Mining Optimization Laboratory

Report Eleven –2022/2023

Mohammad Mahdi Badiozamani
Yashar Pourrahimian
Eugene Ben-Awuah
Ali Moradi Afrapoli
Hooman Askari Nasab



School of Mining and Petroleum Engineering
Department of Civil & Environmental Engineering,
University of Alberta, Edmonton, Alberta, CANADA

Badiozamani, MM., Pourrahimian, Y., Ben-Awuah, E., Moradi Afrapoli, A. and Askari-Nasab, H. (2023), Mining Optimization Laboratory (MOL) – Report Eleven, © MOL, University of Alberta, Edmonton, Canada, 365 Pages, ISBN: 978-1-55195-503-2.

All rights reserved, all material in this report is, unless otherwise stated, the property of the *Mining Optimization Laboratory (MOL)*.

Reproduction or retransmission of the materials, in whole or in part, in any manner, without the prior written consent of the copyright holder, is a violation of copyright law.

The report may be circulated and disposed at your discretion; however, the following copyright notice must be adhered to.

Copyright © 2023, Mining Optimization Laboratory, University of Alberta

Mining Optimization Laboratory sponsors may utilize and disclose the report material and software within their organization with no prior permission of MOL.

Contact information for requests for permission to reproduce or distribute materials available through this report is:

Hooman Askari-Nasab, PhD, PEng
Professor of Mining Engineering
Department of Civil & Environmental Engineering
University of Alberta, Edmonton, Canada
Phone: +1 (780) 492-4053
Cell: +1 (780) 893-9365
Email: hooman@ualberta.ca
MOL Webpage: www.ualberta.ca/mol

Executive Summary

This year, we have prepared a report including 18 papers under three main topics, as; 1) Mathematical programming for mine design and mine planning, 2) Applications of artificial intelligence and simulation in mining optimization, and 3) Implementation of in-pit crushing and conveying (IPCC) in open pit mining. We continue to update all the research results on the MOL webpage www.ualberta.ca/mol on the members section. Sponsors have access to current and past research results, publications, prototype software, and source code. Let's review the contributions in the MOL Report Eleven (2022/2023) 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 mine design and mine planning. The following six students have been the main contributors under this topic:

In **Paper 101, *Samaneh*** presents the results of a comprehensive review of the literature about different mathematical models for open pit mine planning optimization, in deterministic and uncertain conditions, as well as a comparison of the related approaches to control the uncertainty of data. Further, based on the reviewed studies, she has provided a conclusion about the identified gaps in the related research. The gaps are mainly about the ignorance of different uncertainties such as grade and other geological uncertainties in mine design and mine planning. ***Samaneh*** proposes a Mixed Integer Linear Programming (MILP) model in **Paper 103** to maximize the Net Present Value (NPV) of the operations, and at the same time minimize the greenhouse gas emissions resulted from mining operations. The proposed optimization model accounts for the minimum mining width and other mining constraints. Simultaneously, the introduced model investigates production scheduling problems for extraction, mining, and processing steps. Also, implemented approaches to solve the programming models from meta-heuristic to exact solution methods have been compared, and based on that, an exact solution methodology is chosen. To solve the problem for large scale cases, she has applied a Simulated Annealing (SA) metaheuristic algorithm and a Genetic algorithm, and has concluded that the SA algorithm is the better choice for large-scale problems while the exact method is more efficient for short-scale problems.

Hongshuo has addressed a new mining method as the Near-Face Stockpile (NFS) in **Paper 102**, which combines the in-pit crushing and conveying (IPCC) system with a pre-crusher stockpile. While the stockpiles were mainly considered as a "buffer" to improve the stability of the production system in the past, in NFS ore will be dumped into the pre-crusher stockpile located at the bottom of the current pit and will be fed into the crusher after blending to the desired head grade, instead of being dumped directly into the crusher. Theoretically, this design not only retains the high efficiency and high output of IPCC, but also endows the mining system with higher stability. Since the NFS method exhibits distinctive layout and feeding mechanisms that distinguish it from other mining methods, a novel simulation model is required for the accurate modeling of the NFS method and quantitatively evaluating the performance of NFS methods. The paper also proposes an optimization framework for short-term production scheduling for NFS method based on an MILP model. An oil sands mine case study is implemented to verify the proposed simulation model. The simulation results reveals that compared to the traditional mining method, the overall production increased by 5.06%, the transporting distance of minerals by trucks was reduced by 17.87%, and the shovels' and crusher's utilization increased by 4.96% and 4.85%, respectively, when using NFS method was implemented.

Mohammadreza has developed a multi-objective simulation and optimization framework for green truck dispatching in open pit mining, considering fuel consumption in **Paper 104**. The topic of his paper is developing a new framework for truck dispatching, aiming to accomplish four specific objectives: minimizing the deviations from target production rates set by strategic plans, reducing shovel idle time, minimizing truck wait time, and minimizing truck fuel consumption. The significant

contribution of this study lies in the inclusion of Greenhouse Gas (GHG) mitigation by considering fuel consumption reduction as an objective, which brings direct economic and environmental benefits. To account for uncertainty in open-pit mining operations, a discrete event simulation using Arena software is used, and different scenarios are examined based on objective weights. The case study conducted at Gol-E-Gohar iron ore mine, demonstrates that the developed framework successfully reduced fuel consumption by 4.9% per ton of production, equal to a total reduction of over 12,000 liters of fuel.

Soroush has developed an MILP model to optimize the long-term production scheduling of sublevel caving in **Paper 105**. In order to achieve more reliable production scheduling, it is essential to consider the coordination of operations from the development phase to the plant, such as production and stockpiling, to achieve productivity. The primary objective of the developed framework is to maximize the NPV while addressing various operational constraints such as development activities, mining and processing capacities, continuous mining, the allowable number of active mining units, grade blending, and vertical and horizontal sequencing. The authors have developed a Jupyter Notebook-based model to implement this framework and employed the CPLEX solver to obtain efficient solutions. The proposed MILP model offers systematic schedules of all development activities, including vertical shaft and its ventilation, man-way-raises and ventilations, ore passes, and operational developments while ensuring optimal sequences of ore extraction and maximizing the operation's profitability in long-term. The efficacy of the proposed model is demonstrated through the implementation of the model on an illustrative sublevel caving case study. The results highlight the ability of the framework to generate robust schedules that account for the simultaneous occurrence of development activities and ore production throughout the mine life.

Emmanuel has proposed a stochastic MILP framework to optimize the open stope mine production scheduling in **Paper 106**, considering grade uncertainty and stockpiling strategy. As the implementation of traditional geostatistical estimation methods for mine planning have been identified to introduce smoothing effect which results in unrealistic mine production schedules, development of simulation methods with equiprobable orebody realizations as inputs to the mine planning process have gained momentum. It greatly helps in measuring and managing the associated risk due to grade uncertainty. Often, the outcome of the uncertainty related to orebody modelling is crucial and affects the resultant performance of stope designs and stope production. This is directly linked to the failure of meeting set production targets and expected project financial outcomes during the mine life. Uncertainty-based solutions in underground mine production scheduling optimization helps to minimize the variations between planned and actual production key performance indicators. To incorporate grade uncertainty into the strategic mine plan, a stochastic MILP framework is developed to optimize open stope underground mining production schedules, with the objective of maximizing the NPV of the mining project while minimizing the associated risk of deviation from the set production targets, based on simulated orebody realizations.

The second group of papers investigated the applications of different artificial intelligence models and simulation techniques in optimizing the mining operations. The following seven students have been the main contributors under this topic:

Solomon has investigated the implementation of intelligent agent-based simulation and deep reinforcement learning techniques for smart mining operations in **Paper 201**. One of the pivotal concepts in smart mining is the real-time intelligent decision-making in a mining environment with huge amounts of mine operations data. By leveraging a deep reinforcement learning algorithm using the Deep Q Networks (DQN), the objective of this research is to enhance shovel-truck productivity by accurately detecting and overcoming operational obstacles within the mining environment. The research aims to develop an intelligent system that effectively supervises the operations of a short-term open pit mine through the combination

of simulation and intelligent agents. This includes modeling the mining operation and employing agent-based simulation to control equipment fleet, and implementing a reinforcement learning agent for intelligent decision-making. The proposed methodology establishes a virtual experimental environment by incorporating a decision model supported by discrete event simulation. The intelligent supervisory agent is trained using deep reinforcement learning techniques to determine mining zones based on key performance indicators such as ore grade and tonnage. The model's effectiveness and performance are evaluated through the examination of experimental scenarios to verify and validate the proposed approach.

Arman has analyzed the trends and challenges of AI-based fleet management systems in **Paper 202**, based on a comprehensive revision of developed fleet management systems (FMS) for open pit mining industry. The developed frameworks are compared in terms of seven categories of features to pinpoint potential gaps and research directions. The popular (SWOT) analysis method is leveraged to outline the strengths, weaknesses, opportunities and threats associated with the advent of these smart controlling setups in future mines. By and large, advantages outweighed disadvantages. Temporary obstacles are believed to be tackled by increasing pace of technological breakthroughs and propagation of the paradigm of cognitive management systems.

Roberto has investigated the truck fleet dispatching models in open pit mines that are based on AI methods in **paper 203**. He has proposed a reinforcement learning-based truck dispatching system, as a machine learning area that deals with learning an optimal sequential decision-making strategy in an uncertain environment. An open-pit load-and-haul simulation is developed that also captures the truck movements and interactions in the shared road network, and a Neural Network is successfully trained to suggest truck dispatching decisions in real-time.

Sandra has explored the benefits of using Discrete Event Simulation (DES) techniques, as a stochastic mathematical modeling tool, for modeling of mining processes in **Paper 204**. In modern mining operations, it is essential to maximize the productivity through effective decision making, and DES is used to conduct “what if” analysis supporting mining engineers and management in decision making. She has discussed benefits of discrete event simulation compared to other analytical techniques such as spreadsheet analysis. DES can model uncertainty and time changing events, and hence can be used to model complex systems. A case study example of a stochastic framework for equipment selection is presented to elaborate an example of the applicability of DES in modeling and optimizing mining processes. She has presented a summary of the results too.

In **Paper 205**, ***Mohammadreza*** has developed a novel simulation model to assess and determine the optimal configuration of truck fleet type and size for mining operations, aiming to improve the efficiency, productivity, and sustainability of the open pit mining operations. The findings from running different scenarios reveal that the heterogeneous fleet outperforms the homogeneous fleet in terms of meeting production targets and minimizing fuel consumption, effectively striking a balance between productivity and sustainability. Conversely, the homogeneous fleet exhibits higher total fuel consumption and fuel consumption per ton production. Additionally, smaller trucks in the fleet offer greater flexibility in transferring ore materials and prove advantageous in scenarios involving truck failures, with reduced average downtime. Therefore, in presence of truck failure, homogenous fleet of smaller trucks outperforms the heterogenous fleet. The study emphasizes the importance of considering factors such as fleet type and sizing, truck failures, fuel consumption, and production rates in optimizing fleet performance and material flow in mining operations. These insights contribute to the development of strategies for improving overall mining efficiency and reducing costs.

Yaa has prepared a practical guide for using the HAULSIM software to simulate oil sands operations in **Paper 206**. Many sectors around the world want to optimize their operations to give the best and most effective ways of extraction. However, it is difficult to attain such goal since experimenting on the grounds would be expensive. With the introduction of Industry 4.0, many mining companies are entering into an era of using software and digitization to make processes cost-effective and cheaper. The introduction of simulation software has made it easier for researchers to create scenarios to enable them to select the best scenario for the operation. In this paper, the use of HAULSIM that will be used for creating simulations of different scenarios is investigated, and the author has described how the HAULSIM software package can be used to create a haulage network model.

Magreth has developed a numerical simulation model for blast-induced fracturing of jointed rock masses, based on a case study in **Paper 207**. Fragmentation by blasting is a critical process in hard rock mining. The interaction between the rock mass and blast energy influences the outcomes, specifically on the rock mass response to higher stresses and loading rates and the influence of structures. Each rock mass is unique, but some features affect the blast energy similarly, leading to similar outcomes. Having analyzed these features and their influence on blast outcomes, they can be addressed during the blast design to achieve better results. In this paper, she has used the Riedel-Hiermaier-Thoma (RHT) material model in L-S DYNA to model the nonlinear dynamic fracturing of the rock, in order to understand the effects of rock mass properties on the blast outcomes. In a case study, rock mass properties, explosive properties, and design parameters are used as input parameters to the model, and the blast outcomes are used to validate simulation results. The results show that several factors influence the fracturing process by blasting. The formation of damage zones around the charge depends on the rock mass strength and structural properties, which control energy distribution and crack propagation. Furthermore, the simulation results indicates that when the model parameters are calibrated from the existing data, they can be used to simulate the fragmentation process in a more simplified and controlled environment, providing insight to blast design.

