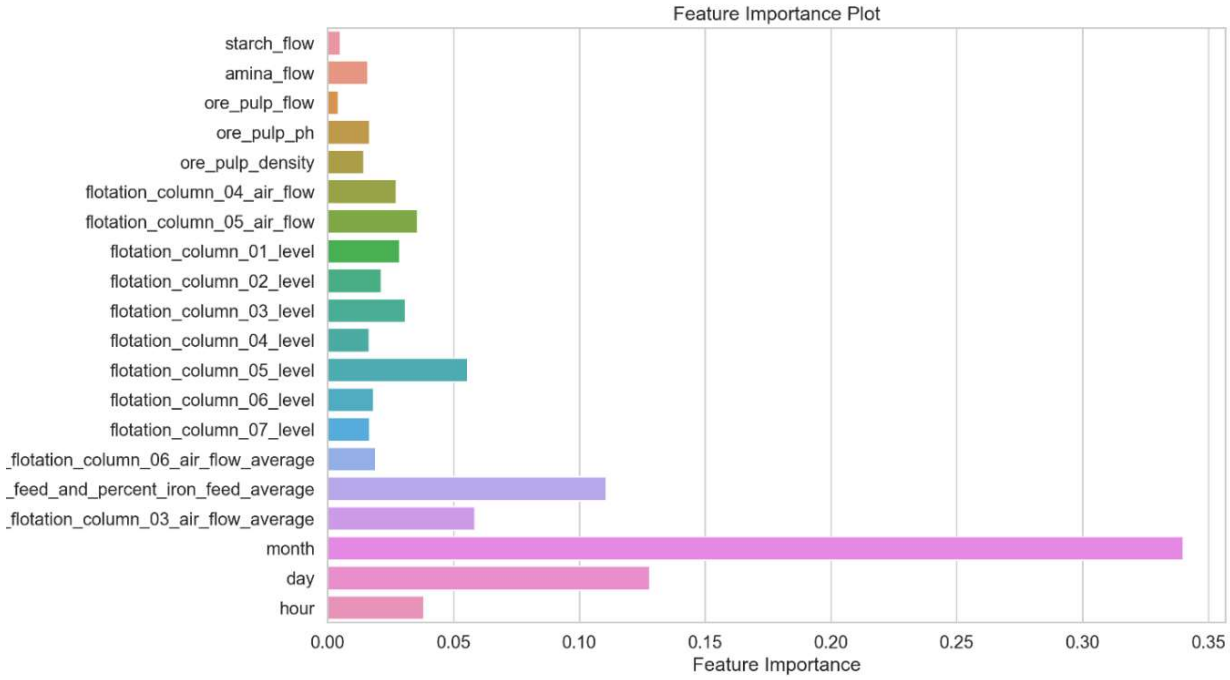

Figure 6. Feature importance plot.

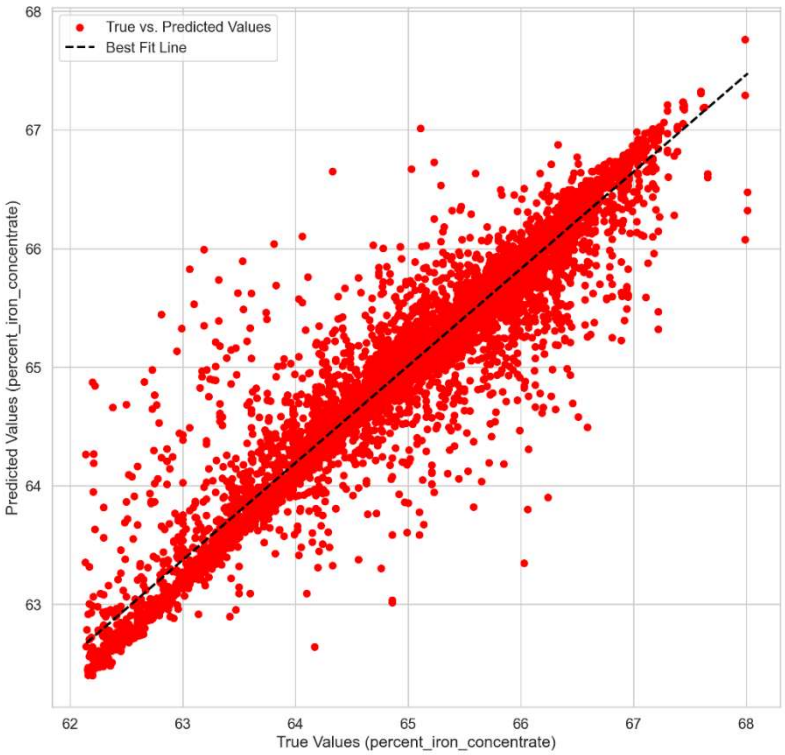

Figure 7. Scatter plot for Iron concentrate on test data set

Similarly, the scatter plot for the second target variable, silica concentrate, is shown in Figure 8. This also indicates a strong positive correlation between the true values and the predicted values of the 2nd target variable on the test data set, having an R-square score of 0.91.

The greater number of training samples helps enhance the model's interpretability, especially given the substantial number of training features (23 in our task). The model can be further tuned by changing the hyperparameters, including the number of estimators and the maximum depth of the estimator. In this study, the model is tuned to the different hyperparameter values, and the best values are chosen for the model after inspecting the outputs of the models.

As the test data was divided into test and validation data sets, the scatter plots for validation data set are also included. Validation is crucial for tuning the parameters of the model to improve the model's performance. In between training and testing, the validation set acts as a compromise. During the training phase, it helps make decisions about the model without jeopardizing the integrity of the test set, which is meant to remain an entirely impartial evaluation of the model's performance. A model that is accurate on known data and performs well on new, unseen data can be developed with the aid of this tripartite data division.

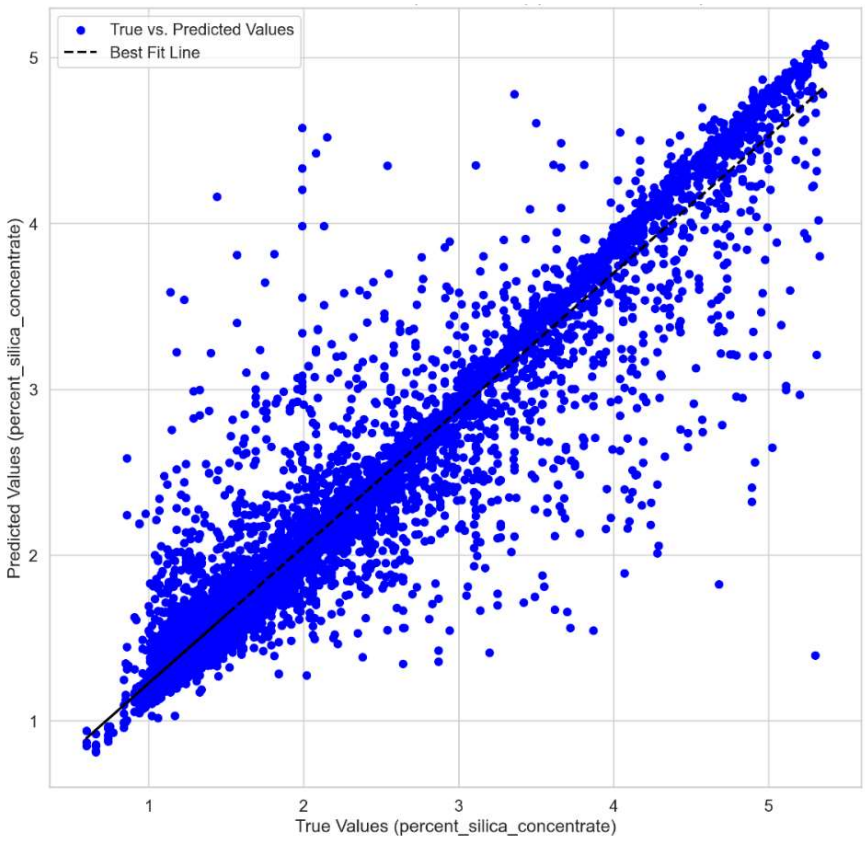

Figure 8. Scatter plot for silica concentrate on test data set.

Error! Reference source not found. Error! Reference source not found. shows the scatter plot of the validation set on the iron concentrate. This plot shows a strong positive correlation between the true and predicted values on the validation data set, having R-square score of 0.9. Similarly, Figure 9 depicts the scatterplot for the silica concentrate. Also, it shows a positive correlation between the true and the predicted values on the validation data set. Table 4 shows the model performance metrics for both the training set and validation set for both variables. Figure 9 represents the scatter plot for the second output variable, silica concentrate on the validation data set.

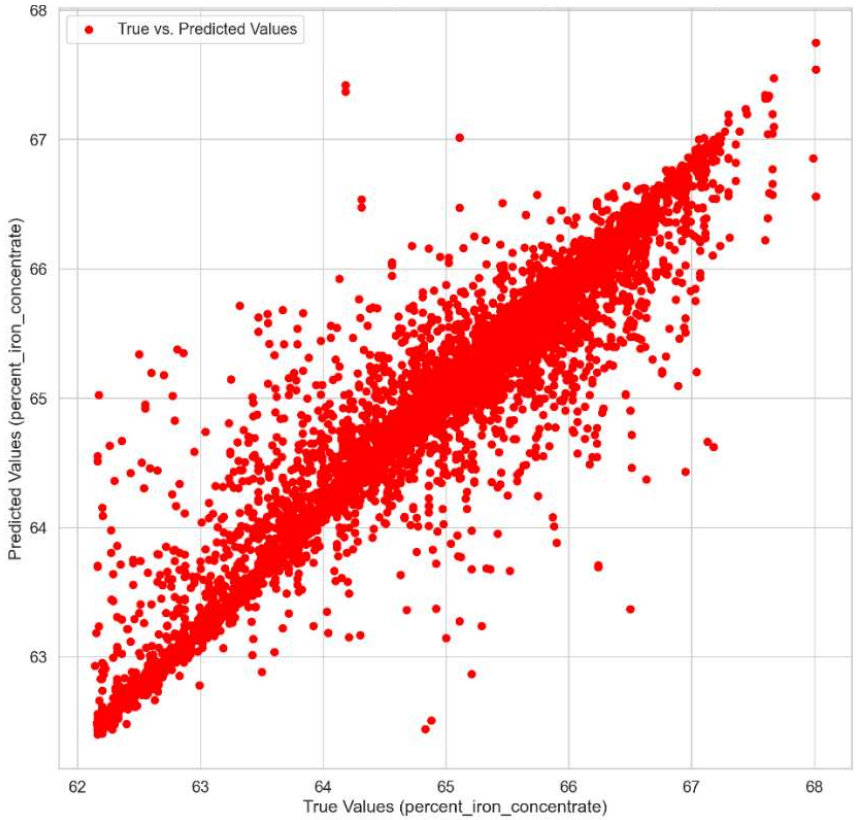

Figure 9. Scatter plot for iron concentrate on validation data set.

Table 4. Model performance metrics.

Model Performance Metrics	Training set		Validation Set	
	Iron Concentrate	Silica concentrate	Iron Concentrate	Silica Concentrate
R-square	0.904	0.904	0.894	0.894
MSE	0.1169	0.1169	0.128	0.128
RMSE	0.341	0.341	0.358	0.358

Such high R-square values demonstrate the model's ability to identify the underlying relationships and patterns in the data. This is especially important considering how difficult it is usually to predict the output depending on 23 features having temporal changes as well. The model's accuracy and effectiveness can lead to lower costs, higher-quality outputs, and improved decision-making. A major factor in attaining these outcomes was the XGBR algorithm's resilience, which is well-known for its effectiveness, scalability, and capacity to handle a range of data types. Key features such as tree pruning techniques, regularization to prevent overfitting, and the ability to handle missing values enhance the model's high predictive power.

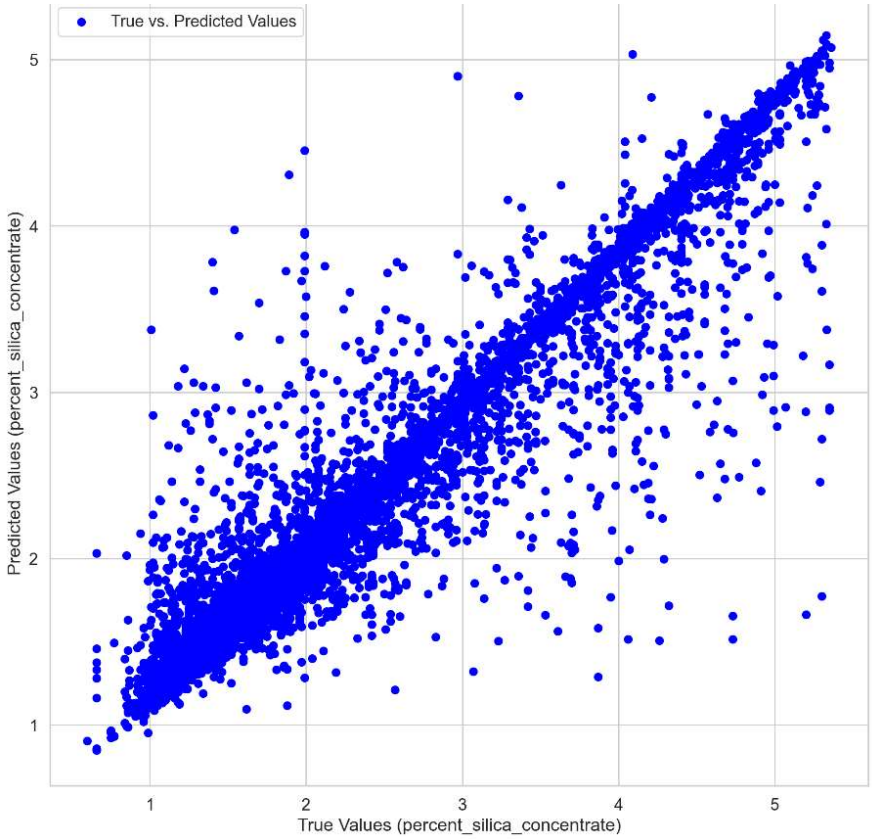

Figure 9. Scatter plot for silica concentrates on the validation data set.

4.2. For LSTM model

The LSTM model for both outputs was trained on the parameters described in

Table 3. Due to limited computation power and large dataset, it was not feasible to run this model on a greater number of layers. Consequently, the model was trained separately with 32 and 64 layers for each output.

A loss curve was generated for train and validation loss in model training as shown in

Figure 10. In the start, the validation loss is lower than the training loss, which is typical. However, after approximately 40 epochs, the validation loss started to rise, and then training loss suggested that the model was overfitting. In the start, it is still learning generalized patterns, but after 40 epochs, the model is not performing better on unseen data despite its improvements on training data, as evidenced by the widening gap where the validation loss surpasses the training loss. Similarly, the model shows the same trend for the other output variable, and even increasing the number of layers did not significantly improve the model's ability to capture patterns and relationships in the data.

Scatterplots for the test set and validation set are shown in Figure 11. It can be seen that the spread of the data is much greater in the validation set and in the test set. Also, the R-square value of test and validation set is 0.574 and 0.566, respectively.

While these values indicate that the model captures some variance in the target variable, it also shows where there is still space for development. This score suggests that the model only explains approximately 57.4% of the variance in our target, leaving a sizable portion unaccounted for. This

observation, along with the loss curve analysis, indicates that further optimization could improve our current model's predictive accuracy and generalization ability, despite it captures some underlying patterns.