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

Nasib has reviewed the recent developments in short-term mine planning and IPCC, and presented a research agenda in **Paper 301**. Equipment allocation is an integral part of short-term planning. In the past few decades, IPCC has gained much momentum to replace trucks partially or fully in large open pit mines because of increasing fuel and labour cost of truck-shovel system, low operating cost and less greenhouse gas emissions of conveyor systems. In this paper, the authors have reviewed the work done on short-term mine planning and IPCC in open pit mines to find research gaps and future research opportunities as the prime means of material handling. The most recent literature since 2010 on short-term planning, based on different formulation and solution approaches, and IPCC, based on primary objectives such as optimum crusher location, economic/environmental comparison etc., have been reviewed. The review reveals that there is hardly any short-term planning model that can generate mine extraction sequences with IPCC integration. The authors propose a theoretical problem formulation to explore this research gap as a future research direction. One of the key contributions of this paper is to point out the fact that developing a short-term planning methodology considering the IPCC system would be a pioneering step in the mine planning literature. In **Paper 302**, ***Nasib*** has developed a shovel allocation model for open pit mines under a semi-mobile IPCC system. The semi-mobile system is one of the IPCC variations, which is relocated every two to five years. The short-term plan needs to be updated accordingly, based on the crusher's optimal location and relocation time. Short-term planning with IPCC is an area of research that has not been explored extensively yet and hardly any model can generate short-term schedules considering an IPCC in place. This paper proposes a mixed integer programming model to generate short-term production plans and near-optimal shovel allocation to mining faces, within a time horizon of 12 months. The

objective of the model is to minimize the cost of material handling and maximize revenue, with respect to plant requirement, maximum allowable tonnage variation and IPCC location constraints, and the production and NPV targets set by the strategic plan. An iron ore mine case including a semi-mobile IPCC system with one relocation is used as the case study to verify the proposed model. The comparison of results between scenarios with and without IPCC justifies the use of IPCC in the iron ore mine from a short to medium-term perspective. The project can be considered a pioneering work in the arena of short-term mine planning with the IPCC.

Alireza has developed a framework to simultaneously optimize the long-term mine production planning and the IPCC location in **Paper 303**. The IPCC system is a solution to decrease the haulage costs in open-pit mining. These costs could be due to the progressive depth of a pit leading to lengthy roads and creating a huge truck maintenance cost or moving towards reducing carbon footprints by using battery electric vehicles (BEVs). Having a shorter route is likely to be more practical for the BEVs where there are multiple problems if they are to be implemented on a longer road. Some of the challenges are recharging times, variable electrical load tradeoffs, and hauling on steep ramps. In this study, the goal is to propose a generalized optimization model which uses the road network to find the best locations for the crusher and generates a mine schedule that maximizes the NPV. Applying this model will enable us to decrease the haulage distance per tonnage of transferable material and optimize the mine plan simultaneously. The model is verified by applying it to an iron ore mine case with two pushbacks. The result shows a significant improvement in terms of NPV compared to an out-pit crusher scenario.

Khaleeq has analyzed the semi-mobile IPCC versus truck-shovel system comparatively in **Paper 304**. Semi-mobile IPCC (SMIPCC) systems are a type of IPCC that have attracted the miners due to their relocation nature as an alternative to conventional Truck-shovel (TS) haulage systems. Most of the mining operational costs arises from purchasing and maintaining haulage trucks to transport material from the working face to the crushers located outside the mine. This paper aims to understand the importance of SMIPCC and its comparison with the TS system, and uses Python programming to develop a code for comparative analysis. This code is based on cost analysis and evaluating the environmental impacts of SMIPCC and TS. The code is run on real-time open-pit mine data to compare the feasibility of SMIPCC and TS in the early stages of a mining project.

In **Paper 305, *Sandra*** has reviewed the factors and constraints of long-term mine planning optimization in presence of IPCC system. She has outlined and compared the different IPCC systems, their usage, benefits and functionality. An overview is given on decision-making factors regarding the inauguration of IPCC in long-term mine planning. In addition, real world technical constraints of IPCC are identified through a comprehensive literature review. Suggestions are given for further research and the implementation of the decisive factors in decision making tools. Finally, an outlook is presented on the implementation of decisive factors and constraints in current and future simulation and optimization tools regarding strategic mine planning.

Mohammad Mahdi Badiozamani
Yashar Pourrahimian
Eugene Ben-Awuah
Ali Moradi Afrapoli
Hooman Askari-Nasab
September 2023

Annual Research Report Eleven
Mining Optimization Laboratory
(MOL) 2022-20223

Table of Contents

Paper	Page	Title
100		**Mathematical Programming for Mine Desing and Mine Planning**
101	1	Review of Deterministic Mathematical Models and Stochastic Optimization for Open Pit Mine Planning Problems *Samaneh Moradi Pirbalouti, Hooman Askari-Nasab*
102	12	Integrated Simulation and Optimization Framework for Quantitative Analysis of Near-face Stockpile Mining *Hongshuo Gong, A. Moradi Afrapoli, H. Askari-Nasab*
103	35	Pit Optimization Design Considering Minimum Mining Width for the Production Scheduling Problem *Samaneh Moradi Pirbalouti, Hooman Askari-Nasab*
104	48	Optimizing Green Truck Dispatch in an Open Pit Mine through a Multi-Objective Simulation and Optimization Framework with Fuel Consumption Consideration *Mohammadreza Kazemi Ashtiani, Ali Moradi Afrapoli, John Doucette, and Hooman Askari-Nasb*
105	69	An Innovative Optimization Model for Long-Term Production Scheduling of Sublevel Caving Mines Using Mixed Integer Linear Programming *Soroush Khazaei and Yashar Pourrahimian*
106	89	A Stochastic Mixed Integer Linear Programming Framework for Open Stope Mine Production Scheduling Optimization Considering Grade Uncertainty and Stockpiling Strategy *Emmanuel John Andrew Appianing, Obinna Kizito Mbadozie and Eugene Ben-Awuah*
200		**Applications of Artificial Intelligence and Simulation in Mining Optimization**
201	128	Intelligent Agent-Based Simulation and Deep Reinforcement Learning for Smart Mining Operations *Solomon Acheampong, Pedro Pablo Vasquez-Coronado and Eugene Ben-Awuah*
202	162	Analyzing Trends and Challenges in Artificial Intelligence-Based Fleet Management Systems for Open Pit Mines *Arman Hazrathosseini, Ali Moradi Afrapoli*
203	178	Truck Fleet Dispatching in Open Pit Mines Using Artificial Intelligence Methods

Roberto Noriega and Yashar Pourrahimian

204 190 Benefits of Discrete Event Simulation in Modeling Mining Processes
Sandra Katharina Fahl and Hooman Askari-Nasab

205 196 Application of Simulation in Truck Fleet Selection and Sizing in Open Pit Mining: With and Without Truck Failure Effect
Mohammadreza Kazemi Ashtiani, Ali Moradi Afrapoli, John Doucette, and Hooman Askari-Nasab

206 220 Oil Sand Operation Simulation Using HAULSIM Practical Guide
Yaa Serwaa Karikari, Hooman Askari-Nasab

207 229 Numerical Simulation of Blast-Induced Fracturing of Jointed Rock Masses Based on A Case Study
Magreth S. Dotto and Yashar Pourrahimian

300 **Implementation of In-pit Crushing and Conveying (IPCC) in Open Pit Mining**

301 254 Review of Recent Developments in Short-Term Mine Planning and IPCC with A Research Agenda
Nasib Al Habib, Eugene Ben-Awuah, Hooman Askari-Nasab

302 290 Short-term Planning of Open Pit Mines with Semi-Mobile IPCC: A Shovel Allocation Model
Nasib Al Habib, Eugene Ben-Awuah and Hooman Askari-Nasab

303 320 Optimizing the In-Pit Crusher Locations and Scheduling the Open-Pit Mine Simultaneously
Alireza Kamrani, Hooman Askari-Nasab1 and Yashar Pourrahimian1 Mohammad Mahdi Badiozamani

304 340 Comparative Analysis of Semi-Mobile In-pit Crushing and Conveying System (SMIPCC) and Truck-Shovel System Using Python Programming: Case Study
Khaleeq Ahmed and Yashar Pourrahimian

305 353 Decisive Factors and Constraints of In-Pit Crushing and Conveying (IPCC) Regarding Long-Term Mine Planning
Sandra Katharina Fahl and Hooman Askari-Nasab

Mining Optimization Laboratory (MOL) Researchers / Graduate Students

Following are researchers and students affiliated with Mining Optimization Laboratory in September 2023.

1.	**Hooman Askari-Nasab**	Professor - Director of MOL
2.	**Yashar Pourrahimian**	Associate Professor, University of Alberta
3.	**Eugene Ben-Awuah**	Associate Professor, Laurentian University
4.	**Ali Moradi Afrapoli**	Assistant Professor, Université Laval

---

5.	**Shahrokh Paravarzar**	PhD, Post Doctoral Fellow - 2022/10
6.	**M. Mahdi Badiozamani**	PhD, Research Assistant - 2018/03
7.	**Rozan Chahardoli**	MSc, Research Assistant - 2019/09
8.	**Magreth Dotto**	PhD Student – 2018/01
9.	**Emmanuel Appianing**	PhD Student – 2018/05
10.	**Hongshuo Gong**	PhD Student – 2018/09
11.	**Nasib Al-Habib**	PhD Student – 2018/09
12.	**Alireza Kamrani**	PhD Student – 2018/09
13.	**Soroush Khazaei**	PhD Student – 2019/09
14.	**Roberto Noriega**	PhD Student – 2019/09
15.	**Pedro P. Vasquez Coronado**	PhD Student – 2019/09
16.	**Milad Rahnema**	PhD Student – 2022/05
17.	**Sandra Fahl**	PhD Student – 2022/09
18.	**Samaneh Moradi Pirbalouti**	PhD Student – 2022/09
19.	**Arman Hazrathosseini**	PhD Student – 2022/09
20.	**Khaleeq Ahmed**	PhD Student – 2023/01
21.	**Behdad Esfahani**	PhD Student – 2023/09
22.	**Mohammadreza Kazemi**	MSc Student – 2019/09

23.	**Solomon Acheampong**	MSc Student – 2020/09
24.	**Bahar Amirmoeini**	MSc Student – 2022/09
25.	**Yaa Karikari**	MSc Student – 2023/01
26.	**Joshua Azorliade**	MSc Student – 2023/09
27.	**Eyram Agozie**	MSc Student – 2023/09
28.	**Kwaku Konadu Akuffo**	MSc Student – 2023/09
29.	**William Junkin**	Meng Student – 2018/09
30.	**Mohammadreza Moghaddam**	Visiting Student - 2021/12

Review of Deterministic Mathematical Models and Stochastic Optimization for Open Pit Mine Planning Problems

Samaneh Moradi Pirbalouti and Hooman Askari-Nasab
Mining Optimization Laboratory (MOL)
University of Alberta, Edmonton, Canada

ABSTRACT

Mine planning problem leads to prioritizing the extraction of blocks. Mine planning includes a wide range of processes of production planning, scheduling the mining operations, cut-off grade optimization, crusher, and conveyor location, and determining pit limits and pushbacks. Researchers in mining problems have proposed different planning problems in three levels short-term, mid-term, and long-term. Because of the nature of open-pit mine planning problems, they have some complexities and uncertainties in data. Also, the mathematical models applied to these problems include a variety of constraints relative to their assumptions. Due to the uncertainty of different parameters in mining operations, some researchers dealt with stochastic optimization in their proposed mathematical models. To solve these problems, they presented deterministic and stochastic models for mining operations. Then the applied methodologies in the last works from meta-heuristic algorithms to exact solution methods are introduced. Therefore, this paper is a comprehensive research in which different mathematical models in deterministic and uncertain conditions and related approaches to control the uncertainty of data have been compared and a conclusion based on related studies is proposed.

1. Introduction

In this section, the definition and importance of the study is mentioned. Mining is the process of extracting valuable resources from deposits. Mining can mainly be divided into two major categories, surface mining, and underground mining. Surface mining is suitable for large, low-grade ore deposits, buried not deep, and is commonly used to mine deposits such as oil sands (Kalantari et al., 2013; Nikbin et al., 2023) coal and copper. Underground mining is used for small, high-grade deposits buried deep beneath overburden and is being used for minerals like zinc, lead etc. In all methods of surface mining, first, overburden is removed by different tools such as earthmovers, draglines and bucket wheels excavators. Then, shovels extract the ore, which is loaded into haul trucks by shovel loaders (There is other types such as placer mines). Surface mining is rewarding because of its low cost and capital requirement, higher rate of recovery, and less labor intensiveness. Studies have shown that about 50% of operating costs in surface mining are allocated to haulage and materials handling (Moradi Afrapoli, A, and Askari-Nasab 2017).

The number can go up to as much as 60% in large open-pit mines (Moradi Afrapoli, A. and Askari-Nasab 2017). Therefore, hauling has the highest operating cost among all the material handling operations in open-pit mines. So, fleet management for mine planning and scheduling has always been the center of attraction for researchers in open-pit mining. In the mining industry, mine planning is considered a fundamental element aiming to obtain a feasible block extraction schedule by

ISBN: 978-1-55195-503-2

maximizing net present value and economic profit. Also, this is important to specify required constraints in mine planning such as environmental and operational ones according to the assumptions of the problem (Koushavand et al., 2014).

Mine planning and scheduling can again be divided into two categories, long-term, and short-term planning. Among the mine planning problems, long-term planning defines the sequence of extraction and displacement of material and mining operations to reach the problem's objectives. In mining research, a long-term production schedule is necessary for short-term planning and operations. So, this is required to design appropriate long-term planning to reach short-term planning. In the long-term production schedule, the capacity and expansion potential of the mine and processing are determined (Askari-Nasab et al., 2010). To reach an ideal mine design and planning, optimization is an important area for different types of mines. It considers forecasting, maximization, and control of financial flows and obtaining the best value of other objective functions in mining operations (Dimitrakopoulos, 2011).

Regarding to the literature review, the motivation of this study can be explored. In the literature, several optimization methods and mixed integer programming[1] models have been proposed in which the ore body is divided into many blocks. The majority of approaches are deterministic and do not consider the uncertainty of data. However, to make the optimization problems close to real-world conditions, some parameters should be assumed as uncertain. In this way, the optimization problem changes to a stochastic optimization problem. The uncertainty of data has several main sources including geological attributes of the deposit, geo-metallurgical properties, economic situation, and market uncertainties (Rimele et al., 2020). In the mining industry, a stochastic optimization mathematical model considers correlated random variables for some coefficients according to assumptions of uncertain parameters. These variables indicate the economic value of a mined block in a deposit (Meagher et al., 2010).