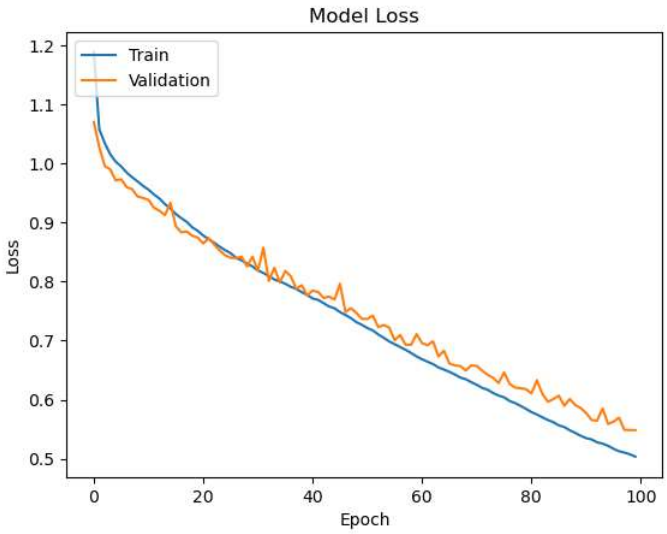

Figure 10. Train and Validation Loss in model training for Silica Concentrate.

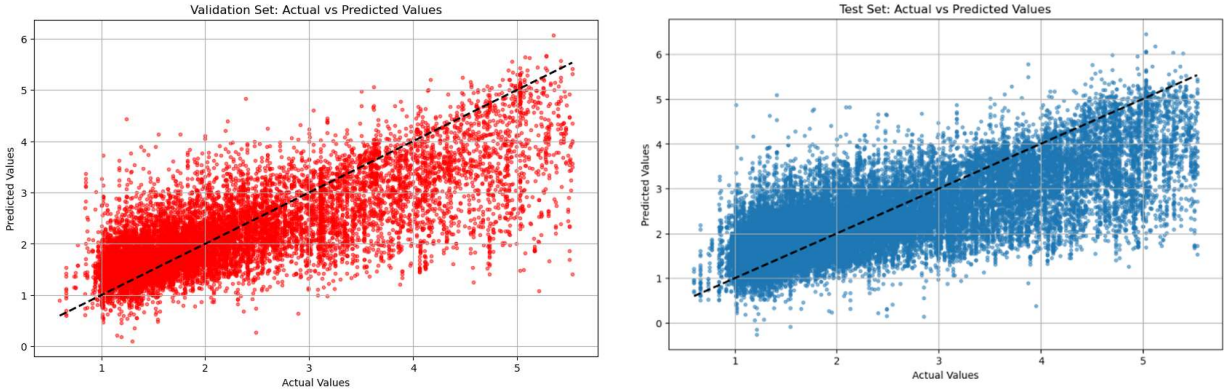

Figure 11. Scatter plot for LSTM model on test and Validation data set for Silica Concentrate.

Similarly, LSTM model is applied to the other output variable and scatter plots are shown in Figure 12. The model could also not capture the patterns and relations in the other output variables.

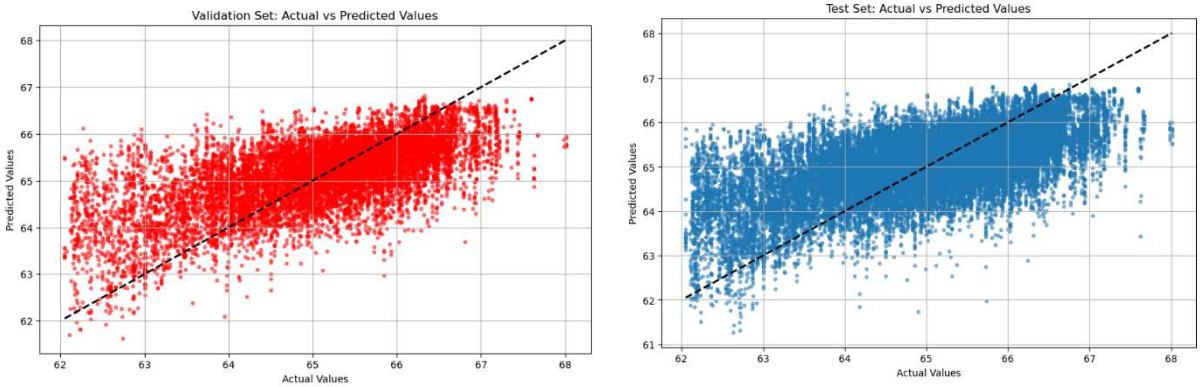

Figure 12. Scatter plot for LSTM model on test and Validation data set for Iron Concentrate.

5. Conclusion

This project has effectively illustrated how machine learning can significantly improve mining processes' efficiency, especially in flotation plants. This study has produced insightful predictions on concentrate purities for iron and waste silica by utilizing two sophisticated predictive techniques: Gradient Boost Regressor (XGBR) and Long Short-Term Memory (LSTM) networks. The use of an extensive dataset—23 variables total—that was gathered every two minutes for a period of six months highlights the stability and dependability of our findings.

XGBR performs better than LSTM in predicting the quality of iron and silica concentrates on both test and validation datasets, according to a comparative evaluation of the two models. This discovery is crucial because it not only confirms that XGBR is efficient at handling the kind of large-scale, complicated datasets that are commonly used in mining operations, but also highlights its superior performance over LSTM in this particular application.

These results have effects that go beyond the specific parameters of this project. Because of XGBR's superior predictive capabilities, flotation plants could benefit from automate control processes, potentially revolutionizing the sector by increasing productivity, cutting costs, and having a minimal negative environmental impact. Furthermore, this project's success in applying both conventional and deep learning machine learning techniques highlights the usefulness and efficiency of these methods in mineral processing engineering.

The study's findings support the mining industry's continued investigation and adoption of machine learning techniques. Subsequent studies might concentrate on improving these models, examining their scalability, and evaluating how well they work in other crucial areas of mineral processing. The ultimate objective would be to fully utilize these technologies in order to achieve more profitable, sustainable, and efficient mining operations .

6. Recommendation

Due to limited computation resources, the LSTM model was not fully tested with changing parameters. Further work can be done to explore the LSTM model's potential in predicting the quality of a floatation process. XGBR model shows significant predictive capabilities in predicting the floatation process quality in silica and iron concentrate.

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Numerical and Field Tests Investigation of The Damage Distribution Under Blast Load

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ABSTRACT

In rock blasting, the intact rock properties and presence of structures affect the intensity and distribution of fractures in the rock mass. The study conducted from the field blast and numerical simulation using the Riedel–Hiermaier–Thoma (RHT) material model in LS-DYNA shows that structures do not necessarily halt the fracturing of the rock mass. Depending on the geometry and mechanical properties, the extent of damage can either be developed or arrested through structures. Structures' material properties and location relative to the blasthole, free face, and the pit wall influence the size and distribution of the fractures on the bench and the formation of the pit wall. Results comparison to the field measurements show general consistency in stress wave pressure and peak particle velocity attenuations, fracture distribution, and formation of the pit wall.

1. Introduction

Drilling and blasting is a controlled rock fracturing process using explosives that are extensively used in mining and civil works. In mining, blasting aims at achieving the average size and size distribution that safeguards the efficiency of the downstream processes of excavation, crushing, and milling while conserving the integrity of the remaining structures and mitigating adverse outcomes such as excessive ground vibration, fly rocks, air blasts, and over breaks. To achieve optimum results, it is important to understand the influence of physical and mechanical properties of the rock mass, the interaction between explosive energy and the rock mass, and rock fracture mechanisms [1, 2].

Rock fracturing by explosives is a rapid process, a combination of the action of higher shock waves and gas pressure from the explosion products in a blasthole. Shock waves cause pulverization around the blasthole and initiate cracks; explosion gases wedge into the cracks and extend them. The pulverized zone around the blasthole is commonly referred to as the crushed zone (CZ) and the tensile cracks dominate the fractured zone (FZ). The crushed zone is dominantly formed when the shockwaves exceed the dynamic compressive strength of the rock and as the stress wave propagates and the rock yields the fractured zone is formed when the stress wave exceeds the dynamic tensile strength of the rock [3-5]. Spalling is formed from the wave reflection at the free face when the reflected wave exceeds the rock's tensile strength [6]. These three are the significant damage zones in blast-induced rock fragmentation for mining processes.

Formation of damage zones varies significantly depending on the type and strength of the explosives and properties of the rock mass both the intact and structural properties. The impedance difference between the host rock and the structures' materials influences stress wave transmission across

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structures [2, 7]. Due to the complexity of studying the blasting process and the influence of structural properties on crack propagation and explosive energy distribution in the field blasts, numerical simulation has been used reliably to offer insight from the reconstructed field scenarios [8]. Numerical simulations have been used to understand the influence of various structural properties such as the structure's stiffness, yield strength, orientation, continuity, location, and fracture frequency on blast outcomes [1, 2, 9-11]. These studies concluded that structures alter the distribution and propagation of stress waves and fractures, hence fragmentation distribution and the extent of damage zones around the blasthole.

Analysis of rock mass in numerical modelling is usually limited to a regular structure or set of structures in a two-dimensional (2D) rock model which is simple and practical. The rock mass comprises the intact rock and a combination of several structures like faults, contacts, dykes, and joints. The analysis of such a system is critical in understanding the fragmentation distribution in bench blasting. In this study, a 2D reconstruction is made in LS-DYNA using the scanline mapping data to analyze the effect of the combination of several structures on blast outcomes. A case study data is used to model the explosive, rock, and discontinuity properties. The accuracy of the simulation results is confirmed by the fragmentation analysis obtained. This study offers insight to blast engineers on the combined influence of structures as a guide to blast designs.

2. Case study description

2.1. Geology and Structural Properties

The study is based on data collected from New Luika Gold Mine, which Shanta Gold owns. The New Luika Gold Mine is located in the Songwe District of Southwestern Tanzania. Shanta Gold operates several open pits and underground mines in this area. Data collection was done in the Shamba pit. Shamba geology comprises granodiorite, granites, and quartzofeldspathic as host rocks. Gold mineralization is hosted in the dipping brittle to brittle-ductile deformational features (shear zones), always accompanied by quartz veins occurring at various scales; a metre scale robust veins to millimetre scale veinlets dispersed throughout shear zones. The mineralized quartz veins strike NE-SW and dip NW 40 to 50 degrees. Dyke intrusives which include dolerite, pegmatite, aplite, and alaskite are observed cross-cutting major lithologies and therefore thought to be younger than the host rocks. The diamond core logging from two boreholes shows the distribution of lithologies by depth as indicated in Figure 1 and the rocks' physical and mechanical properties are shown in Table 1 [12].

The mapping conducted on the eastern, southern, and northern pit walls indicates the distribution of structures, most of which are 5 to 50 mm wide joints, dipping at an average of 67 degrees. Other common features are faults, veins, shear zones, and rock contacts dipping at steep angles between 70 and 80 degrees; the width ranges from a few millimetres to 6.7 m for faults. Most structures are empty or filled with clay, quartz, or hematite. The mapped structures on the pit wall levels 960 and 950 in Figure 2 and*Figure* 3 show the major faults.

2.2. Explosives and Blast Design

Shanta Gold has contracts with African Explosives Limited (AEL) for explosives supply and blasting services. As a blasting agent, the company uses S135 base emulsion density of 1.33 to 1.35 g/cm3. The explosive is sensitized by Sodium nitrite solution from base density 1.33 to 1.25 g/cm^3 as the final cup density. Unlike ANFO and cartridge explosives, the emulsion is cap-insensitive, requiring a booster to initiate. Priming is achieved using surface detonators, a downline detonator, and a booster. An electric current does the shot initiation through an instantaneous electric detonator (IED). The shock wave from its detonation triggers the trunk line initiation, from which the surface detonators are initiated and detonate at their assigned sequence. Surface detonators have shot period

delays (SPD) ranging from 17 to 75 ms. After being initiated, the surface detonator sends a signal to a downline detonator, and 500ms shock tubes are used. The shock tube triggers the booster, and the explosive column is finally initiated from the bottom up.

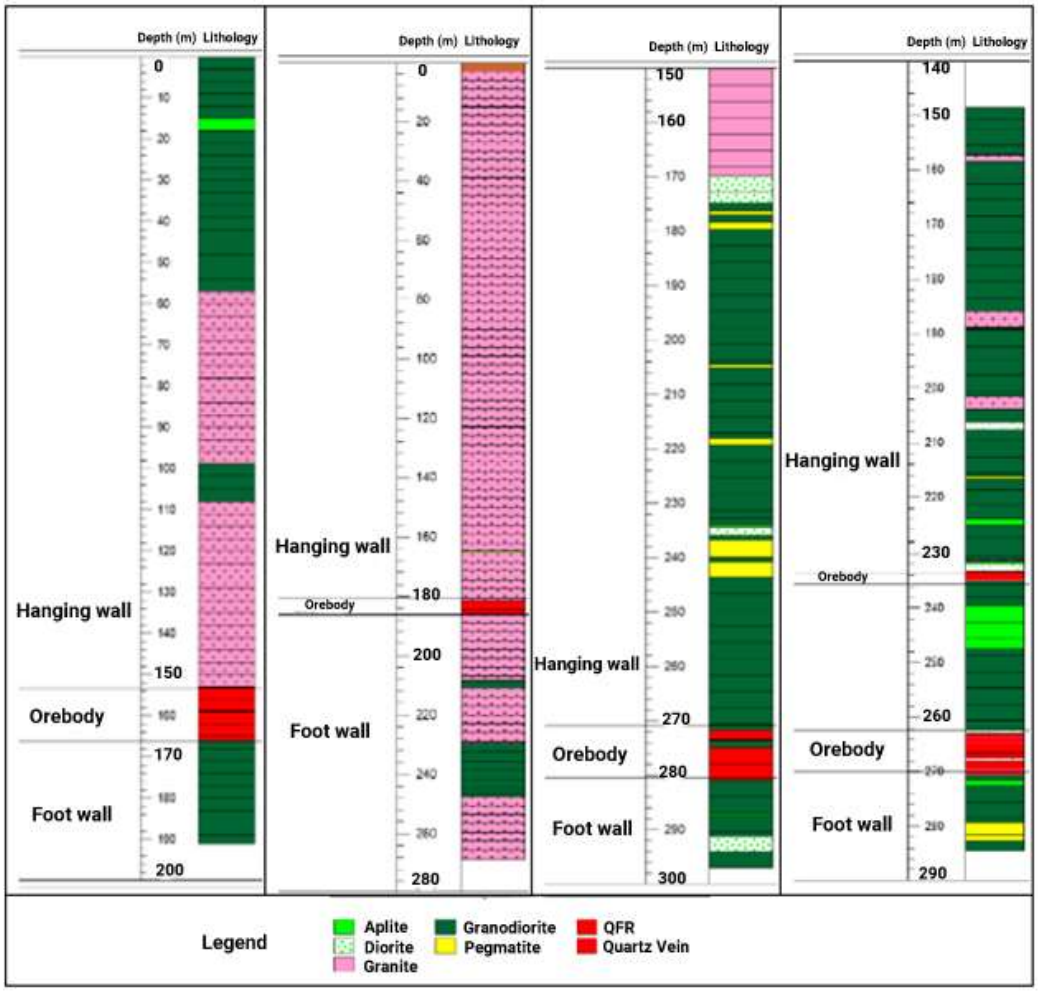


Figure 1: Lithology distribution in New Luika Mine after Hanekom, et al. [12].

Table 1: Rocks' physical and mechanical properties.