In this study, the mathematical models in long-term mine planning problems are investigated. Also, regarding to assessing the related studies and solution methods, the research gap and shortcoming of the last works are proposed. In this way, this is concluded that uncertainty of date and stochastic programming in mining problems is a vital component which last research dealt with less than expected level. In addition, two main concepts in mining problems are introduced which can be considered as uncertain parameters.

This research is organized as follows. Section 2 consists of a review of deterministic, stochastic problems, and Mixed Integer Linear Programming2 models to optimize the mine planning problem. Also, an overview of the related approaches to control the uncertainty of data and solution methods are considered. In section 3 the recommended suggestions for future research are provided. Finally, the conclusion is presented.

2. Review of the literature

According to the concept of this research, the literature review is divided to 3 main sections including deterministic and stochastic models, the role of MILP models, and importance of uncertainty of date in mining problems.

2.1. Deterministic and stochastic mine planning models

Most of the early work on the long-term planning of surface mining (open-pit mining) are linear programming (LP) based. In the long-term context, early LP-based methods focus on solving a blending problem in each time period. Blending requirements are formulated in terms of constraints,

[1] MIP
[2] MILP

putting limits on the number of relevant attributes in produced ore (Krishna Sundar and Acharya 1995; Wilke and Reimer 1977). The objective of these types of problems is to minimize the sum of deviations in the ore blend from required grades by optimizing equipment allocation (Chanda and Dagdelen 1995).

Gurgur et al. (2011) formulated an LP model for optimum shovel assignment to minimize the deviation of the production operation from the set targets in short-term and long-term schedules. This model accounts for the available trucks in each period and it considers the mine as a multi-period optimization problem, which makes it a model that lasts over the lifetime of a mine. However, this model does not consider the lost ton by shovel operation and it assumes continuous variables for discrete production systems. Most of the modern long-term planning models are MILP based with explicit precedence constraints applied.

Blom et al. (2014; 2016) presented a breakdown and MIP-based algorithm for the short-term planning of a supply chain consisting of multiple open-pit iron ore mines and multiple ports. They divided the problem into two parts: mine optimization and port blending. The mining side MIP-based optimization solves MIPs to generate a set of candidate blocks to be extracted in short-term planning horizon. The production-grade is assumed to be normally distributed about the target given as input. Ali Moradi et al. (2019) developed a multi-objective transportation model for real-time truck dispatching to minimize shovel idle times, truck wait times, and deviations from the path production requirements established by the production optimization stage. They implemented their model on a discrete event simulation model of truck-shovel operation to demonstrate that the model can meet the full capacity of the processing plants with a fleet of 30% less trucks than the desired fleet.

Linear optimization problems or linear programming only focuses on a single linear objective function with linear constraints. Goal programming is an extension of linear programming that is capable of handling multiple and conflicting objectives (Ben-Awuah et al., 2018; Maremi et al., 2020). The objective function of the model, therefore, is usually a combination of multiple objectives. It does not get a single optimal solution, but it generates the so called pareto optimal solutions, which means that there is no other solution which is better at all objectives. Only recently, Upadhaya and Askari-Nasab (2016), used goal programming for a simulation optimization-based short-term planning model, to illustrate how proactive decisions can be made in the dynamic environment of mining and operational plans can be synced with long-term planning to reduce opportunity cost, and maximize production and equipment utilization.

Noriega and Pourrahimian (2022) proposed research on a comprehensive review of data-driven and artificial intelligence methods in strategic open-pit mine planning. They identified research trends in the mine planning with data-driven approaches. Afrapoli et al. (2019) investigated a multi-objective transportation problem for a truck dispatching in open pit mines. The presented model includes the trucks to reduce shovel idle times, wait times, and deviations from the requirements of production. Their mathematical model is a benchmark model using a fleet management system in mining.

There are some important research on underground mining (Afum et al., 2021; Shuwei Huang et al., 2020). For example, Huang et al., (2020) presented a Stochastic Mixed Integer Programming Framework for Underground Mining Production Scheduling Optimization Considering Grade Uncertainty. They incorporated grade uncertainty into the strategic mine plan, and presented a stochastic mixed integer programming (SMIP) formulation to optimize an underground cut-and-fill mining production schedule.

Christian Both et al. (2020) proposed a Joint stochastic short-term production scheduling problem with a fleet management optimization for mining complexes. Also, the proposed model was to maximize the metal production and profit of the mining complex. The main methodology was a non-linear mathematical programming model and a Simulated annealing metaheuristic method. The uncertainties of the model were Geological uncertainty, uncertainty related to equipment performances, and cycle time of trucks. Liu (2021) presented a robust optimization model for mine

supply chain planning and employed big data to solve the problem. In this research, he used a mine supply chain including mining, processing, and ore product transportation stages. To control the uncertainty of data he applied robust optimization in the model and several nonlinear constraints. The final results show the robust optimization model is stabilized when the model's data is under disturbance.

2.2. Mixed Integer Linear programming models to optimize mine planning problems

The complexity of the operation and dynamic nature of the mining environment force planners to make reactive decisions once production starts. However, reactive decisions cause mines to lose tons of money as opportunity costs. Therefore, a dynamic decision-making tool can make the life of mine planners easier. Many researchers have formulated models for short-term (Rahnema et al., 2023, N Al Habib et al., 2023) and long-term (Tabesh et al., 2023; Moradi-Afrapoli et al., 2022; Jelvez et al., 2020) mine planning. While some of the existing models are concerned highly about operational details, they do not account for the uncertainties involved in the process. Also, assuming constant production rates from shovels and trucks makes the generated schedule very hard to achieve, which depends significantly on the haulage network and profile, the available number of trucks in the system, and the truck dispatching efficiency.

In the related studies the practical mathematical models have been proposed to manage and optimize mining operations. Moradi Afrapoli et al. (2019) has presented a multiple objective transportation problem for dynamic truck dispatching in surface mines. Their model has three objective functions as the objective functions (1-3):

$$\boldsymbol{f_1} = \sum_{\boldsymbol{i}} \sum_{\boldsymbol{j}} \sum_{\boldsymbol{k}} \boldsymbol{S_{ijk} x_{ijk}} \qquad \forall \boldsymbol{i} \in \{\boldsymbol{1}, \dots, \boldsymbol{N}\} \& \forall \boldsymbol{j} \in \{\boldsymbol{1}, \dots, \boldsymbol{M}\} \& \forall \boldsymbol{k} \in \{\boldsymbol{1}, \dots, \boldsymbol{D}\} \qquad (1)$$

$$\boldsymbol{f_2} = \sum_{\boldsymbol{i}} \sum_{\boldsymbol{j}} \sum_{\boldsymbol{k}} \boldsymbol{T_{ijk} x_{ijk}} \qquad \forall \boldsymbol{i} \in \{\boldsymbol{1}, \dots, \boldsymbol{N}\} \& \forall \boldsymbol{j} \in \{\boldsymbol{1}, \dots, \boldsymbol{M}\} \& \forall \boldsymbol{k} \in \{\boldsymbol{1}, \dots, \boldsymbol{D}\} \qquad (2)$$

$$\boldsymbol{f_3} = \sum_{\boldsymbol{j}} \sum_{\boldsymbol{k}} \boldsymbol{c^-_{jk} + c^+_{jk}} \qquad \forall \boldsymbol{i} \in \{\boldsymbol{1}, \dots, \boldsymbol{N}\} \& \forall \boldsymbol{j} \in \{\boldsymbol{1}, \dots, \boldsymbol{M}\} \& \forall \boldsymbol{k} \in \{\boldsymbol{1}, \dots, \boldsymbol{D}\} \qquad (3)$$

The first objective function indicates minimization of active shovels' idle time. The second objective function is minimization of truck wait time in the operation, and the third objective function aims to decrease deviation from flow rates of the paths. They solved the multi-objective optimization model with a goal programming method.

Also, Moradi Afrapoli et al. (2019) proposed the other paper on a multi-step approach to long-term open-pit production planning in which they dealt with the following constraints; i) The number of incoming trucks to each shovel is equal to the number of outgoing trucks from the same shovel (equation 4), ii) The tonnage a truck can transport in one payload is less that its maximum nominal capacity (equation 5), and iii) Total haulage capacity sent to a shovel is less than the nominal digging rate of that shovel (equation 6).

$$\sum_{\boldsymbol{i}} \sum_{\boldsymbol{k}} \boldsymbol{x`_{ijk}} = \sum_{\boldsymbol{i}} \sum_{\boldsymbol{k}} \boldsymbol{x_{ijk}} \qquad \forall \boldsymbol{j} \in \{\boldsymbol{1}, \dots, \boldsymbol{M}\} \qquad (6)$$

$$\sum_{i}\sum_{k} \boldsymbol{tc_i x_{ijk} \leq T_i} \quad \forall \boldsymbol{i} \in \{\boldsymbol{1}, \dots, \boldsymbol{N}\} \tag{7}$$

$$\sum_{i}\sum_{k} \boldsymbol{tc_i x_{ijk} \leq SC_j} \quad \forall \boldsymbol{j} \in \{\boldsymbol{1}, \dots, \boldsymbol{M}\} \tag{8}$$

Behrang et al. (2014) studied the linear programming model for long-term mine planning in the presence of uncertainty and a stockpile. The objective function of the model as below (9) is to minimize the NPV minus discounted cost of uncertainty which is calculated by simulated realizations.

$$Max \sum_{t} \{ \underbrace{\sum_{i} v_{ti} \times z_{ti} - q_{ti} \times y_{ti}}_{NPV} - 1/L \sum \underbrace{\left[C_{up}(t,l) + C_{op}(t,l) \right]}_{C_u(t)} \} \tag{9}$$

Behrang et al. (2014) conducted another research on Truck-shovel allocation optimization: a goal programming approach in which the main constraints of their model were as following: the lower limit and upper limit (target production) for the designed processing plant production, and the total tonnage of material mined is within the acceptable range of mining equipment capacity.

$$p_l(t) \leqslant \sum_{i=1}^{N} \{T(i) \times z(t;i)\} \leqslant p_u(t) \tag{10}$$

$$m_l(t) \leqslant \sum_{i=1}^{N} \{T_o(i) \times z(t,i)\} \leqslant m_u(t) \tag{11}$$

Askari Nasab et al. (2011) proposed a study on large-scale open pit production scheduling using Mixed Integer Linear Programming with a main objective function of maximizing the discounted revenue generated by selling the product minus the discounted costs involved in extracting the block.

$$d_n^t = \underbrace{\left[\sum_{e=1}^{E} o_n \times g_n^e \times r^{e,t} \times (p^{e,t} - cs^{e,t}) \right]}_{\text{discounted revenues}} - \underbrace{\left[\sum_{e=1}^{E} o_n \times cp^{e,t} \right] - \left[(o_n + w_n) \times cm^t \right]}_{\text{discounted costs}} \tag{12}$$

However, Tabesh et al. (2015) presented a multi-step approach to long-term open-pit production planning in which the profit by including the blocks with the highest value in the pushback has been maximized.

$$\max \sum_{i \in N} p_i x_{ij} \tag{13}$$

In scheduling problems, Upadhaya and Askari (2016; 2019) used goal-based mixed integer programming (MILGP) model with discrete simulation to allocate trucks and shovels in mine faces with four main objective functions as following,

- The production is maximized by optimizing shovel utilization or minimizing negative deviation in production

- Minimize deviation in production received in processing plants from desired
- Minimize deviation from the expected grade of ore
- Minimize material handling time (shovel movement time)

$$\Psi_1 = \sum_s x_s^- \tag{14}$$

$$\Psi_2 = \sum_{d^o} \sum_k \left(g_{k,d^o}^- + g_{k,d^o}^+\right) \tag{15}$$

$$\Psi_3 = \sum_{d^p} \left(\delta_{d^p}^- + \delta_{d^p}^+\right) \tag{16}$$

$$\Psi_4 = \sum_s \sum_f \Gamma_{s,f}^F \times A_s \times a_{s,f} + \sum_t \sum_f \sum_d n_{t,f,d} \times \Gamma_{f,d}^D \times (C_t + \bar{C}_t) \tag{17}$$

The research of S. P. Upadhyay et al., 2016 was Truck-shovel allocation optimization: a goal programming approach while the study of Upadhyay et al., 2019 was about Dynamic shovel allocation approach to short-term production planning in open-pit mines.

There are other important studies on MILP (Badiozamani et al., 2019; Hosseini et al., 2020; Afum et al., 2020 and Shamsi et al., 2022). For example, Shamsi et al. (2022) conducted research on the optimization of open-pit mine production scheduling considering an optimum transportation system in which ore and waste crushers are not located at the same location, and the grade of ore sent to the processing plant is in the acceptable range.

$$o_{t,c} + w_{t,c} \leq 1 \quad for \quad t \in T; c \in C \tag{18}$$

$$\sum_{d \in \{1,2\}} \sum_{n \in N} x_{d,t,n} * W_n * (G_n - Cap_{Min-G}) \geq 0 \quad for \quad t \in \{1, \ldots, |T|\} \tag{19}$$

2.3. Mine planning models with the uncertainty of data

The extent and sequence of mining operations are vital components of an extraction operation in a long-term mine planning problem. Since long-term mine planning includes production sequencing, scheduling, facilities' location, and other economic operations, optimizing this problem results in maximizing the net present value and the net profit (Fathollahzadeh et al., 2021; O.M Badozie et al., 2021; Amponsah et al., 2023). Table 1 proposes a summary of the research works on long-term planning which applied stochastic optimization.

Table 1. The summary of related research on stochastic optimization.

Paper	Area	Uncertain parameters	Other considerations
Gholamnejad et al., 2012	Long-term, open-pit mine	geological uncertainty	binary integer programming model
Benndorf et al., 2013	Long-term, open-pit mine	joint multi-element geological uncertainty	stochastic integer programming formulation
Koushavand et al., 2014	Long-term, open-pit mine	Grade	Linear programming

Rahmanpour et al., 2016	Short-term, open-pit mine	price uncertainty	
Morales et al., 2019	Long-term, open-pit mine	Geo-metallurgical attributes and geological uncertainty	Risk management
Rimele et al., 2020	The long-term, open-pit mine	Geological and commodity price uncertainty	Dynamic stochastic programming
Gilani et al., 2020	Short-term,open-pit mine	Geological uncertainty	stochastic integer programming with PSO[3] algorithm
Tolouei et al., 2021	Long-term, open-pit mine	Grade	Lagrangian relaxation with meta-heuristic methods, bat algorithm, and particle swarm optimization

In the following, two main concepts in which uncertainty can occur, are investigated. The first one is metal supply and the second one is mine design and production scheduling.

2.3.1. Uncertainty in metal supply

The primary attributes of mining deposits result in uncertainty in some related parameters of long-term mine planning models. To control this uncertainty, some studies apply high-order sequential simulation with spatial cumulants. This method is useful for stochastic simulation and one of its most important elements is the notion of high-order spatial cumulants. This method has some significant benefits as below (Dimitrakopoulos et al., 2010; 2011):

- This method does not require data pre-processing.
- This approach deploys high-order relations in the data dominating the simulation process.
- This method is able to generate spatial patterns reproducing distributions and variograms.

2.3.2. Uncertainty in mine design and production scheduling

Mine design and production schedules have some complexities when it comes to long-term mine planning. Due to these inevitable uncertainties, the majority of models implement stochastic optimization. The main objective of stochastic optimization in these models is to maximize the value of NPV during the planning horizon. One of the sources which make the parameters of the model uncertain is the uncertainty of mineralized materials of the mine and their supply. In the literature, there are two main approaches as follows:

- Simulated annealing which is a metaheuristic algorithm (Albor et al., 2009).
- Stochastic integer programming, an exact solution method (Leite et al., 2010).

3. Future Direction in Research

The next leap in MILP modeling should be to quantify the uncertainties present in shovel operation or grade, metal supply and production scheduling. Identifying the distribution of uncertainty present in a system can be a challenge and this is where the focus needs to be. Once the uncertainty of a certain parameter or variable (such as grade, haulage time) is quantified and incorporated, we can modify the existing models to check how they perform under a real stochastic environment.

[3] Particle Swarm Optimization

Moreover, the models can be made more pragmatic and effective by taking factors such as the effect of road conditions on equipment life and tire cost, the impact of accidents and driver behavior on production.

4. Conclusion

Mining has always dealt with minimizing risks, and costs and maximizing the production rate by proper planning in both the long and short term. This research proposed a summary of recent papers on mine planning in short-term and long-term horizons in which there is the uncertainty of data in parameters. These models have applied stochastic optimization approaches and simulation to deal with the uncertainty and manage uncertainties and risks associated with the dynamic mining environment. The models developed thus far will act as a strong basis for how to proceed through to the future of mining research and development. According to investigating the proposed stochastic model in the literature, few research works have considered uncertainty in mine design and production schedules, and supply parameters. Therefore, it is important to consider these parameters uncertain in addition to grade and other geological data in mine optimization problems.

5. References

[1] Al Habib, N., Ben-Awuah, E., & Askari-Nasab, H. (2023). Review of recent developments in short-term mine planning and IPCC with a research agenda. Mining Technology, 1-23.

[2] Afrapoli, A. M., Tabesh, M., & Askari-Nasab, H. (2019). A multiple objective transportation problem approach to dynamic truck dispatching in surface mines. European Journal of Operational Research, 276(1), 331-342.

[3] Afum, B. O., & Ben-Awuah, E. (2021). A review of models and algorithms for surface-underground mining options and transitions optimization: Some lessons learnt and the way forward. Mining, 1(1), 112-134.

[4] Afum, B. O., Ben-Awuah, E., & Askari-Nasab, H. (2020). A mixed integer linear programming framework for optimising the extraction strategy of open pit–underground mining options and transitions. International Journal of Mining, Reclamation and Environment, 34(10), 700-724.

[5] Amponsah, S. Y., Takouda, P. M., & Ben-Awuah, E. (2023). A Multiple Objective Genetic Algorithm Approach for Stochastic Open Pit Production Scheduling Optimisation. International Journal of Mining, Reclamation and Environment, 1-28.

[6] Both, C., & Dimitrakopoulos, R. (2020). Joint stochastic short-term production scheduling and fleet management optimization for mining complexes. Optimization and Engineering, 21(4), 1717-1743.

[7] Blom ML, Pearce AR, Stuckey PJ. 2016. A decomposition-based algorithm for the scheduling of open-pit networks over multiple time periods. Management Science. 62(10):3059-84.

[8] Blom ML, Burt CN, Pearce AR, Stuckey PJ. 2014. A decomposition-based heuristic for collaborative scheduling in a network of open-pit mines. INFORMS Journal on Computing. 26(4):658-76.

[9] Benndorf, J., & Dimitrakopoulos, R. (2013). Stochastic long-term production scheduling of iron ore deposits: Integrating joint multi-element geological uncertainty. Journal of Mining Science, 49(1), 68-81.

[10] Ben-Awuah, E., Askari-Nasab, H., Maremi, A., & Seyed Hosseini, N. (2018). Implementation of a goal programming framework for production and dyke material planning. International Journal of Mining, Reclamation and Environment, 32(8), 536-563.

[11] Badiozamani, M. M., Ben-Awuah, E., & Askari-Nasab, H. (2019). Mixed Integer Linear Programming for Oil Sands Production Planning and Tailings Management. Journal of environmental informatics, 33(2).

[12] Chanda EKC, Dagdelen K. 1995. Optimal blending of mine production using goal programming and interactive graphics systems. Int J Surf Mining Reclam Environ. 9(4):203-8.

[13] Dimitrakopoulos, R. (2011). Strategic mine planning under uncertainty. Journal of Mining Science, 47(2), 138-150.

[14] Fathollahzadeh, K., Asad, M. W. A., Mardaneh, E., & Cigla, M. (2021). Review of solution methodologies for open pit mine production scheduling problem. International Journal of Mining, Reclamation and Environment, 35(8), 564-599.

[15] F. Albor Consquega and R. Dimitrakopoulos, "Stochastic mine design optimization based on simulated annealing: Pit limits, production schedules, multiple orebody scenarios and sensitivity analysis," Transactions of the Institution of Mining and Metallurgy: Mining Technology, 118, No. 2 (2009).

[16] Gholamnejad J. 2008. A zero-one integer programming model for open pit mining sequences. Journal of the Southern African Institute of Mining and Metallurgy. 108(12):759-62.

[17] Gurgur, C.Z., Dagdelen, K., Artittong, S. 2011. Optimization of a real-time multi-period truck dispatching system in mining operations International Journal of Applied Decision Sciences. 4(1):57-79.

[18] Gholamnejad, J., & Moosavi, E. (2012). A new mathematical programming model for long-term production scheduling considering geological uncertainty. Journal of the Southern African Institute of Mining and Metallurgy, 112(2), 77-81.

[19] Gilani, S. O., Sattarvand, J., Hajihassani, M., & Abdullah, S. S. (2020). A stochastic particle swarm based model for long term production planning of open pit mines considering the geological uncertainty. Resources Policy, 68, 101738.

[20] Hosseini, N. S., Ben-Awuah, E., & Pourrahimian, Y. (2020). A two-step approach to incorporate cut-off grade and stockpiling in oil sands mine planning optimization framework. Computers & Operations Research, 115, 104659.

[21] Jélvez, E., Morales, N., & Askari-Nasab, H. (2020). A new model for automated pushback selection. Computers & Operations Research, 115, 104456.

[22] Koushavand, B., Askari-Nasab, H., & Deutsch, C. V. (2014). A linear programming model for long-term mine planning in the presence of grade uncertainty and a stockpile. International Journal of Mining Science and Technology, 24(4), 451-459.

[23] Krishna Sundar D, Acharya D. 1995. Blast schedule planning and shiftwise production scheduling of an opencast iron ore mine. Computers and Industrial Engineering. 28(4):927-35.

[24] Kalantari, S., Ben-Awuah, E., & Askari-Nasab, H. (2013). Towards an integrated oil sands mine plan and composite tailings plan. International Journal of Mining, Reclamation and Environment, 27(2), 103-126.

[25] Liu SQ, Kozan E. 2012. A hybrid shifting bottleneck procedure algorithm for the parallel-machine job-shop scheduling problem. J Oper Res Soc. 63(2):168-82.

[26] Leite and R. Dimitrakopoulos, "Production scheduling under metal uncertainty – Application of stochastic mathematical programming at an open pit copper mine and comparison to conventional scheduling," The Australasian Institute of Mining and Metallurgy, Spectrum Series, 17 (2010).

[27] Morales, N., Seguel, S., Cáceres, A., Jélvez, E., & Alarcón, M. (2019). Incorporation of geometallurgical attributes and geological uncertainty into long-term open-pit mine planning. Minerals, 9(2), 108.

[28] Moradi Afrapoli A, Askari-Nasab H. 2017. Mining fleet management systems: A review of models and algorithms. International Journal of Mining, Reclamation and Environment. :1-19.

[29] Moradi Afrapoli A, Tabesh M, Askari-Nasab H. 2019. A multiple objective transportation problem approach to dynamic truck dispatching in surface mines.

[30] Meagher, C., Abdel Sabour, S. A., & Dimitrakopoulos, R. (2009). Pushback design of open pit mines under geological and market uncertainties. In Proceedings of the International Symposium on Orebody Modeling and Strategic Mine Planning: Old and New Dimensions in Changing World (Vol. 17, pp. 297-304).

[31] Moradi-Afrapoli, A., & Askari-Nasab, H. (2022). Advanced Analytics for Surface Extraction. In Advanced Analytics in Mining Engineering: Leverage Advanced Analytics in Mining Industry to Make Better Business Decisions (pp. 181-203). Cham: Springer International Publishing.

[32] Maremi, A., Ben-Awuah, E., & Pourrahimian, Y. (2020). An automated production targeting goal programming framework for oil sands mine planning considering organic rich solids. Mining Technology, 129(2), 53-67.

[33] Noriega, R., & Pourrahimian, Y. (2022). A systematic review of artificial intelligence and data-driven approaches in strategic open-pit mine planning. Resources Policy, 77, 102727.

[34] Nikbin, V., & Moradi Afrapoli, A. (2023). A Multiple Objective Hybrid Algorithm for Daily Ore Blend in Oil Sands Mines. International Journal of Mining, Reclamation and Environment, 1-16.

[35] Rimélé, A., Dimitrakopoulos, R., & Gamache, M. (2020). A dynamic stochastic programming approach for open-pit mine planning with geological and commodity price uncertainty. Resources Policy, 65, 101570.

[36] Rahmanpour, M., & Osanloo, M. (2016). Determination of value at risk for long-term production planning in open pit mines in the presence of price uncertainty. Journal of the Southern African Institute of Mining and Metallurgy, 116(3), 229-236.

[37] Rahnema, M., Amirmoeini, B., & Moradi Afrapoli, A. (2023). Incorporating Environmental Impacts into Short-Term Mine Planning: A Literature Survey. Mining, 3(1), 163-175.

[38] R. Dimitrakopoulos, H. Mustapha, and E. Gloaguen, "High-order statistics of spatial random fields: Exploring spatial cumulants for modelling complex, non-Gaussian and non-linear phenomena," Mathematical Geosciences, 42, No. 1 (2010).

[39] S. Huang, G. Li, E. Ben-Awuah, B. O. Afum, and N. Hu, "A stochastic mixed integer programming framework for underground mining production scheduling optimization considering grade uncertainty," IEEE Access, vol. 8, pp. 24495-24505, 2020.

[40] Shamsi, M., Pourrahimian, Y., & Rahmanpour, M. (2022). Optimisation of open-pit mine production scheduling considering optimum transportation system between truck haulage and semi-mobile in-pit crushing and conveying. International Journal of Mining, Reclamation and Environment, 36(2), 142-158.

[41] Tolouei, K., Moosavi, E., Tabrizi, A. H. B., Afzal, P., & Bazzazi, A. A. (2021). An optimisation approach for uncertainty-based long-term production scheduling in open-pit mines using meta-heuristic algorithms. International Journal of Mining, Reclamation and Environment, 35(2), 115-140.

[42] Tabesh, M., Afrapoli, A. M., & Askari-Nasab, H. (2023). A two-stage simultaneous optimization of NPV and throughput in production planning of open pit mines. Resources Policy, 80, 103167.

[43] Upadhyay SP, Askari-Nasab H. 2019. Dynamic shovel allocation approach to short-term production planning in open-pit mines. Int J Min Reclam Environ. 33(1):1-20.

[44] Upadhyay SP, Askari-Nasab H. 2018. Simulation and optimization approach for uncertainty-based short-term planning in open pit mines. International Journal of Mining Science and Technology. 28(2):153-66.

[45] Upadhyay SP, Askari-Nasab H. 2016. Truck-shovel allocation optimisation: A goal programming approach. Transactions of the Institutions of Mining and Metallurgy, Section A: Mining Technology. 125(2):82-92.