Rock type	Rock code	UCS(σ_c), MPa	Young Modulus (E), GPa	Poisson ratio	Rock density (ρ_r), kg/m^3	P-wave velocity (V_p), m/s	Tensile strength (σ_t), MPa
Granite	GRN	286.72	61.93	0.31	2,698	4,791	29
Granodiorite	GDIO	284.70	72.05	0.33	2,831	5,045	28
Diorite	DIO	161.87	70.78	0.30	2,952	4,897	16
Aplite /Pegmatite	APL /PEG	229.05	68.00	0.38	2,622	5,093	23

Quartz vein/Quartz feldspar rock	QV /QFP	269.95	83.90	0.13	2,685	5,590	27

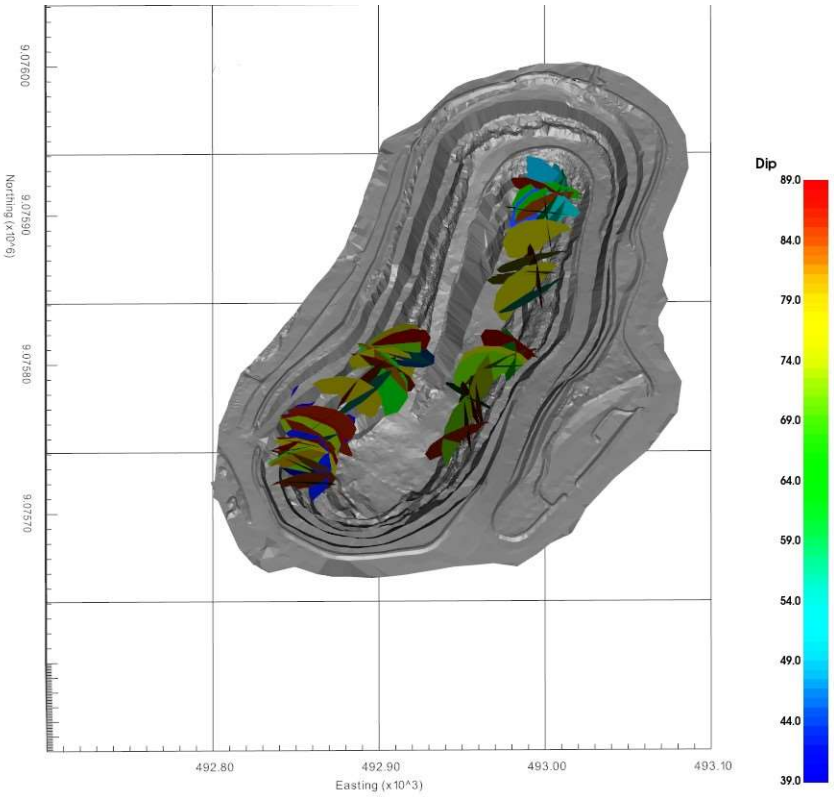


Figure 2: Mapped pit wall joints.

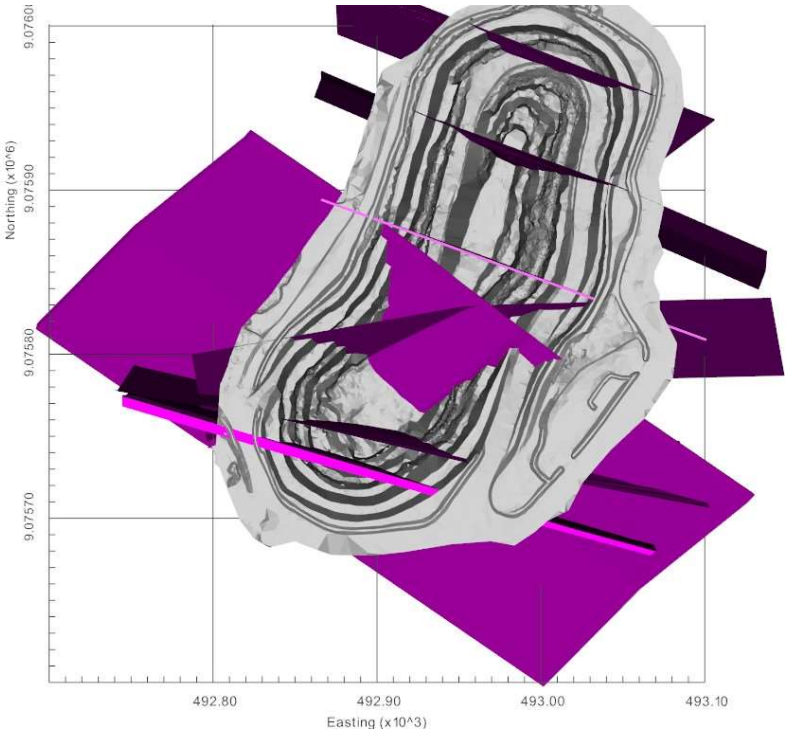


Figure 3: Mapped major faults.

Blast design is categorized into ore or waste shots. To prevent dilution in a narrow orebody, the 5 m bench height is used with 5.5 m blastholes, charged 2.6 m and 2.4 m stemming. For waste shots, 10 m benches are used with the burden, spacing, charging length, and stemming height of 3.7 m, 4.3 m, 6.7 m, and 3.4 m, respectively. The summary of explosive properties and blast design are shown in Table 2.

Table 2: Explosive and blast design parameters.

Explosive properties		**Blast design parameters**		
Explosive type	S135	Parameter (units)	Ore shot	Waste shot
Mixing	35% AN 65% Emulsion	Diameter (mm)	102	127
Max hole depth	40 m	Spacing (m)	3.2	4.3
Density (g/cm3)	1.00 to 1.25	Burden (m)	2.8	3.7
RWS at 100 MPa	111-115	Bench height (m)	5.4	10.1
RBS at 100 MPa	174-178	volume (m^3)	48.384	160.691
Ideal energy (MJ/kg)	2.5 – 2.7	Stemming (m)	2.6	3.4
VOD (m/s)	4500	Charging length (m)	2.8	6.7
Critical diameter (mm)	100	Charge per hole (kg)	28.60	106.09
Initiation	150 g booster and shock tube 500 ms 7 or12m long	Powder factor (kg/m^3)	0.59	0.66

3. Numerical modelling

3.1. Geometrical Design

The numerical model is constructed in LS-DYNA using the RHT model, which is widely used to simulate rock blasting. The model can successfully model the dynamic response of the rock mass and blast-induced damage [13-15]. Model construction in LS-DYNA is comprised of the geometrical design, the definition of the materials model, the interaction between different parts, and the definition of boundary conditions. Geometrical design is formed by the nodes, elements, and parts; in this study, the hexahedral elements with 8 nodes are used for all parts. Three parts, which represent the explosives, rock, and structures, are used. Explosive elements range from 3 to 6 mm, rock elements from 6 mm to 3 cm, and structures, unless limited by the structure's width are 3 cm. The model size follows the bench design; the description of the parameters is summarized in Table 3. The analysis uses two-dimensional (2D) models for the influence of material properties and orientations on the distribution of explosive energy and fractures as well as the formation of pit wall. All model scenarios are based on the mapping data for comparison with the field measurements.

Table 3: Summary of geometrical parameters.

Parameter	Value
Blasthole diamater (mm)	102
Burden (m)	2.8
Spacing (m)	3.2
Boundary conditions	
Free boundaries (free face)	West and top
Transmitting boundaries	East, North, South
Fixed movement	Along the depth

3.2. Material Models

The RHT model parameters are determined using the rock mechanical properties as shown in Table 4. The rock material as seen in Figure 1 comprises mainly granodiorite and granite rock types, which have similar properties. Granite properties are used to estimate RHT material parameters for the rock mass. More information on the estimation of model parameters can be found in the literature [2, 16-19].

Table 4: Granite RHT material model.

Parameter (unit)	Value	Parameter (unit)	Value
Density, RO (kg/m^3)	2698	Compressive strain rate exp, BETAC	0.026
Elastic shear modulus, SHEAR (GPa)	23.64	Tensile strain rate exp, BETAT	0.007
Unit factor, ONEMPA	0	Pressure influence on plastic flow in tension, PTF	0.001
Eroding plastic strain, EPSF	2	Compressive yield surface parameter, GC	0.53
Pore crush par , B0	1.22	Tensile yield surface parameter, GT	0.7
Pore crush par , B1	1.22	Shear modulus reduction factor, XI	0.5
Bulk modulus, T1 (GPa)	54.32	Damage parameter, D1	0.04
Failure surface parameter, A	1.6	Damage parameter, D2	1
Failure surface parameter, N	0.6	Minimum damage residual strain, EPM	0.015

Compressive strength, FC (MPa)	286.72	Residual surface parameter, AF	0.61
Relative shear strength, FS	0.18	Residual surface parameter, NF	1.6
Relative tensile strength, FT	0.1	Gruneisen gamma, GAMMA	0
Lode angle dependency factor, Q0	0.68	Hugoniot polynomial coefficient, A1 (GPa)	54.32
Lode angle factor, B	0.1015	Hugoniot polynomial coefficient, A2 (GPa)	76.05
Bulk modulus T2 (GPa)	0	Hugoniot polynomial coefficient, A3 (GPa)	28.25
Ref compressive strain rate, EOC	3×10^{-5}	Crush pressure, PEL (MPa)	191.15
Ref Tensile strain rate, EOT	3×10^{-6}	Compaction pressure, PCO (GPa)	6
Break compressive strain rate, EC	3×10^{25}	Porosity exponent, NP	3
Break tensile strain rate, ET	3×10^{25}	Initial porosity, ALPHA	1

Emulsion explosive S135 manufactured by AECI Mining Explosives is used for bench blasting. Explosive detonation is described by the high explosive burn material constructive model and the Jones-Wilkins-Lee (JWL) equation of state (OES). The parameters from the explosive properties in Table 2 and constants JWL EOS constants adopted from Hansson [20] are used to define material and EOS parameters as listed in Table 5.

Table 5: Material and JWL EOS parameters of S135 emulsion.

Explosive Type	Density (kg/m^3)	VOD (m/s)	Pcj (GPa)	A (GPa)	B (GPa)	R1	R2	ω	Eo (GPa)	vo
Emulsion (S135)	1,250	4,500	6.328	2.43	7.67	4.99	1.967	0.499	2.7	0

Structural properties are categorized as joints, quartz veins, and faults. Clay is modelled for joints infill material as plastic kinematics with properties defined in Table 6 [2]. Fault material (diorite) is modelled using RHT material models from the mechanical properties in Table 1, considering the weakening of its properties from shearing. Quartz veins are mostly intact and are modelled using the RHT material model using properties in Table 1.

Table 6: Clay-filled joints properties.

Density, (kg/m^3)	Young's Modulus, (GPa)	Poisson ratio,	Yield stress, (MPa)	Tangent Modulus, (GPa)	Hardening parameter	Failure strain
1,600	5	0.35	0.4	4	0	0.5

LS-DYNA makes it possible to model the interaction between the solid material with fluids. Rock and structures are modelled as Lagrangian parts while the explosive (explosion gases) are modelled as Arbitrary Lagrangian-Eulerian (ALE) parts. The coupled charge is adopted where the size of the charge diameter is the same as the blasthole diameter. Coupling between Lagrange and ALE parts is established using constrained Lagrange in solid with Lagrange parts as slaves and ALE parts as masters.

3.3. Model Validation and Verification

An intact rock model is constructed for granite using the parameters discussed in sections 3.1 and 3.2 above, and the simulation is run for 2.5 ms. Simulation results obtained are compared with the results obtained from the field measurements using the approach presented in Dotto et al. [21] for estimation of the size of damage zones. Esen et al. suggested that the size of the crushed zone is a function of borehole pressure, blasthole radius, and rock dynamic properties [4]. Using the data

collected on explosive and rock properties, the size of the crushed zone (CZ) is estimated to be 87.71 mm, which is 1.72 times the radius of the blasthole.

Fracture zone (FZ) is estimated from the peak particle velocity (PPV) monitoring using Forsyth (22) expression to determine the critical PPV of the stress wave that can induce fractures in a rock mass. PPV monitoring conducted in five (5) shots indicates the PPV attenuation in the rock mass described in Figure 4. From the PPV attenuation and the rock's dynamic tensile strength, the fracture zone's size is estimated to be 3.02 m. More information on the estimation of the crushed zone and fracture zone can be found in Dotto et al. [21].

Shot Number	Distance (m)	Mass per 8ms delay (kg)	SD ($m/kg^{0.5}$)	PVS, (mm/s)
SH_OB_955 _D04D05	117.4	125	10.15	26.07
SH_WB_960 _E04E05	180.7	336	7.19	23.75
SH_OB_950 _D07D08	38.7	117	5.56	36.03
SH_WB_950 _E05E06	744.7	236	34.74	3.26
SH_OB_955 _D04D05	117.4	52	12.47	14.56

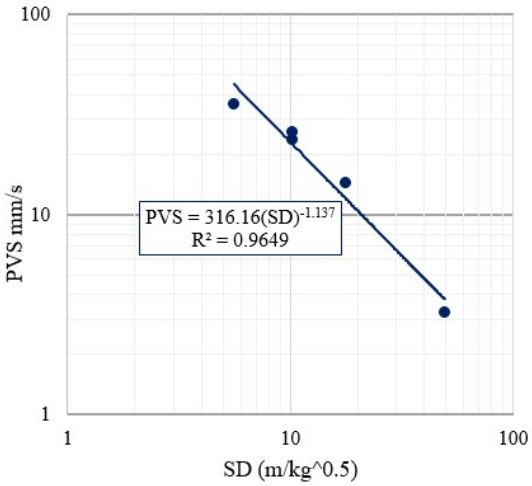


Figure 4: Peak particle velocity attenuation in the rock mass.

The simulation shows that after explosive detonation, higher pressure from the explosion products causes blasthole expansion from 51 mm to 68 mm. The crushed zone of 93.09 mm forms at 0.12 ms, and at the end of the simulation, the fractures extend to 3.1 m in the fractured zone as seen in Figure 5. Further cracking is seen on the free face side, which is caused by spalling from the stress wave reflection at the free face. Table 7 compares the results obtained from the simulation using the analytical approach by Dotto et al. [21]. From the comparison, the two approaches offer similar results with minor variations that can be due to the presence of structures in the rock mass from the field measurements that are not accounted for in the simulation. The simulation model is feasible since it performs as expected and offers comparable results.

Table 7: Results Comparison.

Approach	CZ radius (mm)	Pressure at the end of CZ (MPa)	PPV at end of CZ (m/s)	FZ radius (m)	PPV at the end of FZ (m/s)
Dotto et al. [21]	87.71	1,397	90.25	3.02	1.74
Simulation	93.09	1,290	102.00	3.1	2.35

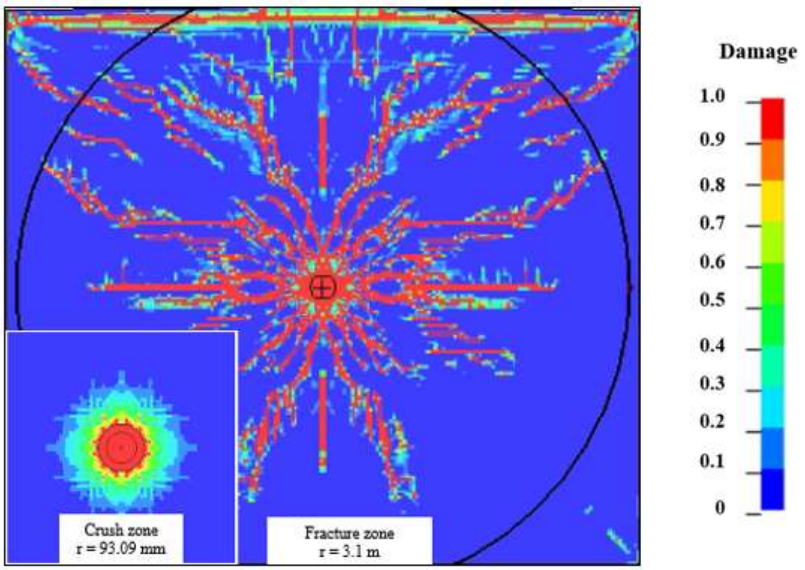


Figure 5: Simulated damage zone sizes.

4. Fracturing Analysis and Discussion

The analysis focuses on the ore shot SH_OB_955_D04D05, which in this study is termed shot 1. The design, firing direction, and material movement are shown in Figure 6(a) and (b). Centre lifting is applied due to the absence of a free face, where material movement is towards the centre. Centre lifting is usually discouraged due to the large number of movements in variable directions, which causes ore dilution. With centre lifting, higher and most variable vertical movements are observed in the control line (trunk line), and greater movements in the mid-bench cause higher dilution. Dilution can be minimized by moving the control line away from the boundaries of ore blocks.