[46] Wilke FL, Reimer T. 1977. Optimizing the short term production schedule for an open pit iron ore mining operation. :425-33.

Integrated Simulation and Optimization Framework for Quantitative Analysis of Near-face Stockpile Mining[1]

Hongshuo Gong[a], Ali Moradi Afrapoli[b] and Hooman Askari-Nasab[a]
Mining Optimization Laboratory (MOL)
[a] University of Alberta, Edmonton, Canada
[b] Université Laval, Québec City, Canada

ABSTRACT

A new conceptual mining method called the near-face stockpile (NFS), which combines the in-pit crushing and conveying IPCC system with a pre-crusher stockpile, has recently been proposed for large open pits with sufficient pit bottom width. In the past, stockpiles mainly act as a "buffer" to improve the stability of the production system. However, in NFS ore will be dumped into the pre-crusher stockpile located at the bottom of the current pit and be fed into the crusher after blending to the desired head grade, instead of being dumped directly into the crusher. Theoretically, this design not only retains the high efficiency and high output of IPCC, but also endows the mining system with better quantity and quality stability. Verifying these advantages and objectively evaluating the NFS method has become a problem worth studying. Since the NFS method exhibits distinctive layout and feeding mechanisms, which distinguish it from other mining methods, a novel simulation model is required for the accurate modeling of the NFS method and quantitatively evaluating the performance of NFS methods. In addition, this paper also proposes an optimization model for short-term production scheduling for NFS method based on the mixed integer linear programming (MILP) method. An oil sands mine case study is implemented to verify the proposed simulation model. One year simulation results reveal that compared to the traditional mining method, the overall production increased by 5.06%, the transporting distance of minerals by trucks was reduced by 17.87%, and the shovels' and crusher's utilization increased by 4.96% and 4.85%, respectively, when using NFS method.

Keywords*: near-face stockpiling; mixed integer linear programming; simulation and optimization; production planning*

1. Introduction

Truck-shovel (TS) system is the most widely used method in open pit mining, and its efficiency and benefits have been significantly improved by the application of large-scale equipment [1]. However, with the increase in the mining depth and transportation distance, the economic benefits of the TS system deteriorated. To address this issue, various improvements have been proposed and applied, among which the in-pit crushing and conveying (IPCC) method has been successful [2]. As the name

[1] This paper is submitted to Simulation Modelling Practice and Theory on 24 April 2023, and available online from 14 July 2023.

ISBN: 978-1-55195-503-2

shows, the IPCC method moves the crusher to the bottom of the pit to reduce the trucks' transportation distance and improve its efficiency. The IPCC method offers considerable flexibility in selecting the in-pit crusher. Based on mobility, the crusher can be divided into three types: fully mobile, semi-mobile, and fixed. The crushed material in in-pit crushers is transported to the processing plant or waste dump using conveyor belts. Since the transportation cost of the conveyor belts is only one-fifth to one-third of that of trucks [3-4], a large portion of the operating expenses can be saved. Past research and practices have shown that although the IPCC method has disadvantages, such as heavy initial investment, complex management, and being restricted by terrain, and other constraints, its financial practicality outperforms the traditional TS method in the long run [5].

However, a major drawback of the traditional mining method is its susceptibility to risks, which are not addressed by the IPCC and has prompted the development of the near face stockpile (NFS) mining method, a novel concept that combines IPCC with a pre-crusher stockpile. Specifically, this risk is that the mining subsystem and the crushing subsystem are closely linked. Any accident or unexpected failure in one of the subsystems will affect the other subsystem, which will eventually lead to a reduction in production. To tackle this problem, a stockpile is arranged at the bottom of the open pit, ahead of the crusher. Unlike the IPCC method, where trucks dump the material directly into the crusher, in the NFS method, all materials are first dumped into the stockpile and then fed to the crusher through a reclaim shovel.

It should be pointed out that, regardless of the traditional TS or the IPCC mining method, the connection of the two most significant subsystems of an open pit mine: the mining subsystem and processing subsystem, solely rely on the hauling subsystem. A problem with any of the three subsystems will lead to a chain of shutdowns [6]. As shown in Figure 1, the fundamental difference between the NFS method and the other two methods is that its stockpile can decouple these two subsystems and reduce their mutual influence, improving the fault tolerance of the whole system. In addition, unlike the traditional pre-crusher stockpile, which mainly assumes the role of "buffer", the stockpile in the NFS method can upgrade the traditional truck-by-truck blending to batch blending, reducing the grade deviation fed to the crusher [7]. Besides, in theory, in addition to these new advantages, NFS retains the respective advantages of IPCC and the pre-crusher stockpile itself, such as reduced demand for trucks, transportation distances, and transportation costs. Those benefits will bring enterprises higher equipment utilization, more stable product quality, and better net present value (NPV).

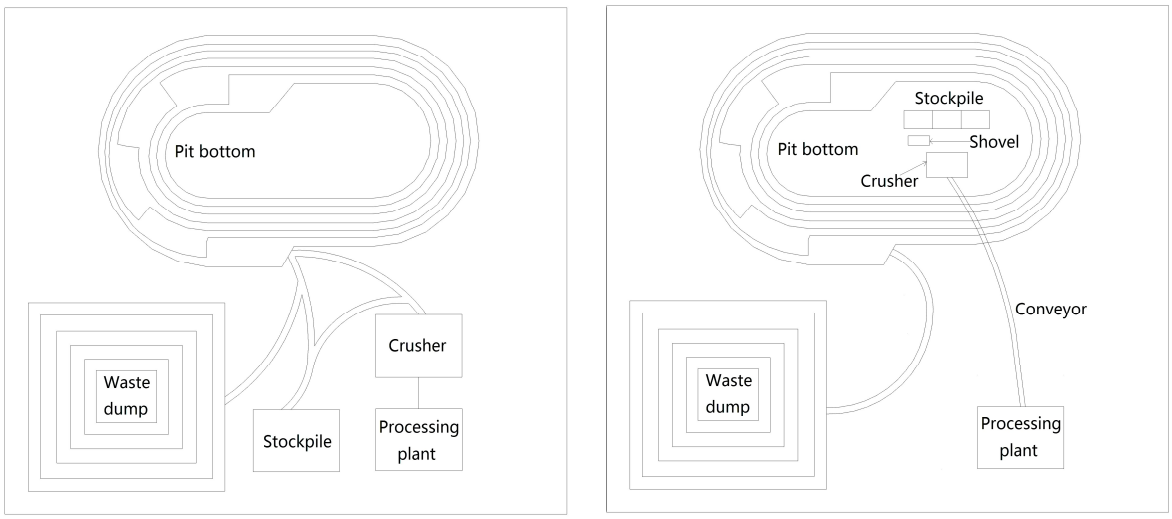


Figure 1. Traditional mining method layout (left) and NFS method mining method layout (right).

Despite the various theoretical advantages of the NFS over other methods, it is still in the conception stage and those advantages are not verified. Therefore, the objective of this study is to understand and measure the performance of the near face stockpile mining method objectively and quantitatively and compared it to the traditional out-pit crusher scenario.

Simulation is a widely used time-saving, cost-saving technology in addressing theoretical "what-if" questions [8]. Therefore, simulation models which can cover the characteristics of the NFS and TS methods and assess uncertainty around the key performance indicators (KPIs) of the mining system are built in this study. Meanwhile, those models can also assist in understanding and measuring the interaction of interrelated activities within the NFS system and TS system and their overall performance.

In addition to the simulation model, an optimal or near-optimal mining schedule is also indispensable for an objective evaluation of a mining method. Therefore, a mathematical short-term mining schedule optimization model based on mixed integer linear programming is also proposed for the NFS method to generate an optimal or near-optimal mining schedule. Through feeding the generated schedule to the proposed simulation model, a comprehensive optimization-simulation framework is completed to evaluate the performance of a mining method.

Afterward, we carry out a case study of an oil sands mine, which adopted the traditional TS method in real operation. The framework is first applied to the traditional TS method and by comparing the simulation results against the real dispatch production data, the framework is validated. The validated simulation results of the TS method are then taken as a benchmark to evaluate the performance of the NFS method under the optimization-simulation framework. The main contribution of this work is creatively proposing a simulation model for the NFS method and combining it with a short-term mining schedule optimization model and quantitatively measuring the performance of the NFS method and verifying its theoretical advantages.

However, in addition to advantages, NFS also has some obvious disadvantages and deficiencies. The first is that the requirements for initial investment are even higher than that of the IPCC method. Secondly, although the operating cost of the conveyor is relatively low, the consequences of its damage are far more serious than the failure of one or two trucks. Besides, the NFS method has higher requirements on the bottom size of the open pit than the IPCC method and is more suitable for ore bodies with lower strip ratios. Furthermore, the added reclaim shovel is an additional risk and also one of the potential bottlenecks of this system. These shortcomings may limit the further generalization of the NFS method.

The second chapter of this article is the related literature review. Since the NFS is a new concept, the literature reviewed in this chapter is mainly about past research on the IPCC simulation and mining schedule optimization with a stockpile. In chapter three, we formulated the optimization model and showed the logic and process of building simulation models. The fourth chapter is the validation of the integrated framework and quantitatively compares the performance between the TS method and the NFS method. In the fifth chapter, we summarize and analyze the comparison results, and conclude. In addition, the limitations and future work of this research are also stated.

2. Literature Review

Stockpile is one of the crucial components of the mining system, series linear optimization models and nonlinear optimization models that consider stockpile were proposed. As Jupp [9] described, the near crusher stockpile plays four roles simultaneously: storing, buffering, blending, and grade separation. The quality of stockpiles is managed manually in the early stage while the on-site operational staff routinely records relevant data of essential stockpiles. A MILP model for long-term optimization production planning that considers grade uncertainty and a stockpile was proposed by Koushavand [10]. Their objective function maximizes the profit while including the cost of uncertainty by considering both under-production and over-production scenarios. Smith and Wicks

[11] proposed a MIP for medium-term production planning with a stockpile in a copper mine. However, the authors avoid nonlinearity by not keeping track of elements' grades going to and reclaimed from the stockpile. Instead of using classical linear programming, in which only one objective can be satisfied, a goal programming model that aims at reducing stockpile fluctuation was proposed by Souza [12]. In the model, minimizing the operating cost and grade deviation were set up as two goals to be achieved. However, although the author claims the model could provide support for short-term and medium-term scheduling, it was only tested by a database from the author and no simulation was conducted.

There are also nonlinear models proposed for optimization which incorporate stockpiles. Bley [13] added a non-convex quadratic constraint for stockpiles in each period and used the primal heuristic method to find feasible solutions for a specific problem. Paithankar [14] proposed a mathematical model based on a genetic algorithm to optimize production sequence and dynamic cutoff grades simultaneously. The final goal is set to generate the highest NPV. The model assumes that the stockpile has infinite capacity and no fluctuation in yearly mining capacity, which is not realistic in actual operation. However, although most of the proposed nonlinear models claimed a higher NPV under the case study, more variables are needed than linear models, especially for stockpiles which caused inefficiency issues. Besides, overall optimal or near-optimal results are not guaranteed, and the time consumption is much higher than those linear models.

The IPCC was first proposed and applied in 1956 in Germany [15]. Ever since, academic research on IPCC has continued, and simulation technology's support has promoted the development and maturity of the IPCC method. The simulation of the IPCC mining method involves modeling the process of extracting materials and transporting them to a processing plant using a combination of mobile/semi-mobile/fixed crushers, conveyor belts, and trucks. One of the earliest IPCC simulation studies was carried out in the early 1980s for a copper mine. The study investigated the mining fleet optimization problem under IPCC conditions and used simulation to decide the number of trucks required to increase efficiency [16]. In the late 1990s, the Australian mining company, Rio Tinto, began a series of studies to evaluate the use of IPCC systems in their operations. These studies used simulation technology to model different scenarios for haulage distances, equipment selection, and production rates [17]. Since then, IPCC simulation has continued to play an essential role in the design and optimization of mining operations and is widely used by mining companies and consulting firms to evaluate the feasibility of different mining methods and equipment configurations. Relevant research includes but is not limited to 1. IPCC economic benefit analysis over the traditional TS system, which proves that IPCC can achieve higher profits within the scope of life of mine [18, 19]; 2. Crusher and other equipment’s selection and corresponding capacity determination[20–22]; 3. Optimization of the location of the crusher, which can minimize operating costs and increase profits [4, 23, 24]; 4. Assessment of different truck dispatch rules [25, 26]. Those studies helped to optimize the IPCC system's design by evaluating different scenarios in a virtual environment before implementation, resulting in improved productivity, reduced operating costs, and enhancement in the safety. With the aid of those studies, it has become common knowledge that IPCC can achieve better economic benefits in deeper open pit mines than the TS system. Nowadays, IPCC has been implemented in more than 500 mines [5].

In summary, the common shortcomings found in the literature are 1. Linear optimization models and corresponding simulation models that consider stockpiles adopt perfect blending assumption, leading to a difference between real reclaimed material grade and hypothesized reclaimed grade.; 2. Simulation models build for IPCC are not suitable for NFS; 3. Nonlinear optimization models cannot guarantee overall optimal or near-optimal results. The first and second drawbacks are addressed in this research by proposing a new optimization model and simulation model, in which material grade reclaimed from the stockpile can be tracked precisely.

3. Framework and Formulations

Figure 2 shows the integrated optimization-simulation framework and the interactions between the optimization model and the simulation model. The importance of mining scheduling and its optimization cannot be overstated. No mining method can deliver its value without a practical production schedule and cannot be measured objectively and fairly. Therefore, before building and running a simulation model, it is necessary to build an optimization model to optimize its mining schedule according to the characteristics of the NFS method. The MILP approach is selected to optimize the short-term schedule due to its flexibility, efficiency, and guarantee of optimality. It should be noted that the MILP optimization model we proposed in this section is based on Tabesh and Askari-Nasab's previous work [27].

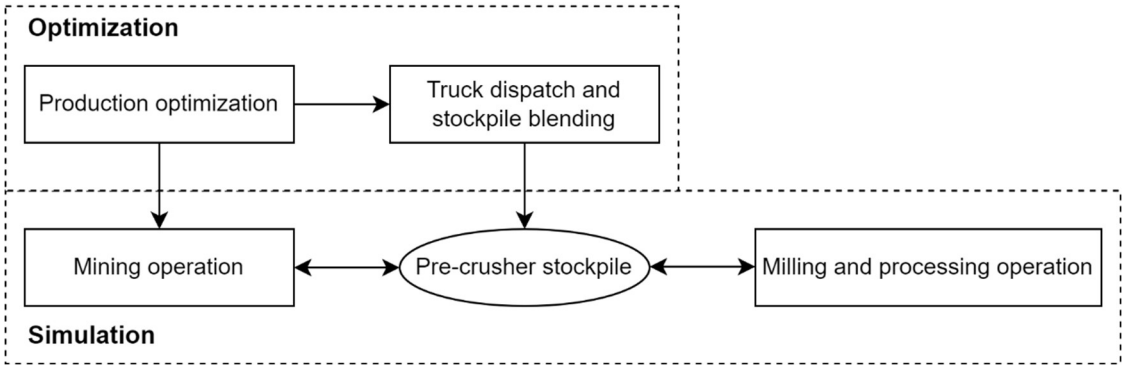


Figure 2. Integrated optimization-simulation framework.

3.1. Optimization Model

In the following, the defined indices, sets, parameters, decision variables, the objective function, and the constraints of the optimization model are presented.

Indices

k	Block indices ($k \in \{1, 2, \ldots K\}$)
t	Period indices ($t \in \{1, 2, \ldots T\}$)
d	Destination indices (stockpile or waste dumps)
s	Zone indices ($s \in \{1, 2, \ldots S\}$)

Sets and parameters

r_s^t	Discounted revenue generated by sending one unit of material from stockpile zone s in period t to crusher minus the dozing, reclaiming, crushing, conveying, processing and selling cost
wt_k^t	Discounted cost of hauling all waste materials to waste dump in block k in period t
ot_k^t	Discounted cost of hauling all ore materials to in-pit stockpile in block k in period t

o_k	Ore tonnage in block k
o_r	Ore tonnage in reserve
w_r	Waste tonnage in reserve
c_s	Capacity of stockpile zone s
g_k	Average grade of material in ore portion of block k in percent
gcu^t	Upper bound of crusher acceptable grade in period t in percent
gcl^t	Lower bound of crusher acceptable grade in period t in percent
pu^t	Upper bound on ore processing capacity in period t in ton
pl^t	Lower bound on ore processing capacity in period t in ton
mu^t	Upper bound on mining capacity in period t in ton
ml^t	Lower bound on mining capacity in period t in ton
C_k	Set of the blocks that must be extracted prior to mine block k
n_k	Number of blocks in set C_k

Decision variables

$x_k^t \in [0,1]$	continuous variable, representing the portion of block k to be mined in period t, fraction of x characterizes both ore and waste included in the block
$b_k^t \in \{0,1\}$	binary integer variable controlling the precedence of extraction of blocks. b_k^t is equal to one if extraction of block k has started by or in period t, otherwise it is zero
$f_s^t \geq 0$	continuous variable, representing the tonnage of material reclaimed from stockpile zone s in period t

Objective function and constraints

$$\max \sum_{t=1}^{T} \left\{ \underbrace{\sum_{s=1}^{S} (r_s^t \times f_s^t)}_{\text{Discounted revenue}} - \underbrace{\sum_{k=1}^{K} (wt_k^t \times x_k^t)}_{\text{Discounted waste haul cost}} - \underbrace{\sum_{k=1}^{K} (ot_k^t \times x_k^t)}_{\text{Discounted ore haul cost}} \right\} \quad (1)$$

$$ml^t \le \sum_{k=1}^{K}(o_k + w_k) \times x_k^t \le mu^t \qquad \forall t \in \{1,...,T\} \tag{2}$$

$$\sum_{t=1}^{T}\sum_{k=1}^{K} o_k \times x_k^t \le o_r \qquad \forall k \in \{1,...,K\}, \quad t \in \{1,...,T\} \tag{3}$$

$$\sum_{t=1}^{T}\sum_{k=1}^{K} w_k \times x_k^t \le w_r \qquad \forall k \in \{1,...,K\}, \quad t \in \{1,...,T\} \tag{4}$$

$$pl^t \le \sum_{s=1}^{S} f_s^t \le pu^t \qquad \forall t \in \{1,...,T\} \tag{5}$$

$$\sum_{k=1}^{K} o_k \times x_k^t - S \times c_s \le \sum_{s=1}^{S} f_s^t \qquad \forall t \in \{1,...,T\} \tag{6}$$

$$\sum_{s=1}^{S} f_s^t \le \sum_{k=1}^{K} o_k \times x_k^t + S \times c_s \qquad \forall t \in \{1,...,T\} \tag{7}$$

$$(\sum_{k=1}^{K} g_k \times o_k \times x_k^t) / (\sum_{k=1}^{K} o_k \times x_k^t) \ge gcl^t \qquad \forall t \in \{1,...,T\} \tag{8}$$

$$(\sum_{k=1}^{K} g_k \times o_k \times x_k^t) / (\sum_{k=1}^{K} o_k \times x_k^t) \le gcu^t \qquad \forall t \in \{1,...,T\} \tag{9}$$

$$\sum_{t=1}^{T} x_k^t = 1 \qquad \forall k \in \{1,...,K\} \tag{10}$$

$$n_k \times b_k^t - \sum_{b \in C_k}\sum_{i=1}^{t} x_{\mathrm{b}}^i \le 0 \qquad \forall k \in \{1,...,K\}, \quad t \in \{1,...,T\} \tag{11}$$

Equation (1) is the objective function. Its goal is set to produce the best discounted net present value of a project in the given period. The expression of NPV in this formula is the sum of discounted revenue minus discounted waste hauling cost by truck minus discounted ore hauling cost by truck in each period. It should be pointed out that the dozing and reclaiming cost of ore material in the stockpile, as well as the subsequent crushing, conveying, processing, and selling costs, have been deducted from the discounted revenue. Equation (2) ensures that total material mined in each period matches the mining capacity. Equation (3) and Equation (4) enforce that the total tonnage of ore and waste being mined will not exceed the available reserve in the deposit. Equation (5) ensures that the material reclaimed from the stockpile matches the desired processing capacity. Equation (6) and (7) limits ore tonnage reclaimed from stockpile in each period. The reclaimed tonnage should not be less than ore material mined in that period minus stockpile capacity, or more than ore material mined in that period plus stockpile capacity. We defined equations (8) and (9) for grade control. Constraint (8) ensures that the average grade of material reclaimed from stockpile in each period does not fall below the lowest acceptable head grade for the processing. Similarly, constraint (9) ensures that the average grade reclaimed from stockpile does not exceed the upper bound of the required processing head grade. Equation (10) requires all blocks to be fully extracted without leftovers. Equation (11) ensures that all predecessor blocks are fully extracted before mining the current block.

3.2. Simulation Model

To simulate mining operations in the IPCC or the traditional TS mining method, the mining, transportation, crushing, and processing processes, are closely related and cannot be considered separately. Figure 3 shows the typical framework for simulating traditional open pit mining operations. However, since in the NFS method, the mining part is decoupled from the milling part, making them two independent subsystems, it is possible to simulate them separately. The two subsystems are connected through the stockpile. This paper proposes a combination of relatively independent but interrelated frameworks to simulate an open pit mining operation that uses the NFS method in Figure 4 (framework of the mining process in the NFS method), Figure 5 (the inner logic of the dumping zone decision sub-model that is shown in Figure 4), and Figure 6 (framework of the crushing and processing processes).

Figure 3 illustrates that in the traditional mining process, trucks play a pivotal role in connecting various processes. Once the shovel is assigned to each working surface as required, the truck first interacts with the shovel to complete the loading of materials and then drives along the completed road network to the crusher/waste dump. Subsequently, upon reaching the destination, the materials are dumped in order, and the truck is emptied to the next loading location as required. However, in this setting, the efficiency of trucks is tied to the flow of materials, and the longer the road, the less efficient the truck becomes. Moreover, the link between the mining system and the crushing system is fragile, and trucks can easily cause them to affect each other or be impacted by them. For instance, if the shovel stops working unexpectedly, the truck will have no material to deliver, resulting in the crushing system's stoppage. Additionally, if there is a problem with the truck or road, even if it is a short-term issue, the mining system and crushing system will come to a halt simultaneously. Although the IPCC method addresses the low efficiency of long-distance transportation, the NFS method further enhances the system's ability to withstand uncertainty while also improving its stability.

Figure 4 depicts that the direct transfer of materials from the truck to the crusher has been replaced with the transfer of materials to a pre-established stockpile. This alteration has resulted in the mining-related activities and the stockpile forming a relatively closed subsystem. Although the stockpile still experiences material exchanges with outside, the system can operate autonomously for a considerable duration, which is positively correlated to the stockpile's capacity. Additionally, the stockpile comprises multiple zones (three zones in this model, each with four dumping spots) which necessitate the addition of a logical judgment module to determine the zone for receiving materials each time. The capacity of each zone can feed the crusher for 8 hours without a new supply.

Figure 5 illustrates the proposed logical judgment module, which aims to enhance communication efficiency with external systems by sequentially dumping materials by area. For safety, each zone can only receive new dumping after the reclamation is fully finished. If the other two zones meet their capacity during this period, the dumping trucks will wait in line until the reclamation of the current zone is completed. At the same time, if a zone is in the refill phase and the other two zones are empty, the reclaim activity will be suspended until the current zone is fulfilled. Dumping and reclaiming must be performed strictly from zone 1 to zone 3. The incorporation of this module enables effective stockpile management and improves safety.

Similarly, the stockpile, crusher, conveyer, and other processing equipment form another relatively closed system, as shown in Figure 6. It is noteworthy that, in contrast to other mining methodologies, the NFS approach requires additional equipment to effectively reclaim materials from the stockpile. Furthermore, the reclaiming activity demands the incorporation of a logical module that facilitates a harmonious interplay with the dumping decision reclaim module. The objective is to ensure an optimal reclaiming sequence and avert potential conflicts between the two systems. The logic module is encapsulated in a dotted box in the figure for clarity. Notably, the post-crushing process in NFS follows the same sequence as the IPCC approach.

The truck request module and dispatch module in the two charts share the same principles. Specifically, the truck request module prioritizes the minimum travel distance, while the truck dispatching module favors the minimum queue length at the shovels. In scenarios where the queue lengths are identical, the shortest distance between the empty truck and the shovels assumes the highest priority. These criteria are instrumental in ensuring the efficient and expedient allocation of resources, thereby optimizing the productivity and profitability of the mining operations.

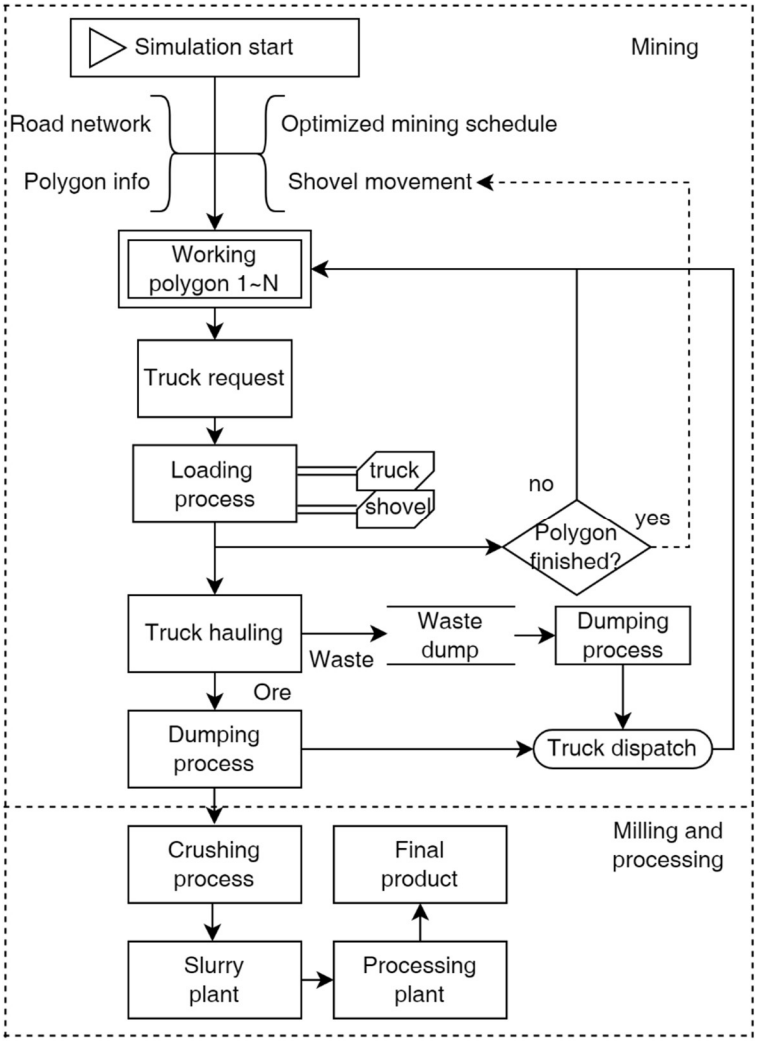


Figure 3. Flow chart of traditional out-of-pit crusher mining method.