4.1. Scenario 1-Two Intersecting Joint

Four interesting scenarios are re-created in LS-DYNA to explain the fragmentation and pit formation that were obtained in the field. The first scenario is the formation of oversize fragmentation and a hard dig muckpile in fragmentation analysis BF 30. The simulation model was created for the position of blasthole and structures as shown in Figure 7(a). Survey data shows that the fragmentation analysis was conducted on the opposite side of the intersected joints from the blasthole. From the fragmentation image taken from the muckpile and analysis done on wip-frag software in Figure 7(c) and (d), fragmentation on the incident side of the joint is fine while the opposite side is less fractured [23]. This is also observed in the re-created simulation results in Figure 7(e).

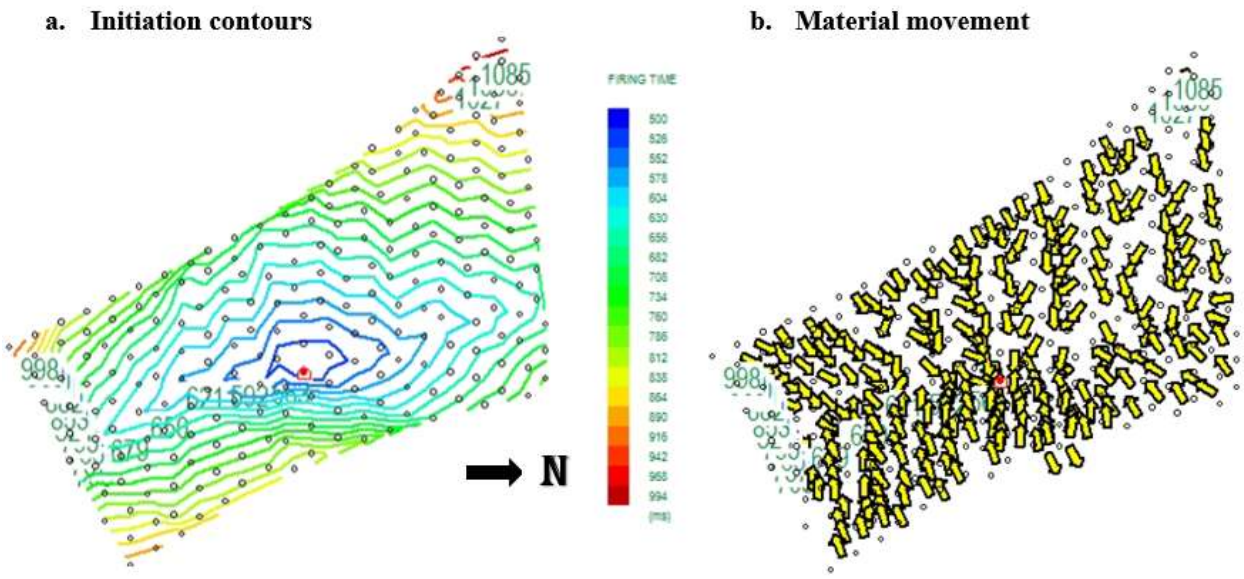
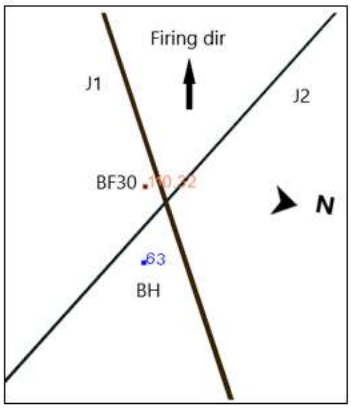


Figure 6: Shot initiation sequence and material movement.

a. Field mapping and survey

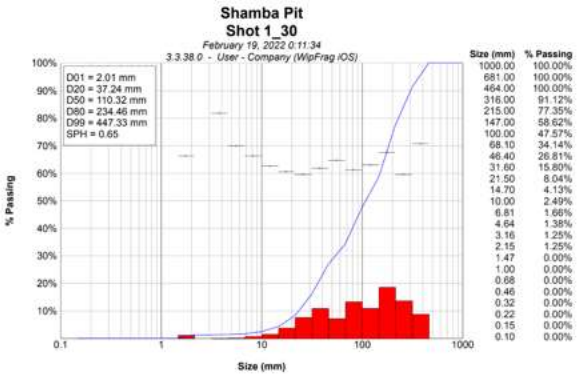


b. Joints properties

Structure	Joint 1 (J1)	Joint 2 (J2)
Dip (°)	80	60
Dip/strike direction (°)	160/250	290/20
Width (cm)	5	2
Infill	clay	clay
Firing direction	West	

c. Fragmentation image

d. Fragmentation analysis



e. Scenario 1 simulation in 2D

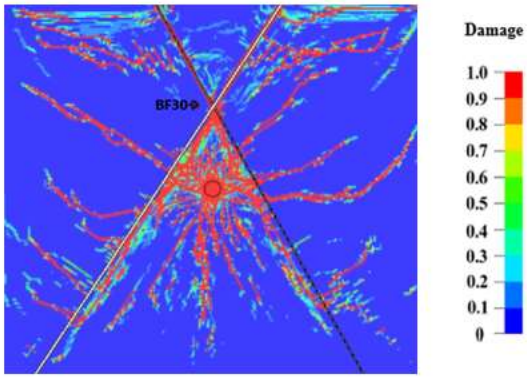


Figure 7: Scenario 1 Analysis.

The fragmentation image in Figure 7(c) also shows that the opposite side of the joint has minimal material movement, which can be due to the escape of explosion gasses through the interface between the rock and the joint. Simulation results show most of the stress wave energy is reflected at the interface, especially on the wider joint side. In addition to partial reflection, there is a re-direction stress wave when the two joints intersect, as described in Figure 8(a). That in addition to double reflection towards the free face, leaves the majority of the middle wedge on the free face uninterrupted as seen in Region 5 of Figure 8(b). Region 1 experiences better fragmentation if compared to Figure 5 (intact rock) by being on the incident side of the reflected stress wave. Fragmentation in regions 3 and 4 can be improved by adding extra blastholes on the opposite side of the joints.

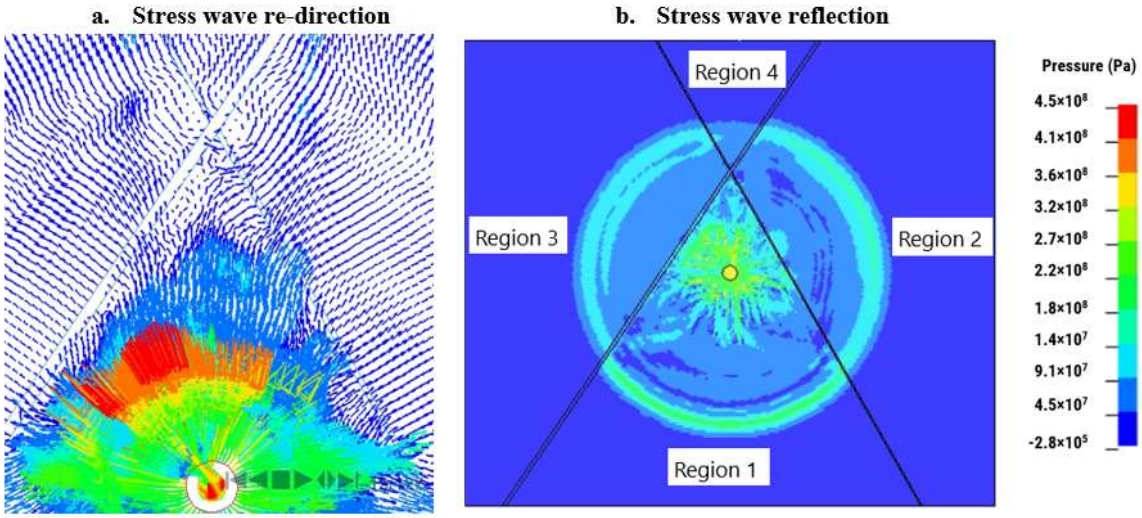


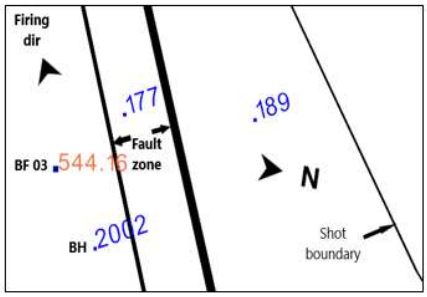
Figure 8: Energy reflection and re-direction at the joints.

4.2. Scenario 2-Fault on the Shot Boundary

The second scenario is the formation of oversize material with P50 and P100 of 0.54 m and 1.26 m, respectively, on the northern boundary of the shot. The fault is 0.97 m from the last blasthole on the shot boundary and is 1.5 m wide. The fault material is a mixture of diorite and granodiorite. The layout of the blasthole relative to the structure and fragmentation analysis point is shown in Figure 9(a), and the fragmentation image and its distribution are presented in Figure 9(c) and (d). The analysis suggests a mixture of smaller and bigger fragments with fragments less or equal to 0.4 m contributing only 40% of the muckpile. The remaining fragmentation ranges from 0.5 to 1.3 m.

From the recreation of the scenario in a numerical model, it is observed that the stress wave is reflected/attenuated as it crosses the interface between the rock and the fault (Figure 10(a)), causing more fracturing on the incident side, as seen in Figure 9(e). Fractures can still form on the fault because the material is weaker (softer) than the rock, although they are widely spaced due to an increase in rock strength caused by increased confinement when the stress wave crosses the second interface, as described in Figure 10(b). A combination of stress wave reflection on the free face and wave enhancement on the second interface forms fractures on the opposite side of the fault. The oversized fragmentation is caused by the spaced fractures on the fault and the quarter of the bench on the fault opposite the free face, which is almost uninterrupted. Since this was a shot interface, the oversized fragmentation could also be due to the escape of blast energy through the fractures formed by prior blast shots.

a. Field mapping and survey

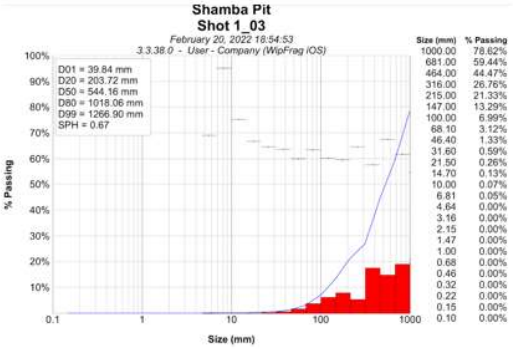


b. Fault properties

Structure	Fault
Dip (°)	75
Dip/strike direction (°)	22/112
Width (cm)	1500
Infill	Diorite
Firing direction	West

c. Fragmentation image

d. Fragmentation analysis



e. Scenario 2 simulation in 2D

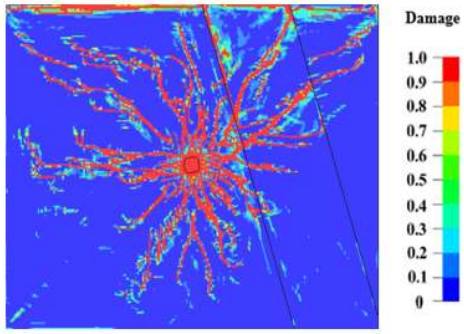
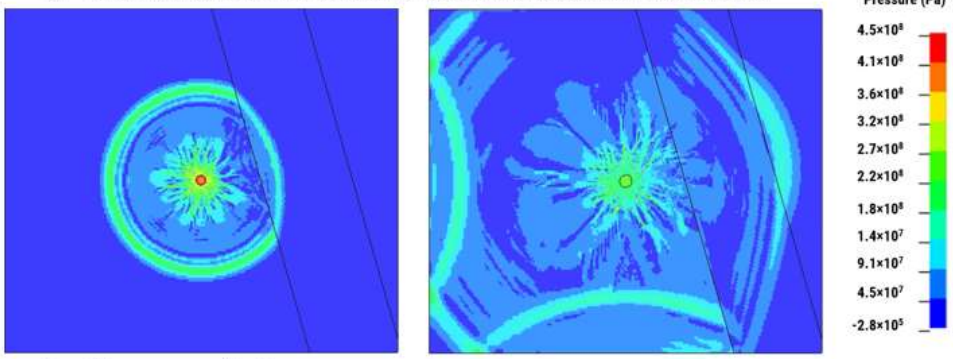


Figure 9: Scenario 2 Analysis.

a. Stress wave reflection and enhancement on the first and second interfaces



b. Stress wave reflection

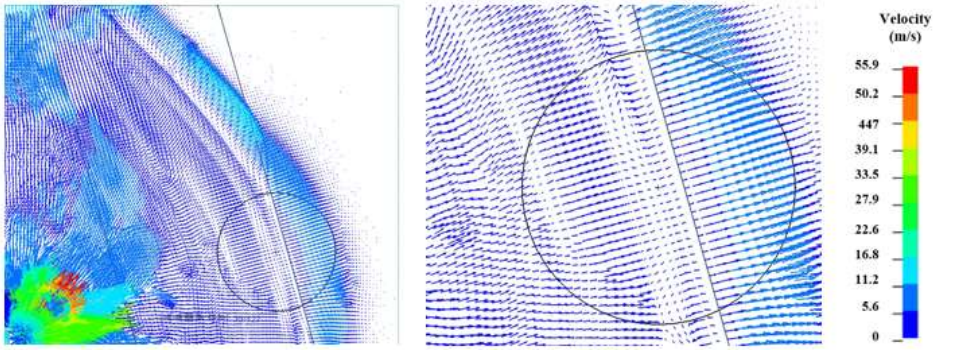


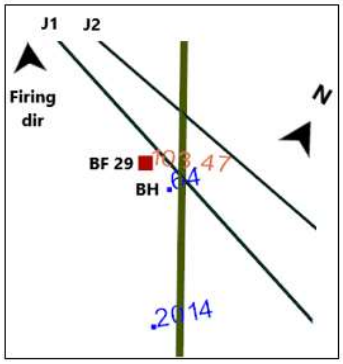
Figure 10: Stress wave distribution across the fault.

4.3. Scenario 3-Quartz Vein with Intersecting Joints

The third scenario presents fragmentation across the quartz vein intersected by the joints. The layout of the scenario, fragmentation image, and fragmentation analysis are presented in Figure 11(a) to (d). The reconstruction of the scenario in a numerical model is shown in Figure 11(e). From the fragmentation image and the simulation damage plot, the fines and good fragmentation are formed from the wave reflection on the first joint interface and good fragmentation of the quartz vein. Bigger fragments are formed between the joints from increased confinement and on the opposite side of the second joint since most of the energy is reflected or used up in multiple joint deformations [1].