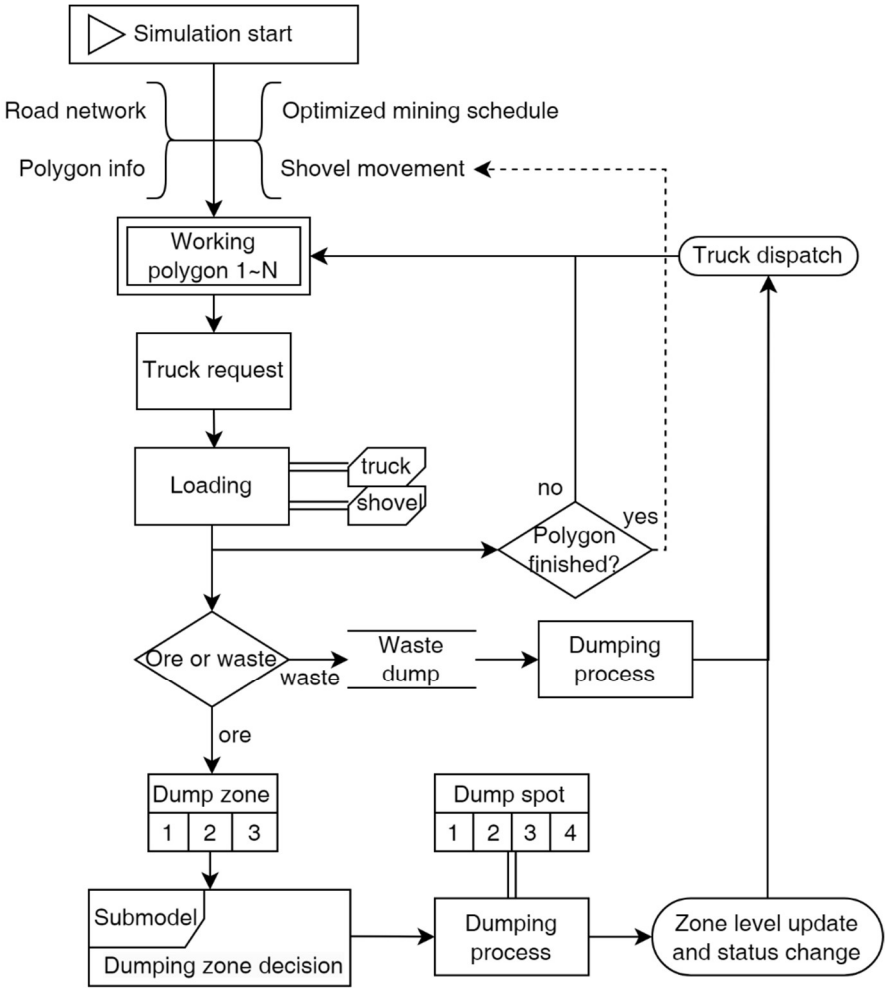


Figure 4. Diagram of mining process in the NFS method.

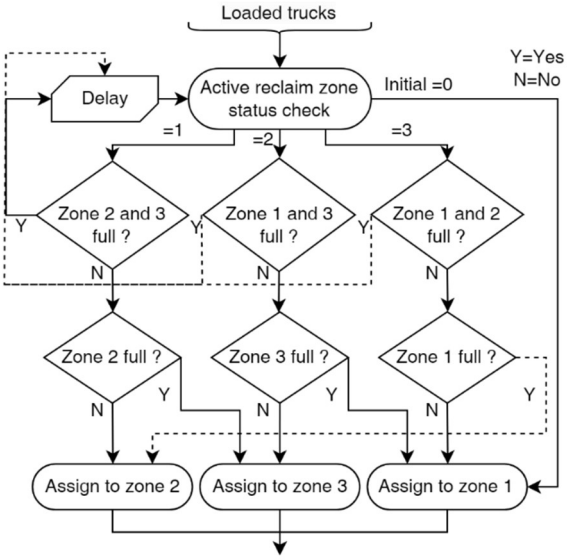


Figure 5. Logic of dumping zone decision sub model.

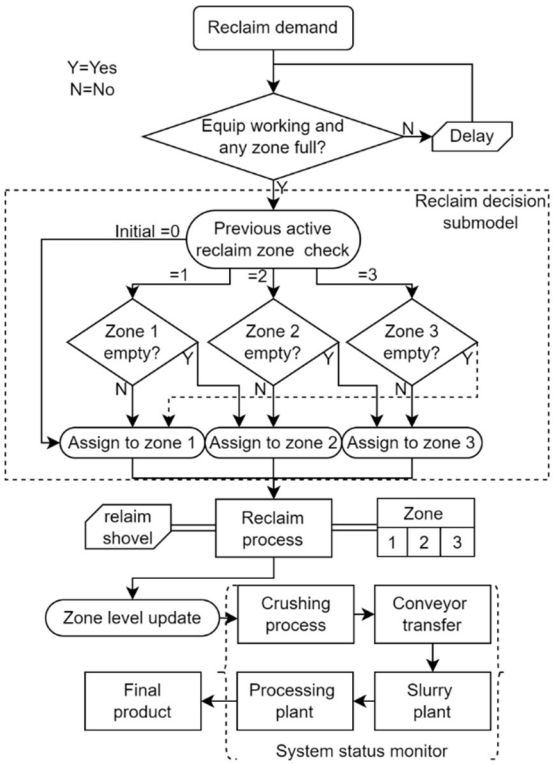


Figure 6. Diagram of crushing and processing process in the NFS method.

Once the optimization and simulation models are developed, they will be incorporated into a comprehensive framework capable of assessing the performance of a mining method. Specifically, the integration process involves importing the output of the optimization model, which is an optimized mining schedule, into the simulation model as an input parameter. This ensures that the mining sequence of blocks remains both reasonable and practical throughout the simulation process. In this study, Arena [28] is chosen as the simulation software to facilitate the simulation of various operations associated with different mining methods. The complete procedure for running the optimization-simulation framework is depicted in Figure 7.

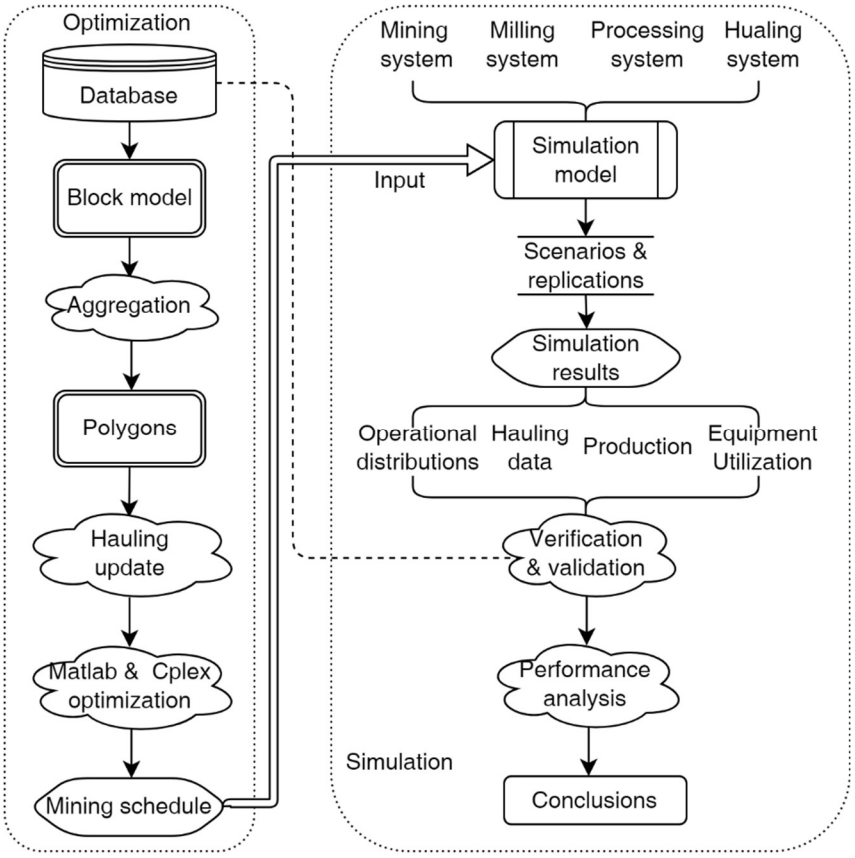


Figure 7. Optimization and simulation procedures needed to complete the case study.

4. Framework validation and NFS evaluation

In the preceding chapters, the author established a comprehensive optimization-simulation framework to evaluate the performance of a mining method. However, prior to using this framework to assess the NFS method and address the research objective, its effectiveness must be verified. To validate the framework, we will implement an oil sands mine case study using the traditional method and take the resulting outcomes as a benchmark for further evaluation. The validation process will entail running the optimization model according to the block model and obtaining a near-optimal and practical mining schedule. Subsequently, we will use this optimized schedule as the input of to the simulation model and run it for ten replications to reduce errors and enhance result reliability. Finally, we will compare the simulation results with actual operating records across multiple dimensions to verify the effectiveness of the framework. After the validation, a detailed comparison between the NFS model and the traditional model is conducted, leading to a conclusion that the NFS mining method outperforms the traditional mining method across multiple metrics.

4.1. Validation

An oil sands mine case study, with two working shovels and sixteen trucks is implemented to verify the proposed simulation and optimization model. The historical data retrieved from the mining fleet management system reveal that, in 2016, the enterprise mined a total of 93.09 million tons of material, consisting of 60.73 million tons of ore material with an average density of 2.1 ton/m3 and average grade of 11.38%. The remaining is different types of waste and the density fluctuate between 2.0 to 2.5 ton/m3.

The total material is assumed to be excavated from 1773 blocks, each with a child size of 50m (length) by 50m (width) by 10m (height), and the total assumed volume is 44.325 million cubic meters. Combining with the total tonnage excavated in reality, the overall density is 2.1 ton/m3, which is close to reality. It is noteworthy that the enterprise's mining and processing capabilities are limited to a monthly output of 9.4 million tons and 6 million tons, respectively. Meanwhile, the minimum acceptable mining tonnage per month is 5.4 million tons. These upper and lower limits are crucial in determining the feasibility and effectiveness of the mining operations and must be considered in any operational strategy or planning. The discount rate of revenue and costs in the case study is set to one percent per month.

Although 1773 blocks are insignificant, when put into the optimization model, 42588 decision variables will be generated, dramatically slowing down the optimization speed. Therefore, the author aggregates the blocks into mining cuts, which have a bigger size. The hierarchical clustering algorithm adopted in this paper was developed by Tabesh [29]. Their algorithm considers max cluster size, the distance between blocks, block grade difference, rock type difference, and many other factors. Different weights could be given based on preference. The mining cuts obtained using this algorithm can maintain the relative physical position between the original blocks so that the mining sequence generated after aggregation remains reasonable. After aggregation, thirty-eight new "blocks" were obtained. Then, two short-term near-optimal mining sequences are generated for the case study. One is for the traditional out-of-pit crusher mining method, and the other is for the NFS mining method. Formulations used for TS optimization are proposed by Tabesh and Askari-Nasab, as referenced earlier. The traditional one is taken as a benchmark, and its formulations are listed in [30]. Both optimization models are formulated in MATLAB [31] and solved by CPLEX [32] through API. Meanwhile, a simulation model for traditional method is also developed based on the flow chart shown in Figure 3. The processes needed to finish the simulation and optimization-model are shown in Figure 7. Six independent variables and two dependent variables are defined as key performance indicators (KPIs) in Table 1 to validate the proposed simulation model.

Table 1 KPIs to be measured and compared.

Type	Variables
Independent variables	Average tonnage/truck (ton)
	Loading time (min)
	Dumping time (min)
	Empty speed (km/h)
	Full speed (km/h)
	Haul distance (km)
Dependent variables	Cycle ready time (min)
	Ton per gross operating hour (TPGOH) (ton/h)

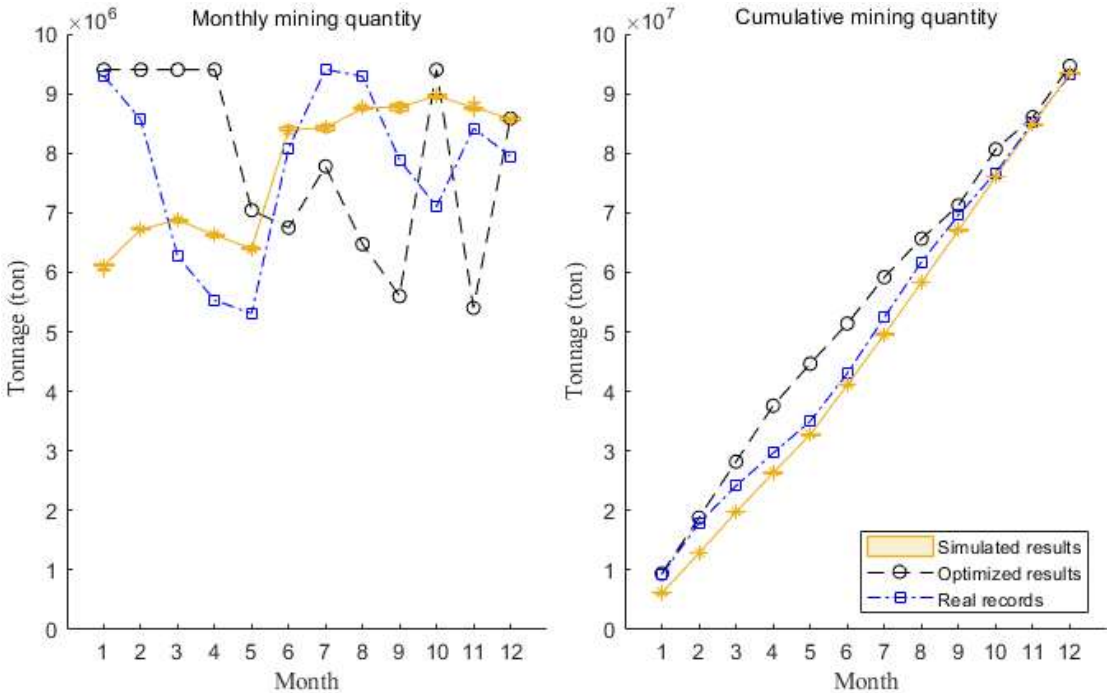


Figure 8. Monthly mining quantity (left) and cumulative mining quantity (right) of traditional mining method under three scenarios: optimized mining schedule, simulated mining schedule and original mining schedule.