Quartz material offers good stress wave transmission (Figure 12(a)) due to its hardness and stiffness and since it is brittle, it fractures easily. It should also be noted that when the stress wave meets the joint perpendicularly, depending on its intensity, fractures have a good chance to propagate to the other side of the joint (Figure 11(e) and Figure 12(a) to (c)). Comparing the rock mass to the quartz vein, the stress wave is enhanced more by crossing from the joint to the quartz vein (due to increased impedance difference) than the rock mass, increasing fracturing on the upper right corner, as seen in Figure 11(e).

a. Field mapping and survey

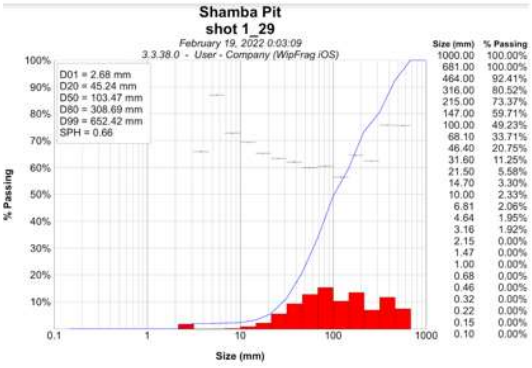


b. Vein and joints properties

Structure	Qz vein	J1	J2
Dip (°)	60	77	60
Dip/strike direction (°)	30/ 120	167/ 257	160/ 250
Width (cm)	20	5	6
Infill	Qz	clay	clay
Firing direction	West		

c. Fragmentation image

d. Fragmentation analysis



e. Scenario 3 simulation in 2D

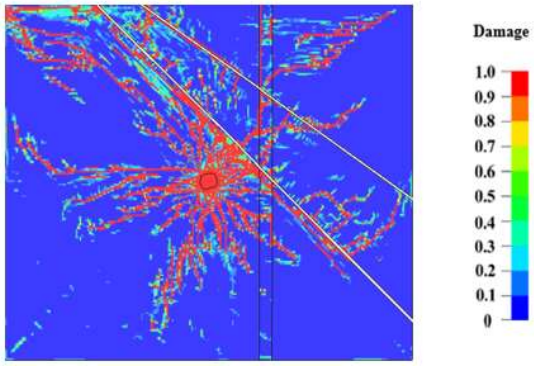


Figure 11: Scenario 4 Analysis.

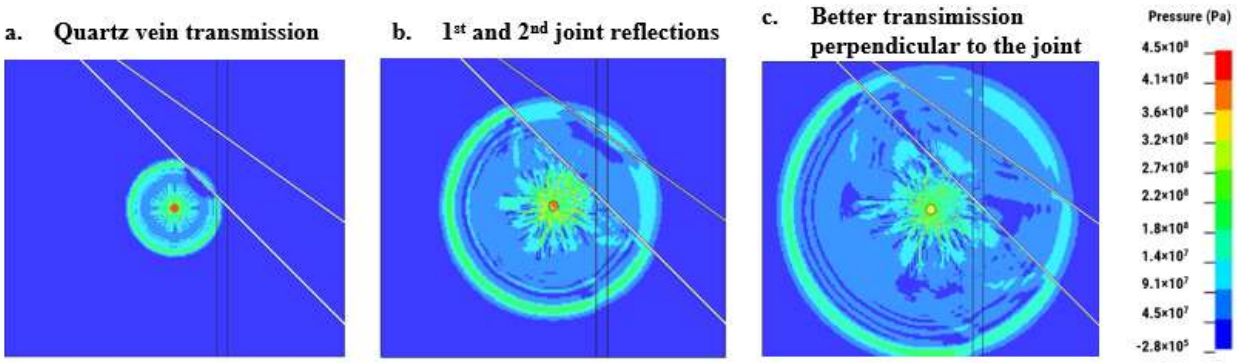


Figure 12: Stress wave propagation through a quartz vein and joints.

4.4. Scenario 4-Joints Intersecting Behind the Blasthole

The third scenario analyses the influence of joints on the pit wall formation. Mapped structures and surveyed actual toe line of shot 1 are shown in Figure 13. Comparison of the design to the actual toe line in Figure 14(a) shows under break, specifically mid-shot where joints intersect behind the perimeter blastholes. The zoomed image of the analyzed scenario and the joint properties are presented in Figure 14(b). A numerical model is created to simulate this scenario, and the results are shown in Figure 14(d) and (e).

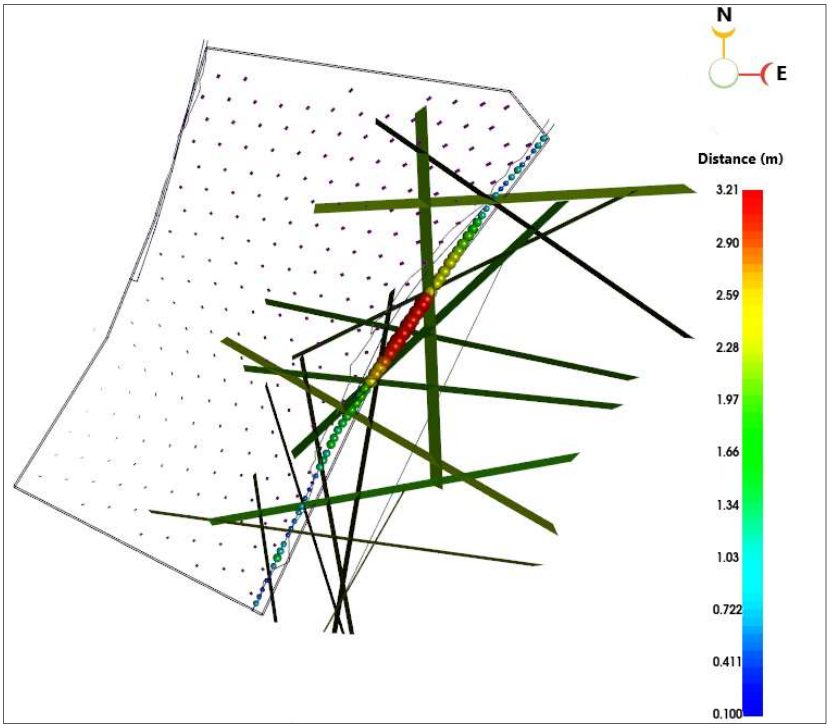
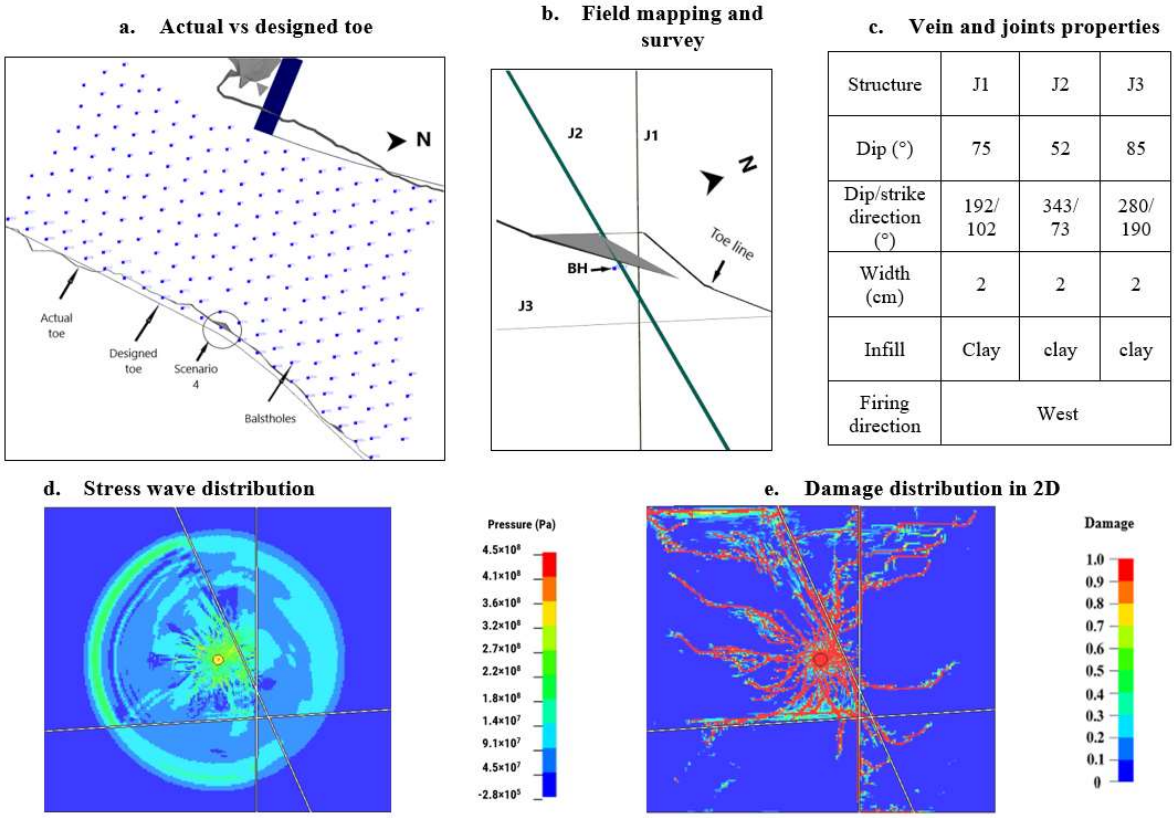


Figure 13: Structure distribution and toe formation on shot 1.

The analysis shows that the joints behind the blasthole reflect most of the stress wave unless they intersect at 90 degrees angle or close to 90 degrees. The absence of a free face hinders fracturing from reflected waves. Since the confinement increases as the wave travels toward the wall, an attenuated stress wave does not cause any fracturing. When crossing multiple joints, the stress wave is attenuated rapidly, leaving the area behind the blasthole uninterrupted while increasing fracture extents on the opposite side of the intersection.

Comparing this case to the analysis in scenario 1 (Figure 7e), when the joints intersect on the free face side, the energy gets thrown back towards the wall; this can result in pit wall/toe line over break, as seen in the bottom of Figure 13. To achieve uniform pit wall formation, pre-split is recommended to allow stress waves to reflect and cause minimum damage to the pit wall while initiating spalling to assist in fracturing the rock on the opposite side of the joints.



Structure	J1	J2	J3
Dip (°)	75	52	85
Dip/strike direction (°)	192/ 102	343/ 73	280/ 190
Width (cm)	2	2	2
Infill	Clay	clay	clay
Firing direction	West		

Figure 14: Scenario 4 Analysis.

5. Conclusion

This study is focused on analyzing the influence of structural features on the blast outcomes mainly the fragmentation size and the distribution and the formation of the pit wall. The analysis shows that the properties and position of the structure relative to the blasthole influence fragmentation and pit wall formation.

When the structure material is weaker and less stiff than the rock mass, the energy is reflected, causing higher damage on the incident side and oversized or uninterrupted rock mass on the opposite side of the structure. Conversely, when the structure is stronger and stiffer than the rock mass, it transfers most of the stress wave energy, and since it is brittle, it fractures easily, adding the finer fragmentation. When less stiff/weaker structures cross stiffer/stronger structures, the same concept applies to the transmission or reflection of the stress wave. Design modification can be necessary in a jointed rock mass to ensure uniform distribution of explosive energy between the reflecting joints.

The joints' positions and points of intersection relative to the free face, the blasthole, and the pit wall influence the fragmentation size and distribution across the bench and the formation of the pit wall. Joints crossing (intersecting) in front of the blasthole have the potential to cause a pit wall overbreak, while the ones crossing (intersecting) behind the blasthole cause a pit wall underbreak. Pre-split blasting is recommended to redirect explosive energy and achieve a pit design.

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Modeling Production Rate in Rock Excavation Operations by Predicting Rock Properties Using Neural Networks

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ABSTRACT

In mining operations, the production rate is significantly influenced by the physical properties of the rock, such as density, compressive strength, and abrasiveness. These properties directly determine the extent of fracturing and extracting the rock, which in turn affects the overall production rate. To illustrate the importance of how to measure these rock features, this study used neural network models to estimate two key rock properties: density and point load strength. Experimental data was collected from rock samples with varying compositions and divided into separate sets for training and testing the models. After preparing the data, neural network models with several dense layers and non-linear functions were built and trained, incorporating techniques to prevent overfitting. The models performed well in predicting density and point load strength, achieving low error rates when evaluated on the test sets. By integrating predictions of these rock properties into production rate models, it became possible to quantify how factors like density and strength influence excavation productivity. This allows for optimization by relating controllable parameters to the target production rate while considering the site-specific rock characteristics. This study demonstrates how integrating machine learning techniques, such as neural networks, can improve predictive models used in rock excavation operations.

1. Introduction

In open pit mining, excavation and hauling activities are decisive for productivity and costs. This study aims to create a model to predict haulage costs in blasting operations, considering different factors that affect the excavation process.

The research predicts a shovel's production rate. This is calculated by multiplying an ideal maximum productivity rate by operational efficiency [28] . To calculate the production rate, the research employs two deep learning libraries TensorFlow and Keras [23] . These libraries allow the creation, training, and deployment of deep neural network models. Two predictive models were created: one to estimate rock density based on aluminum oxide (Al_2O_3) content, and the other to predict the point load strength index ($I_s(50)$) using both density and Al_2O_3 content.

The rock density prediction model is implemented using Al_2O_3 grade. To predict the values of $I_s(50)$, the model uses a combination of density and Al_2O_3 dataset to predict $I_s(50)$. Using the predicted values, the model can estimate haulage rates.

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Theoretical models and machine learning prediction are used in this study to enhance the analysis and prediction of the haulage rates in open pit operations. Specifically, the objective of the research is to contribute to the enhancement of mining rock excavation processes taking into consideration rock properties such as density and point load strength. Thus, this will enhance operational effectiveness and efficiency in resource utilization and equipment allocation.

2. Literature Review

In this section, recent developments in production rate modeling, variables influencing the excavation process, the prediction of rock properties, and the use of machine learning techniques in the mining sector are all covered.

2.1. Current Approaches to Production Rate Modeling in Open Pit Mining

Researchers have experimented with a variety of techniques, such as computer simulations that mimic the production of ore by employing models like Petri nets. These techniques give better estimates than older methods [17] . These models have been further enhanced with agent-based approaches to evaluate production targets and track fuel consumption by haul trucks [22].

Comprehensive models that combine pit design and production planning have been developed to maintain smooth processing plant operations and steady ore feed [6] . Researchers have also utilized simulations and mathematical techniques to optimize production schedules and maximize cash flow throughout the mine's life [7, 25].

Mining production capacity is limited by the processing plant's capacity and the average ore grade [15] Studies on cut-off grade optimization have revealed that balancing mining and processing capacities is crucial for maximizing production.

2.2. Factors Affecting Excavation Processes

Several factors affect mining operations, including safety, environment, and other related activities. Lukashuk et al. [18] looked at how to control excavators in open pit mines. The authors found that the mechanics of lifting and thrusting to work together were key to achieving good digging. An experiment used a computer program to test the operating conditions of an excavator's bucket movement along a planned path, resulting in a digging algorithm and control functions based on the bucket's position, which can be used to design control systems for open-pit excavators.

Zhang et al. [35] showed the importance of keeping slopes stable which helps to ensure safety in open pit operations. Having knowledge about slope stability and soil properties helps prevent rock falls in open pit mines. Cao et al. [5] added that knowing the state of in situ rock formations assists in understanding the effect of blasting on slope stability.

Kolapo et al. [16] reviewed case studies of slope failures in mining operations, explained failure modes and influencing factors, and highlighted the importance of monitoring and evaluating slope stability. The authors proposed the integration of analytical methods with artificial intelligence to improve prediction accuracy and security.

2.3. Methods Used for Rock Property Prediction

Predicting rock properties is extremely important for various engineering and construction projects, most especially in mining. The key characteristics that indicate rock mechanical strength and behavior are density and point load index.

Several studies have looked at the connection between rock point load index (PLI) and uniaxial compressive strength (UCS) for different rock types. Singh et al. [29] discovered a strong correlation between PLI and UCS across various rock types. The research was important because it helped to

estimate a rock's strength based on PLI, which can be a useful tool for predicting rock properties and optimizing mining operations [29].

Another study by Heidari et al. [9] focused on predicting the compressive and tensile strengths of gypsum rock using point load testing. The authors proposed a method to estimate rock strength from point load tests. The method can be used on various rock types, helping predict rock properties and improving mining operations [28].

Mohamad et al. [20] used particle swarm optimization and backpropagation to predict rock strength. Their method could be combined with existing techniques such as standalone ANN-based PSO and BP models, which could improve the planning and execution of mining activities [20].

Artificial intelligence techniques, including neural networks, fuzzy inference systems, and genetic programming, have improved the accuracy of property predictions made using P-wave velocity, density, and Schmidt hammer rebound numbers [2].

2.4. Application of machine learning in mining operations

Suleymanov et al. [30] developed a machine-learning workflow using artificial neural networks (ANNs) to predict petrophysical properties such as porosity, mineralogy, and pore fluid content from elastic properties. This research showed that ANNs are good for understanding complex rock data.

Machine learning has gained popularity in mining since 2018, with applications covering mineral exploration, extraction, and reclamation phases [14] . These techniques have yielded significant improvements in various aspects of mining operations [2, 26, 34]:

- Optimization of truck dispatch, increasing operational efficiency by 10%
- Potential energy cost reduction of 2.9% in underground mining through machine learning models for refrigeration-ventilation systems
- Equipment performance monitoring and process optimization using unsupervised learning and action learning methods

The implementation of artificial intelligence, machine learning, and autonomous technologies in mining has led to cost savings, increased productivity, and improved worker safety [11].

Inapakurthi [12] demonstrated the use of Recurrent Neural Networks (RNN) with genetic algorithm-tuned hyperparameters to control nonlinear industrial grinding circuits, achieving 97% accuracy.

3. Problem Statement

For operational planning and optimization, it is crucial to predict haulage rates in open pit mining operations. However, this process is complex due to the variability of factors influencing excavation performance, such as rock properties, equipment characteristics, and blasting parameters.

The main problem is the difficulty of integrating these diverse factors into a reliable predictive model. Traditional methods often rely on simplified approximations or operator experience, which can lead to inaccurate estimates and, consequently, no optimal planning of mining operations. Additionally, there is a discrepancy between the theoretical models proposed in academic literature and their practical application in real mining environments. Variability in the properties of the rock at a mining site presents another difficulty. Haulage rate prediction becomes more challenging when the density and strength of the rock fluctuate over shorter distances. Therefore, a mixture of theoretical models and machine learning methods are used in this study to fill in these gaps. Thus, developing a system to predict haulage rates in rock excavation is the purpose of research study.

Developing a system to forecast haulage rates in rock excavation is the goal. This system will employ neural networks to estimate the Al_2O_3 content of rocks to determine their density and point load index. Haulage rates will be calculated by a predictive model using these estimates. As a result, haulage rates can be better predicted, considering changes in rock properties and other operational factors.

4. Research Methodology

Details of the methodology used to implement and evaluate the extraction rate prediction model in mining operations are shown in Figure 1.

Figure 1. Research methodology.

4.1. Data Set

The models were developed and validated using experimental data sets that included values for rock density, Al_2O_3, and $I_s(50)$.

4.2. Data Preprocessing

Before the model was trained, the data was prepared to ensure quality and consistency such that:

- Missing values were handled using imputation techniques.
- Outliers were removed based on the Mahalanobis distance.
- Features were normalized using min-max normalization in TensorFlow.

4.3. Model Design and Training

Two prediction models were developed:

4.3.1. Density Prediction Model

Rock density was estimated based on Al_2O_3 content by this model. A dense neural network with several hidden layers and an output layer was used to predict density.

4.3.2. $I_s(50)$ Prediction Model

$I_s(50)$ is predicted using density and Al_2O_3 content as inputs by this model. The model structure was like the density prediction model.

An example of a neural network is illustrated in Figure 2. This diagram shows the typical structure of an artificial neural network, including input layers, hidden layers, and output layers. The interconnected nodes demonstrate how information flows through the network, with each connection representing a weighted input.

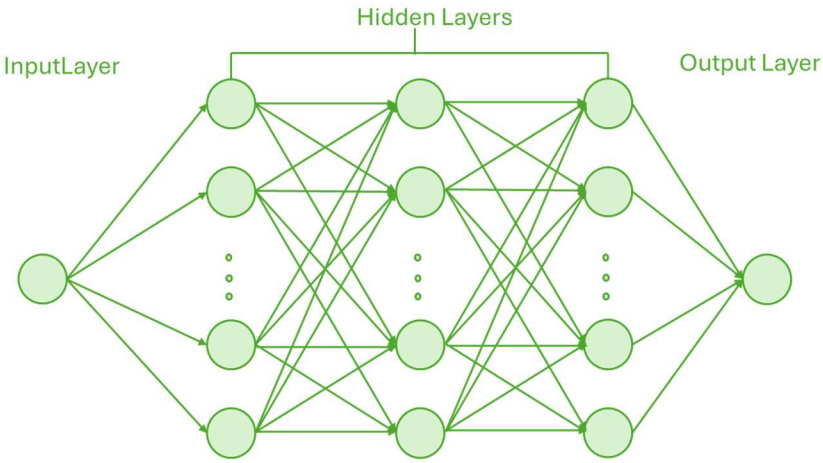

Figure 2. Example neural network.

The models output were used to calculate mucking rates using the production Eq. (1) and Eq. (2) . The extraction rate is calculated by this formula by multiplying an ideal maximum productivity rate by operating efficiency. The efficiency is determined by rock strength (calculated from predicted density and I s (50)), nominal bucket capacity, explosive energy concentration, and three other coefficients.

$$Q = Q^0 e^{-kf_s/B_p} \left[\frac{\sigma^2}{\left(E - E^0\right)^2 + \sigma^2} \right] \tag{1}$$

$$f_s = 0.0015 p_r - 3 + 0.264 I_{s(50)} \tag{2}$$

Where:

Q^0:	Maximum rate
k:	Coefficients in the mathematical mode
f_s:	Rock strength factor
Bp:	Nominal load of the excavator
E:	Powder energy factor
E^0:	Inicial powder energy factor
σ:	Scale factor.
p_r:	Rock density
$I_{s(50)}$:	Point load strength index

The models were trained using training datasets. The mean square error loss function was optimized with the Adam optimizer [36] . Regularization techniques [21] were used in conjunction with hyperparameter tuning to improve model performance.

4.4. Predictive Performance Evaluation

The performance of the model was evaluated using a separate data set. The following metrics were calculated:

- Mean Squared Error (MSE): The average squared difference between predicted and actual values was measured. Lower MSE indicates better model fit.
- Mean Absolute Error (MAE): This measure measures the average absolute difference between predicted values and actual observed values.
- Absolute Percentage Error (MAPE): It measures the average percentage difference between predicted values and actual observed values

Scatter plots and residual plots were also created to visualize the relationship between predicted and actual values and to detect patterns in prediction errors.

4.5. Additional Experiments

More experiments were conducted to explore how different setups affected predictive performance:

- Different model structures were tried, changing the number of hidden layers, neurons per layer, and activation functions.

These results were compared with the initial model and the setup that performed best according to the evaluation metrics was chosen.

5. Case study

The optimal mine design was created using GEOVIA GEMS [31] and further optimized with Minkah [19] . The final design of the pit had a total tonnage of 3,003 Mt, of which 1,566 Mt was ore with grades of 51% Al_2O_3 and 5% SiO_2.

The mine was divided into three pushbacks [3] as presented in Figure 3 for more control and better cash flow. Each pushback has its access ramp. The available material generated by GEOVIA Whittle [32] , the designed pit boundary and pushbacks are presented in Table 1.

Table 1. Summary of material tonnages [10].

Description	Total tonnage (Mt)	Ore tonnage (Mt)
Whittle optimum pit shell	2763.0	1610.0
Designed pit shell	3003.0	1566.0
Pushback 1	822.0	402.0
Pushback 2	1260.0	587.0
Pushback 3	912.0	544.0

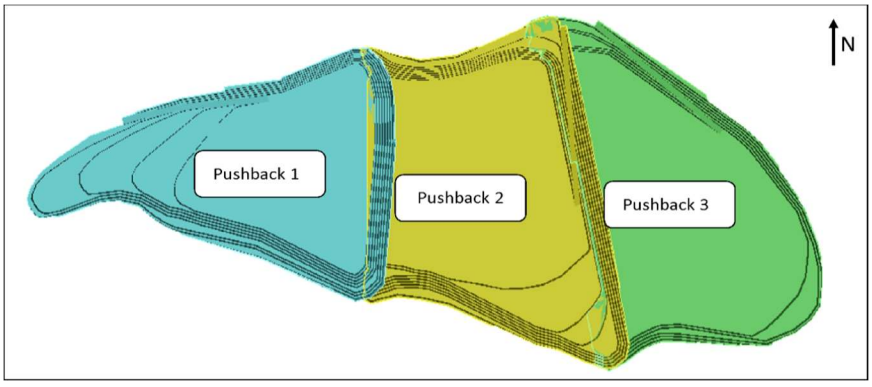

Figure 3. Pushback designs [10].

Economic parameters considered for GEOVIA Whittle [32] to generate the final pit and pushbacks are shown in Table 2.

Table 2. Economic parameters [18].

Description	Value
Reference mining cost	$3.16 /tonne
Reference processing cost	$9.6 /tonne
Reference stockpile cost	$0.5 /tonne
Selling price	$0.76 /%mass
Discount rate	10 %

The design includes a truck transportation system with two loading points and a crushing site. It also includes switchbacks, roads, reclaimers, process plants, tailings, and waste deposits. This conceptual layout is shown in Figure 4.

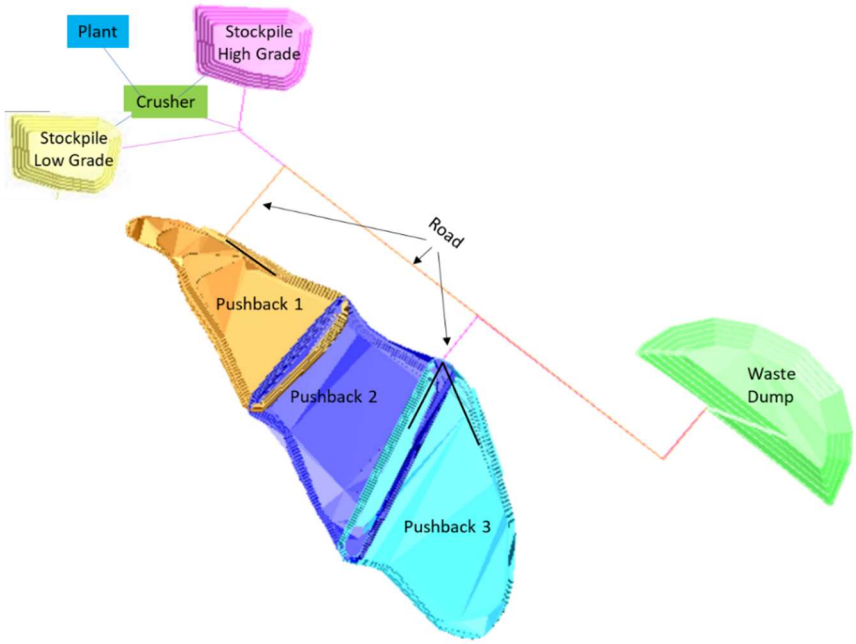

Figure 4. The conceptual design of the operating system [10].

The strategic plan generated in GEOVIA Whittle [33] shows a mine life of 47 years, with a mining rate of 65 Mtpa and processing rates of 25 Mtpa (years 1-19) and 37 Mtpa (year 20 onwards). The mining and processing capacity schedule are presented in Figure 5 and Figure 6 respectively.

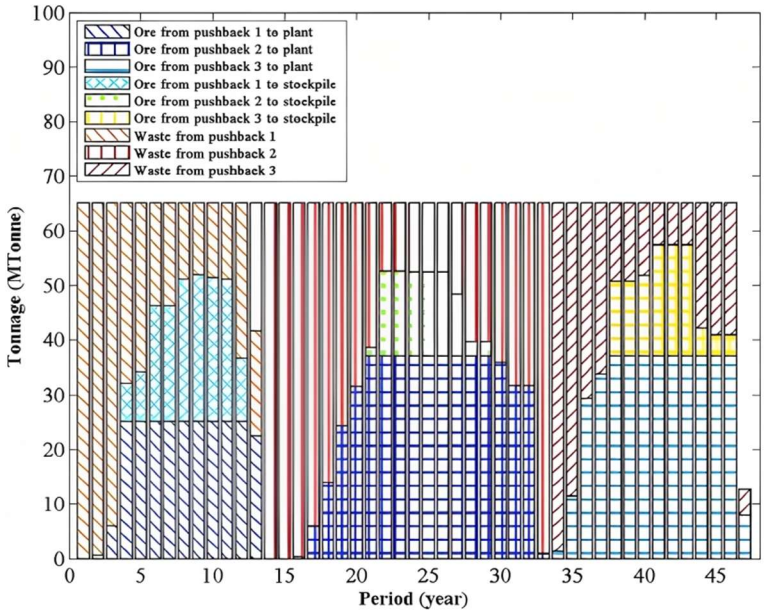

Figure 5. Mining activity in each pushback [10].

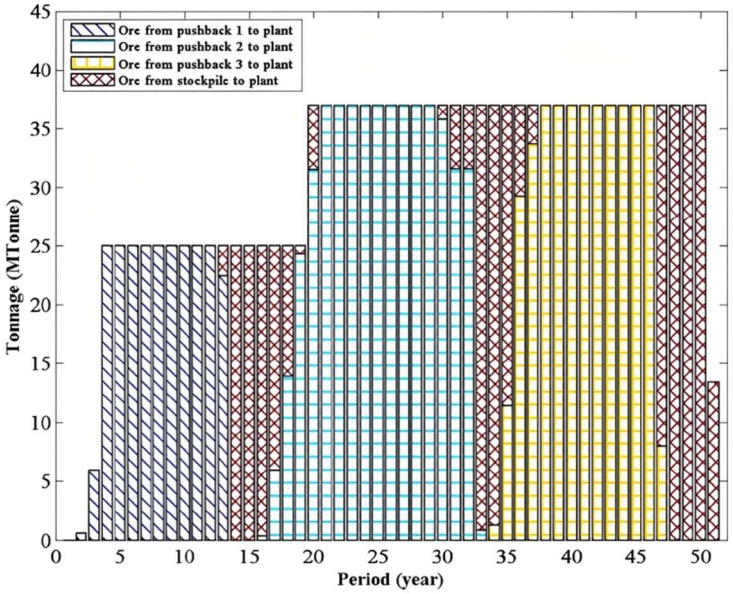

Figure 6. Processing plant material tonnage schedule [10].

A short-term (annual) production schedule was used. The database was extracted from Period 8 of Pushback 1, as this period had a good representation of the material flow of the entire mine.

6. Implementation

Two neural network models were created: one to predict Al_2O_3 content based on density, and the other to estimate $I_s(50)$ using density and Al_2O_3 content. These models were built on TensorFlow and Keras [21] . The results were applied to the production formula to estimate the production ratio of the shovel. In the following subsections, the processes of the model's implementation are explained including development, training, and evaluation.

6.1. Dataset

A database containing information on density, Al_2O_3 content, and Is(50) was required. Information was found in NI 43-101 reports, geological reports, articles, mining magazines, and theses [1, 4, 8, 24, 27]. The database was created with density, Al_2O_3 grade, and $I_s(50)$ as shown in Table 3.

Table 3. Dataset.

Density (kg/m^3)	Al_2O_3 (%)	$I_s(50)$ (Mpa)
3100	85	
1600	55.1	
1790	50.4	
1870	50.9	
2782		1.21
3000		5.36
2800	43.22	
3000	44.78	
1640	51.99	
1880	52.5	
1910	52	
2110	49.1	
2280	53.38	
1980	51.7	
2050	52.03	
2679		4.14
2467		1.39
2778		6.54
3068		4.62
2100		4.97
1850		3.17
1800		2.93
2980	43.623	5.18

6.2. Data Preprocessing

A new database was extracted from the original database. This new database contained only the density and Al_2O_3 values. The data was separated to prepare it for different analyses.

6.3. Neural Network Model for Al2O3 Content Prediction

A neural network model was developed to predict the Al_2O_3 content in a material using its density. A machine learning approach using neural networks was used to find the relationship between these two variables.

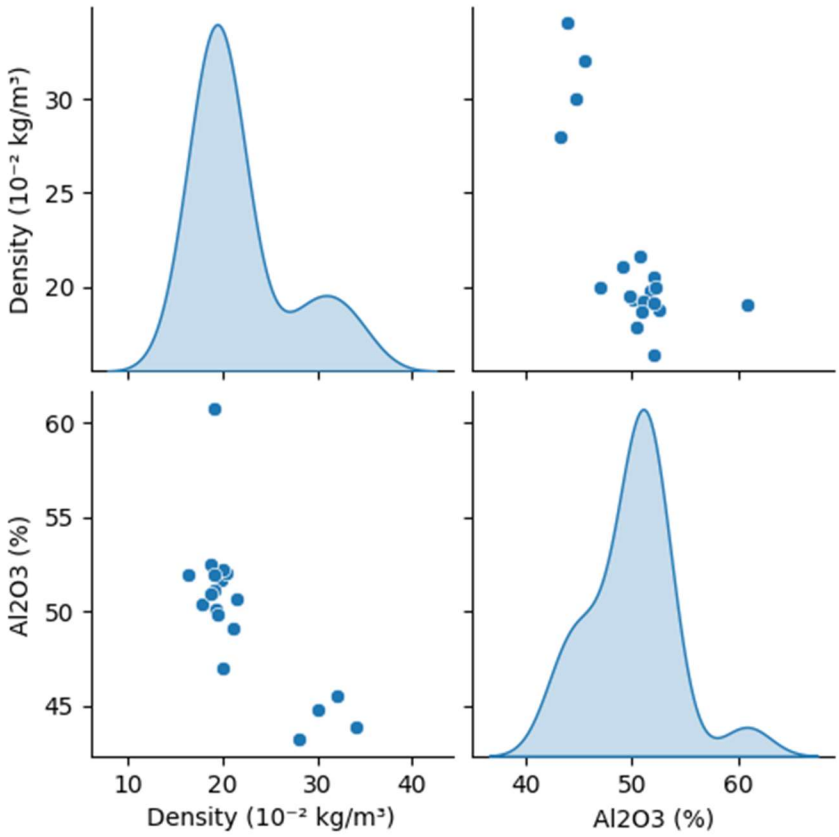

Figure 7. Multivariate Analysis: Density and Al_2O_3 relation.

Figure 7 illustrates the dataset used to train a machine learning model that predicts Al_2O_3content from density. The scatter plot shows the general relationship between these two variables, where higher density tends to be associated with higher Al_2O_3content, although with considerable scatter. The density plots reveal that both the density and Al_2O_3 values follow an approximately normal or bell-shaped distribution.

The algorithm loads a data set containing density and Al_2O_3 content values for different samples. Then, splits the data into training (80%) and test (20%) sets. Before feeding the data to the model, a normalization process was performed. This method scales the input features to a standard range. It helps the model converge faster and perform better. The deep neural network (DNN) model was built using Python's TensorFlow library [23] . The model had four dense layers with 256, 128, 64, and 1 neuron, respectively. The neural network model is defined with several hidden layers and Rectified Linear Unit (ReLU) activation to extract features and learn complex relationships, for the hidden layer.

The input of the model was density, and the output was the Al_2O_3 content. Different layer configurations and numbers of neurons were tested to optimize the model architecture. The goal was to optimize the model architecture to achieve a good fit to the data, without overfitting or underfitting problems. Overfitting occurs when a model learns too much from the training data, capturing noise and performing poorly on new data, while underfitting happens when a model is too simple, failing to capture the underlying patterns in the data [13].

Figure 8 shows how the training loss of the neural network model changes during the training process. The blue line represents the loss on the training data, and the orange line represents the validation loss on the validation data. At the beginning of training, both losses start very high. As the

model learns from the training data, the losses decrease rapidly. The training loss decreases more than the validation loss because the model fits the training data better. After about 4000 epochs (training iterations), the losses stabilize and only decrease slightly. This indicates that the model has learned all it can from the training data and its performance is no longer improving significantly. In general, the validation loss is expected to be low and stable, meaning that the model generalizes well to new data.

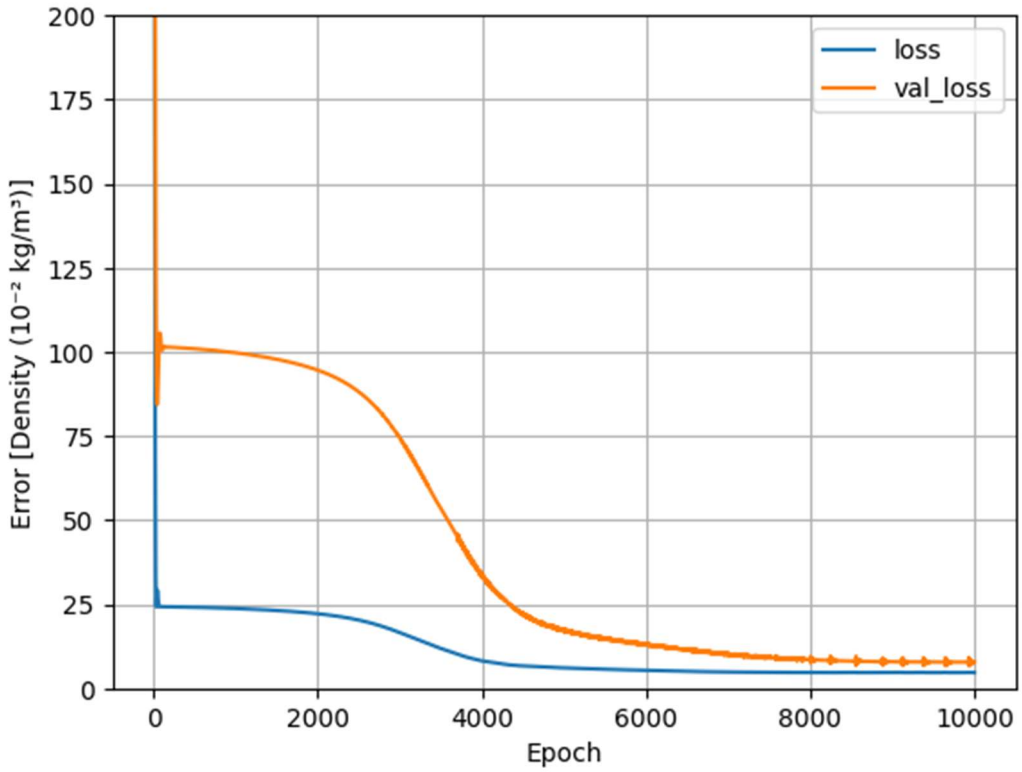

Figure 8. Train and valuation loss during the neural network training process for Al_2O_3.

Figure 9 compares the actual Al_2O_3 values in the data with the predictions made by the neural network model. The horizontal axis represents the Al_2O_3 content, while the vertical axis represents the density. The blue dots show the actual density and Al_2O_3 values in the data. The black line represents the model predictions. For low Al_2O_3 values, the blue dots and the black line coincide almost perfectly, meaning that the model predicts the density values for those Al_2O_3 levels with high accuracy.

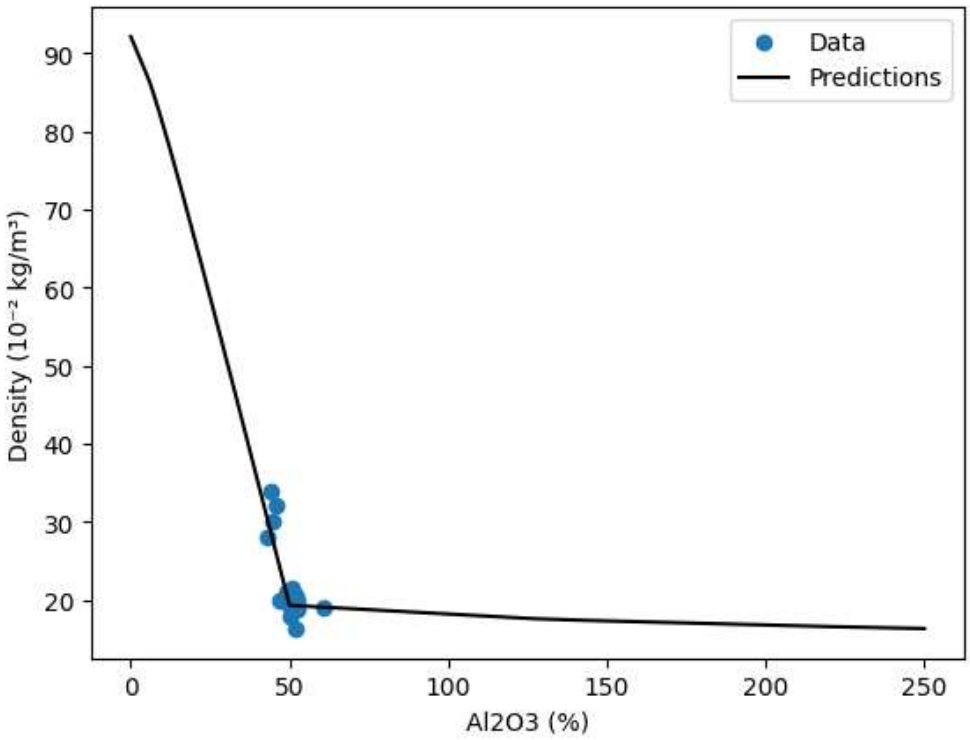

Figure 9. Al_2O_3 vs Density: Model Predictions and Actual Data Comparison.

The model is trained using the Adam optimization algorithm [36] which is used to minimize the loss function during the training of neural networks. During training, the model learns to map the density values to the corresponding Al_2O_3 values. Below are those corresponding to different metrics used to evaluate the performance of a machine learning model.

- Accuracy: The model achieved a Mean Squared Error (MSE) of 11.32, a Mean Absolute Error (MAE) of 2.74, and an Absolute Percentage Error (MAPE) of 13.04. These values present some level of error, but it is an improvement over traditional methods that use linear regression.
- Sensitivity: The model demonstrated higher sensitivity to density values in the medium range (2000-2500 kg/m^3), where most operational decisions are made. This sensitivity allows for more balanced predictions in the density range which is most critical for mining operations.
- Practical improvements: By accurately predicting Al_2O_3 content from density measurements, which are easier and quicker to obtain in the field, this model can significantly speed up the process of ore grade estimation. This can lead to faster decision- making in ore selection and processing.
- Implementation challenges: The main challenge in implementing this model was ensuring consistent and accurate density measurements across the mining operation.

Once the pre-trained model was built, the density was predicted based on Al_2O_3 for a large database. The new database was saved and used later.

6.4. Neural network model for $I_s(50)$ prediction

A neural network model was developed to predict the $I_s(50)$ value for its density and Al_2O_3 content, employing a machine learning approach to find the relationship between these variables. The process began by loading the dataset containing density, Al_2O_3 content, and $I_s(50)$ values. The data was

randomly split into training (80%) and test (20%) sets to ensure impartial evaluation and avoid overfitting.

Figure 10 presents several graphs illustrating the data set used to train and evaluate the machine learning model that predicts the value of $I_s(50)$ from the density and Al_2O_3 content. The dataset is showcased through several graphs, demonstrating that densities, Al_2O_3 amount, and $I_s(50)$ target value follow normal distributions. Although with a significant scatter of points around the linear trend, there is a positive correlation between density and Al_2O_3 content. To better understand the nature of the data and see the relationships the model is trying to record, these pictures are helpful because they show the distributions and relationships between the key variables (density, Al_2O_3 content, and $I_s(50)$) in various formats.

Before using the data in the model, a normalization step was carried out to ensure the input is within a range that improves convergence and predictive performance. This DNN model was built using Python's TensorFlow library and has four hidden layers with 128, 128, 64, and 1 neuron. These parameters allow the model to progressively reduce dimensionality, capturing essential patterns in the data. The layers with ReLU and Sigmoid activations were chosen to balance complexity, prevent vanishing gradients, and support probability estimation. The first three layers use ReLU functions, and the last used Sigmoid function. The model was trained for 10,000 rounds with a batch size of 64. During this, both training loss and validation loss were monitored to assess performance and detect potential overfitting or underfitting.

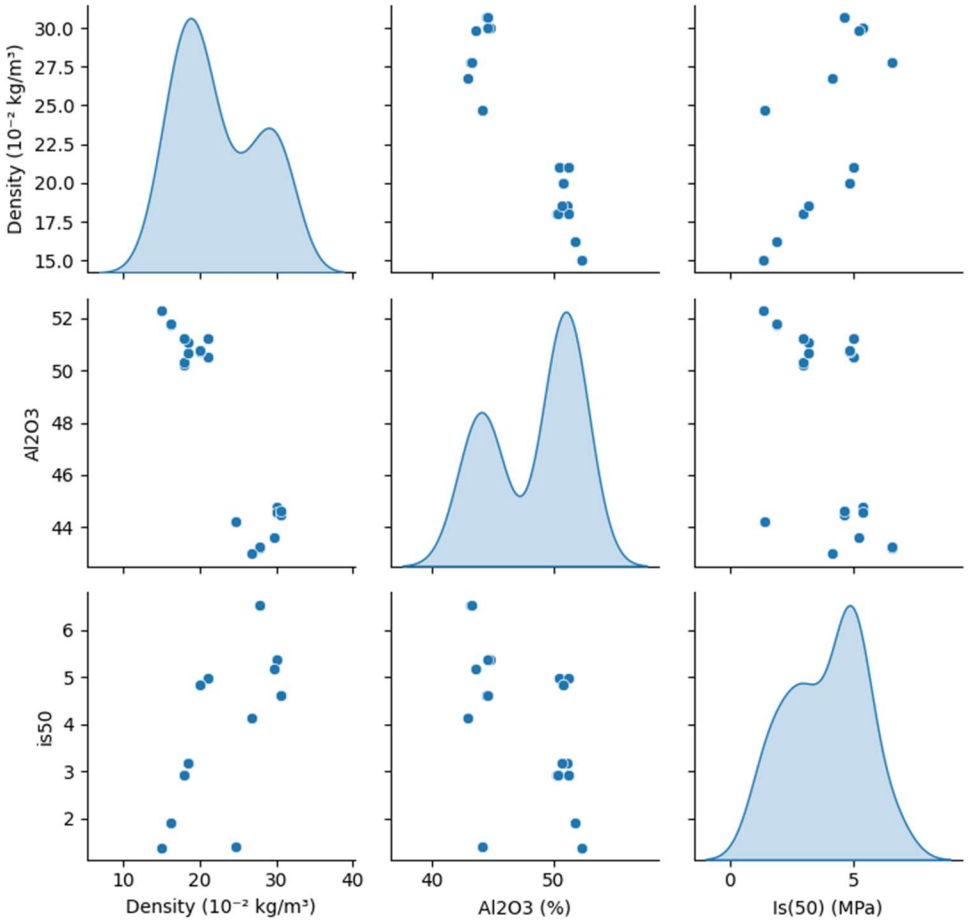

Figure 10. Multivariate Analysis: Density, Al_2O_3, and I_s50 Relationships.

Figure 11 shows the train and valuation loss during the neural network training process for I_s50, with the blue line representing the training data loss, and the orange line showing the validation data loss. Initially, both losses start very high but decrease rapidly as the model learns from the training data, with the training loss decreasing more significantly due to better fit.

After about 4000 epochs (training iterations), the losses stabilize and only decrease slightly. This indicates the model has converged. Once the training process was completed, the performance of the model on the test data set was evaluated.

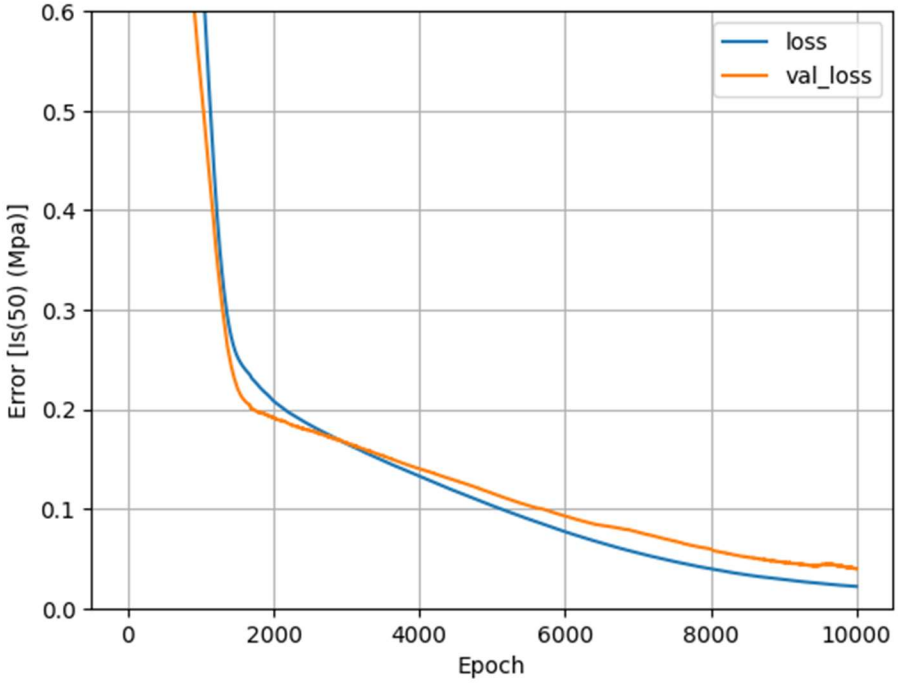

Figure 11. Train and valuation loss during the neural network training process for Is50.

Figure 12 present the predictions of the model vs real values for $I_s(50)$ in the test data set. On the graph, the x-axis shows real values, and the y-axis shows predictions. The diagonal line shows where predictions would match real values perfectly. Each blue dot is a data point from the test set.

Most blue dots are close to the diagonal line, meaning the model's predictions are usually close to the real values. Only one blue dot is a bit far from the line, showing as an outlier.

Overall, this graph shows that the model has excellent predictive performance, with high accuracy in predicting the target property values over almost the entire range of values.

The $I_s(50)$ prediction model, using both density and Al_2O_3 content as inputs, showed exceptional performance:

- Accuracy: With a Mean Squared Error (MSE) of 6.21e-10, Mean Absolute Error (MAE) of 1.87e-05, and Mean Absolute Percentage Error (MAPE) of 1.38e-06, this model demonstrates extremely high accuracy, surpassing traditional empirical methods for estimating rock strength.
- Sensitivity: The model showed high sensitivity to both input parameters, with slightly higher sensitivity to density. This allows for accurate predictions even with small variations in either density or Al_2O_3 content.

- Practical improvements: Accurate $I_s(50)$ predictions can significantly enhance blast design optimization and excavation planning. For example, areas with higher predicted $I_s(50)$ values might require increased explosive charges or different drill patterns.
- Implementation challenges: The accuracy of this model relies on the accuracy of both density and Al_2O_3 content inputs.

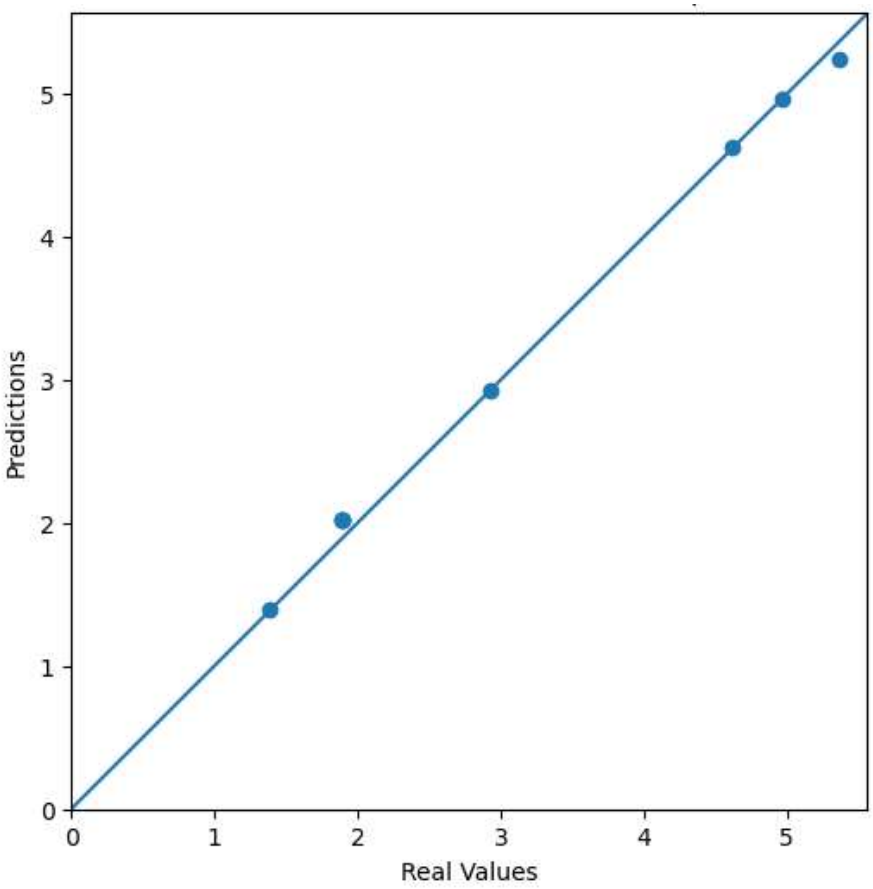

Figure 12. Model Predictions vs Actual Values.

6.5. Production Rate Estimation

Once the pre-trained model is built, $I_s(50)$ is predicted for a large database. The new database is saved with the predictions to be applied in Eq (1).

To apply the model, the predicted values were used in the production formula to estimate shovel rates. In the implementation, the following parameters were used:

- BP (nominal load of the excavator): 80 tons
- Maximum rate of the ideal shovel: 2455 ton/h
- Coefficient k: 12.4 tons
- E (powder energy factor): assumed to be equal to E0 (optimal energy concentration)

Other parameters were kept constant for this experiment. This approach allows us to estimate how changes in rock properties (as predicted by the model) might affect shovel productivity in a mining operation.

Figure 13 presents the relationship between material density and the production rate of the excavator shovel. A clear trend was observed: as the density of the material increases, the production ratio of the blade decreases significantly. The production rate showed an inverse relationship with material density, peaking at medium-low densities (2000-2200 kg/m³) before declining sharply and stabilizing at higher densities.

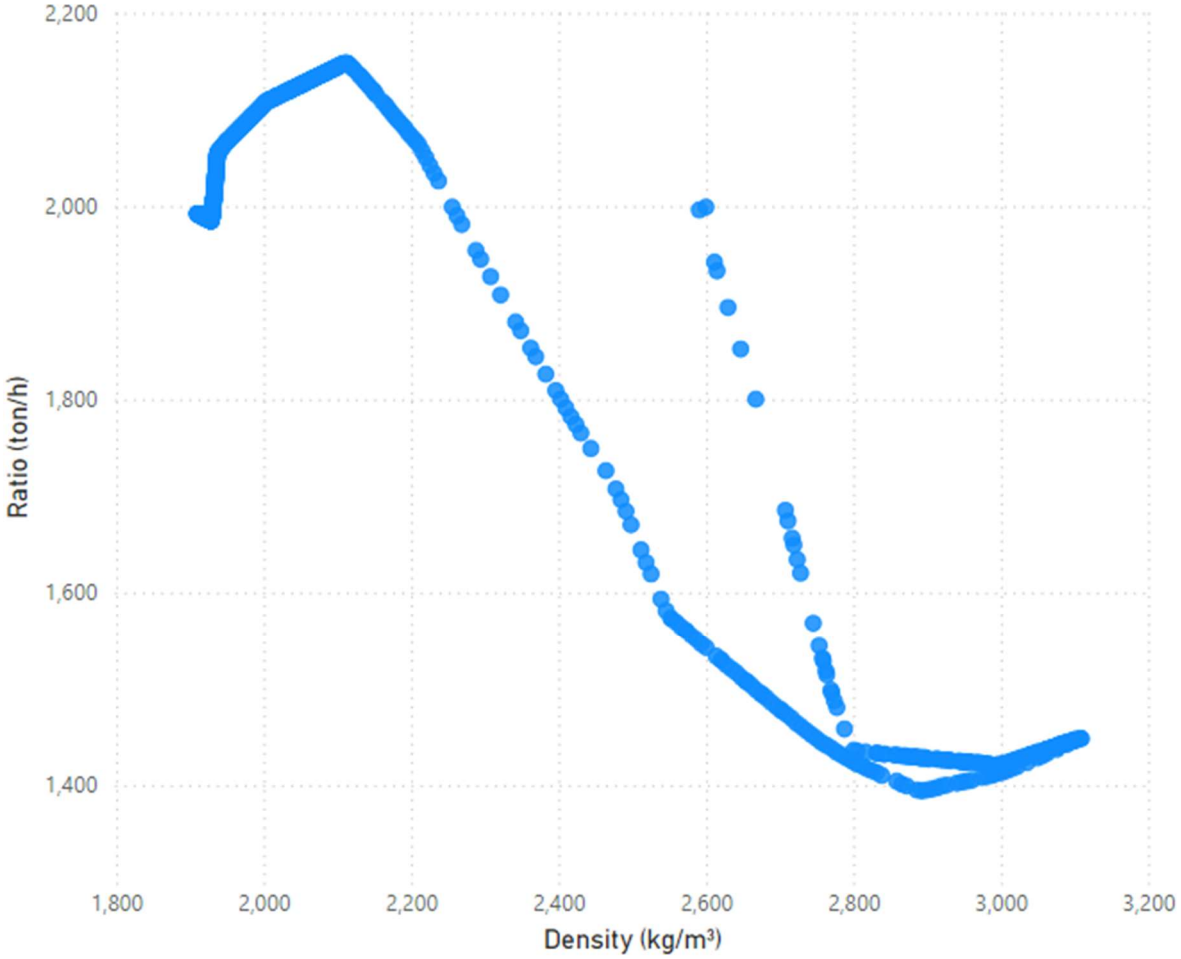

Figure 13. Relation Ratio and Density.

The shovel production ratio location in the selected mining area is presented in Figure 14. It is observed variability in productivity across the pit. It allows the identification of areas with high and low efficiency, which can influence decisions on excavation routes, extraction sequence, and the possible need for specialized techniques or equipment in specific areas. After integrating the predictions from both models into the production rate formula, we observed significant insights were observed:

- The relationship shows that in areas with denser material lower production rates should be expected, resulting in additional digging time and potentially higher fuel consumption and operating costs.
- The production ratio map revealed variability in productivity across the pit, with higher ratios on the center-left portion. This spatial variation in productivity could significantly influence decision-making in mine planning and operations.

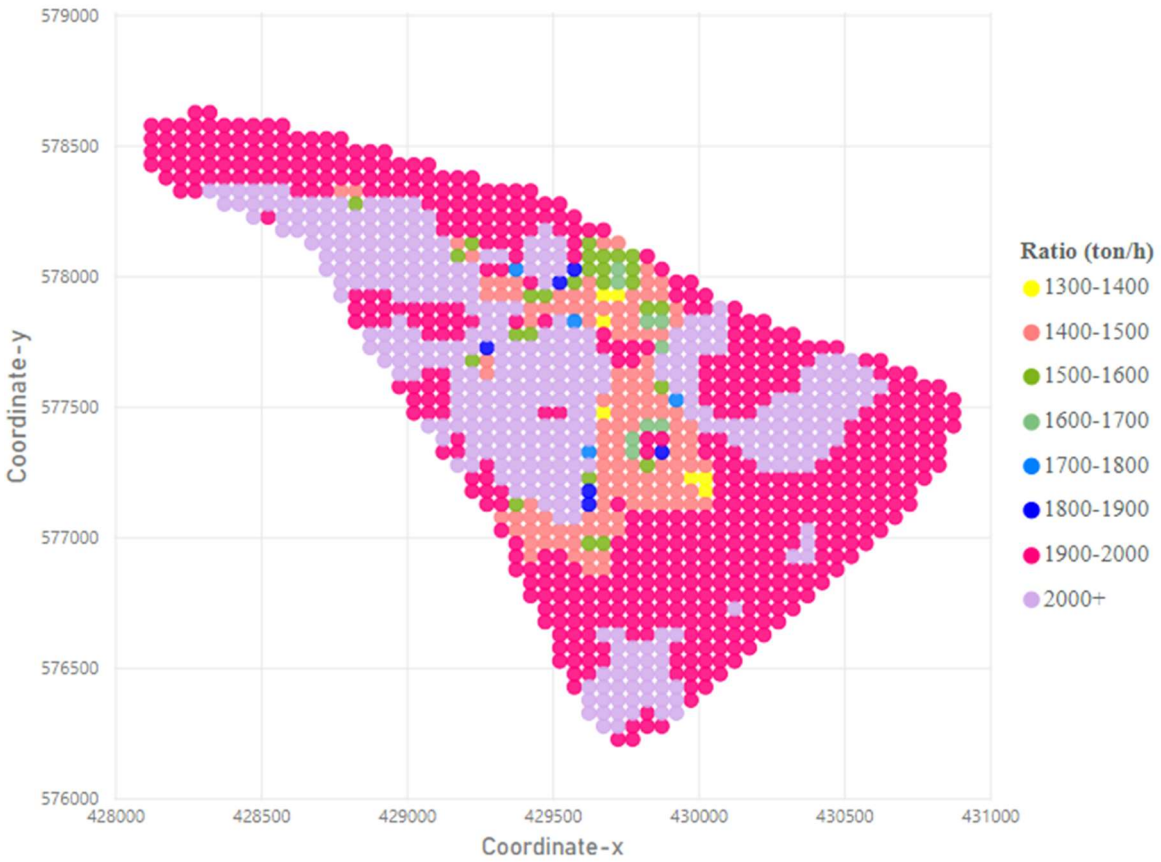

Figure 14. Production Ratio Map.

7. Practical Implications for Mining Operations

These predictive models and their integration into production rate estimation offer several practical benefits for mining operations:

- Improved planning: Mine planners can use these predictions to optimize extraction sequences, prioritizing areas with favorable density and strength characteristics to maximize productivity.
- Equipment allocation: Understanding the spatial variation in production rates can inform decisions on equipment allocation. For instance, more powerful excavators might be assigned to areas with higher predicted $I_s(50)$ values.
- Blast design optimization: Areas with higher predicted $I_s(50)$ values may require adjusted blast designs to ensure optimal fragmentation, potentially saving on explosive costs in areas with lower strength predictions.
- Operational forecasting: More accurate predictions of production rates can lead to improved short-term and long-term production forecasts, enhancing overall mine planning and scheduling.
- Cost estimation: By better understanding relationships between the geology and production rates, excavation operations can be cost-estimated more accurately, improving financial planning.

8. Conclusion

A new approach to predicting production rates in rock excavation operations was developed to forecast shovel production rates in a bauxite mine. Two neural network models were developed: one to estimate rock density from the Al_2O_3 content, and another to predict the $I_s(50)$ using density and Al_2O_3 content as inputs. Rock density and strength predictions were incorporated into a production model to calculate mucking rates.

Deep learning techniques were employed to predict production rates considering the properties of the rock in the deposit. Excavation plans and operations can optimize and maximize the efficiency and utilization of your resources by incorporating predictions of rock characteristics.

This research has the potential of improving mining efficiency and sustainability, using production rate predictions that would manage to more optimal resource allocation, reduce energy consumption, and minimize negative environmental impacts.

This research shows how machine learning combined with traditional mining models can make mines more adaptive and data-driven. Despite further validation may be needed, the study has demonstrated the promising potential of the proposed approach in improving open pit mining operations.

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