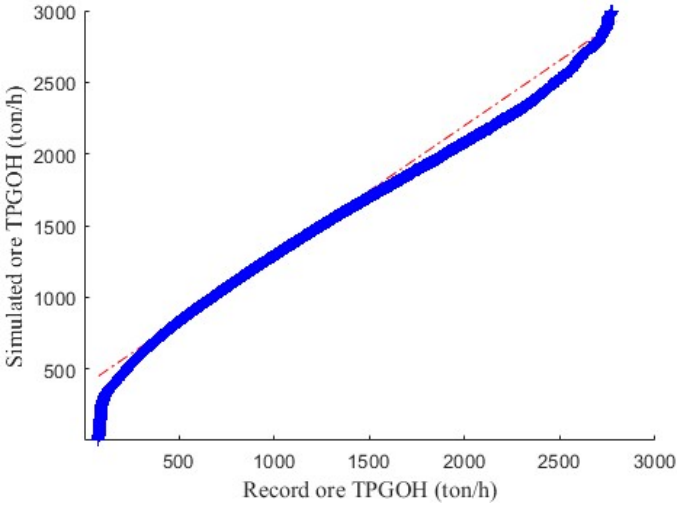


Figure 9 QQ plot of ore TPGOH under real operation versus simulated ore TPGOH under traditional mining method.

The simulation length was set to 12 months and 366 days, considering the leap year of 2016, to obtain results for comparison after running the model for 10 replications. The left graph in Figure 8 displays the total tonnage moved in each month under three schedules: optimized, real, and simulated. Although the simulation model takes the optimized schedule as input, the simulated schedule is not the same due to the incorporation of numerous uncertainties into the system. Nevertheless, in comparison to the other two schedules, the simulation model performed well, with results fluctuating within a reasonable range and never exceeding its nominal capacity or falling below the minimum acceptable value. The right graph in Figure 8 shows the cumulative tonnage excavated within the given period. The simulation results followed the same trend as operations under the real schedule and achieved almost the same level of production, which clearly validated the simulation model.

However, the primary focus of mining companies has always been on the ore material. In this regard, Figure 9 displays the QQ plot of the TPGOH distribution of ore between the simulated and recorded results. The primary distribution area does not exhibit any significant differences except for TPGOH values lower than 200 and higher than 2800. This consistency in the results demonstrates that the simulation model can effectively represent real operations.

Besides, the comparisons of predetermined KPIs between simulated results and record are presented in Table 2, which also serves as compelling validation for the simulation model. 'Rec' in table represents record and 'SimTra' in tables and ‘TRA’ in figures represent the simulated result of the traditional mining method. Taking the average payload of trucks per cycle as an example, the difference between the simulated data and the records is only 0.62%, and the difference between the annual mining tonnage is 0.31%. Although the average difference of other independent variables increased slightly, the difference range only fluctuates in a narrow range, indicating that the consistency of these variables is confirmed. As for the dependent variables, the difference is about 7%, which also falls within an acceptable range. These observations clearly demonstrate the model's ability to capture real mining operations. It worth mentioning that all the simulation results provided in this paper have 95% confidence intervals.

Table 2. Comparison of KPIs between record and simulated results.

Operational data	Range	Mean	Summation
Average tonnage/truck(ton) - Rec	470	337	93,090,766
Average tonnage/truck(ton) - SimTra	470±0	335±0.32	93,374,636±189,085
Difference	0.00%	-0.59%	0.30%
Loading time(min) - Rec	5	2.42	668,739
Loading time(min) - SimTra	5±0	2.89±0	805,227±1,968
Difference	0.00%	19.42%	20.41%
Dumping time(min) - Rec	2.67	0.95	263,116
Dumping time(min) - SimTra	1.64±0.2	0.95±0	265,428±398
Difference	-38.58%	0.00%	0.88%
Empty speed(km/h) - Rec	65	28.06	-
Empty speed(km/h) - SimTra	64±2.7	28.62±0.02	-
Difference	-1.54%	2.00%	-
Full speed(km/h) - Rec	65	26.49	-
Full speed(km/h) - SimTra	58.44±0.38	26.1±0.04	-
Difference	-10.09%	-1.47%	-
Haul distance(km) - Rec	8	3.91	1,078,647
Haul distance(km) - SimTra	7.99±0	3.88±0.01	1,079,935±2,252

Difference	-0.12%	-0.77%	0.12%
Cycle ready time (min) - Rec	75	26.48	7,308,292
Cycle ready time (min) - SimTra	100±52	24.6±0.03	6,851,909±13,464
Difference	33.33%	-7.10%	-6.24%
TPGOH- Rec	2,829	917.1	253,155,367
TPGOH- SimTra	2,957±662	980±1.81	272,966,328±651,926
Difference	4.35%	6.39%	7.83%

4.2. Distance and TPGOH

After the validation of the simulation model, the following sections will compare the results of the simulation model of the NFS method the traditional method from various aspects and quantitatively analyze the performance of the NFS method. Like the IPCC method, the crusher in the NFS method is located at the pit bottom, which can significantly reduce the truck transportation distance of the ore material. In this case study, compared to the traditional method, the average ore moving distance by truck in the NFS method decreased significantly.

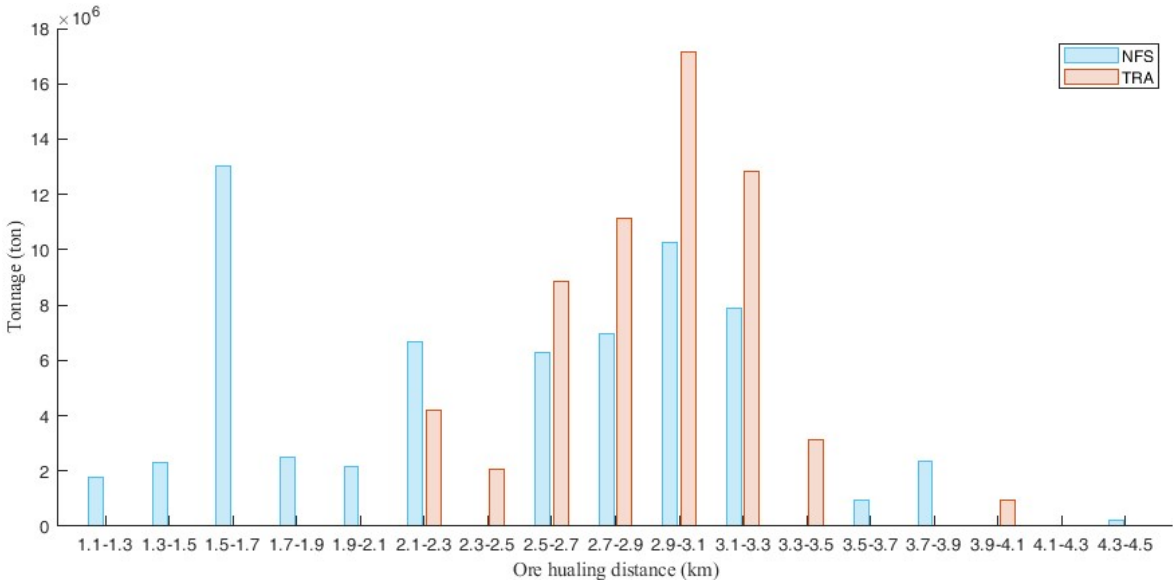


Figure 10. Cumulative ore tonnage comparison in each hauling range under NFS mining method and traditional mining method

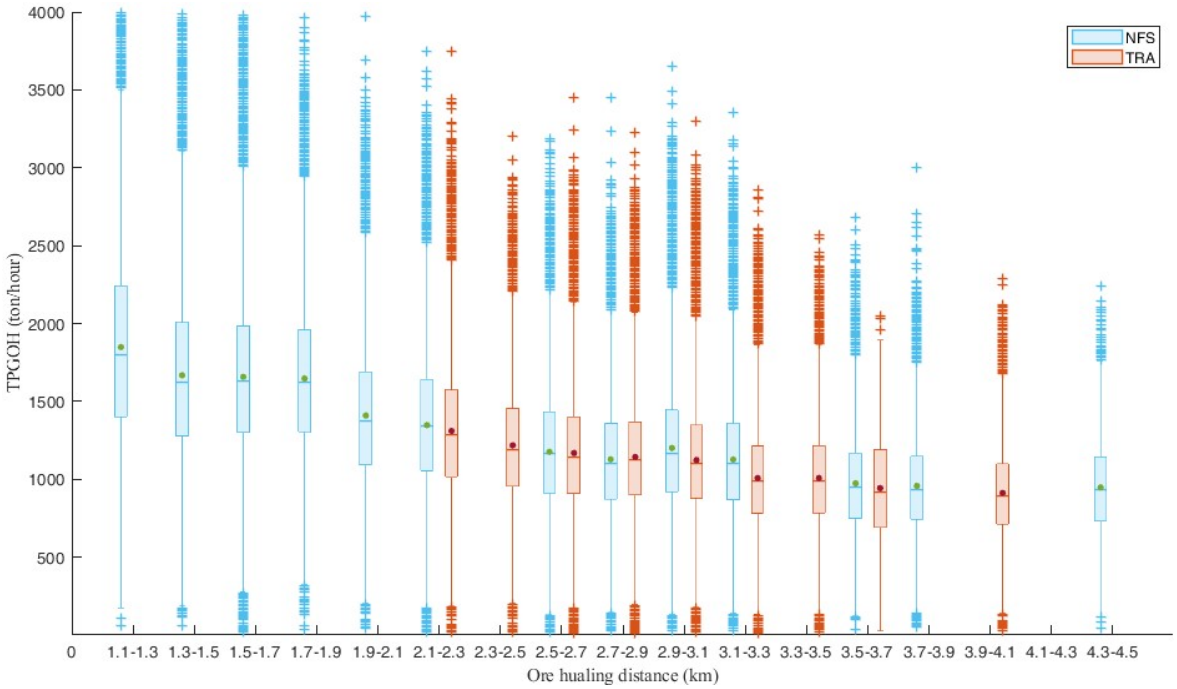


Figure 11. Ore TPGOH comparison in each hauling range under NFS mining method and traditional mining method.

Figure 10 is presented to illustrate the total tonnage of ore material in different distance ranges, before and after applying the NFS method. The minimum distance for ore transportation by truck was found to be between 2.1 and 2.3 kilometers before the application of the method, which decreased to a range of 1.1 to 1.3 kilometers after implementation. With the exception of 3 million tons of ore, most of the material experienced a reduction in haulage, with an average drop of 17.87% as shown in Table 3. The reduction in transportation distance resulted in a direct benefit of a 16.30% decrease in the average cycle time of ore trucks, which significantly improved operational efficiency. Additionally, it is well-known that shorter transport distances lead to higher TPGOH. To demonstrate this, Figure 11 shows the simulation results of ore TPGOH under different hauling ranges and mining methods. Table 3 indicates that the TPGOH of ore material in the NFS method increased by 19.71%.

Since the waste material is still transported to the out-of-pit dump locations only with trucks, there were no significant differences in the transportation efficiency and cycle time of waste material between the two methods, which is consistent with expectations. Similarly, 'SimNfs' in chart and ‘NFS’ in figure represent simulation results of the NFS model.

Table 3. Distance related simulation data comparison of two methods.

Operational data	Range	Mean	Summation
Ore cycle time(min) - SimTra	568±52	19.81±0.06	3,585,891±16,839
Ore cycle time (min) - SimNfs	331±467	16.58±0.08	3,145,992±16,078
Difference	-41.73%	-16.30%	-12.27%
Waste cycle time(min) - SimTra	165±24	33.46±0.08	3,266,018±11,407
Waste cycle time(min) - SimNfs	169±51	32.33±0.09	3,324,474±8,519

Difference	2.42%	-3.38%	1.79%
Ore haul distance(km) - SimTra	1.81±0	2.91±0	526,510±1,209
Ore haul distance (km) - SimNfs	3.34±0	2.39±0	453,376±864
Difference	84.53%	-17.87%	-13.89%
Waste haul distance (km) - SimTra	7.98±0	5.67±0	553,425±2,205
Waste haul distance (km) - SimNfs	7.98±0	5.55±0.01	570,972±2,014
Difference	0.00%	-2.12%	3.17%
Ore TPGOH - SimTra	2,726±662	1,122±3.11	203,170,229±455,307
Ore TPGOH - SimNfs	3,590±1740	1,344±343	254,946,861±1,047,751
Difference	31.69%	19.79%	25.48%
Waste TPGOH - SimTra	2,957±365	715±1.59	69,796,099±215,856
Waste TPGOH - SimNfs	2,853±245	737±2.53	75,797,750±220,647
Difference	-3.52%	3.08%	8.60%

4.3. Productivity

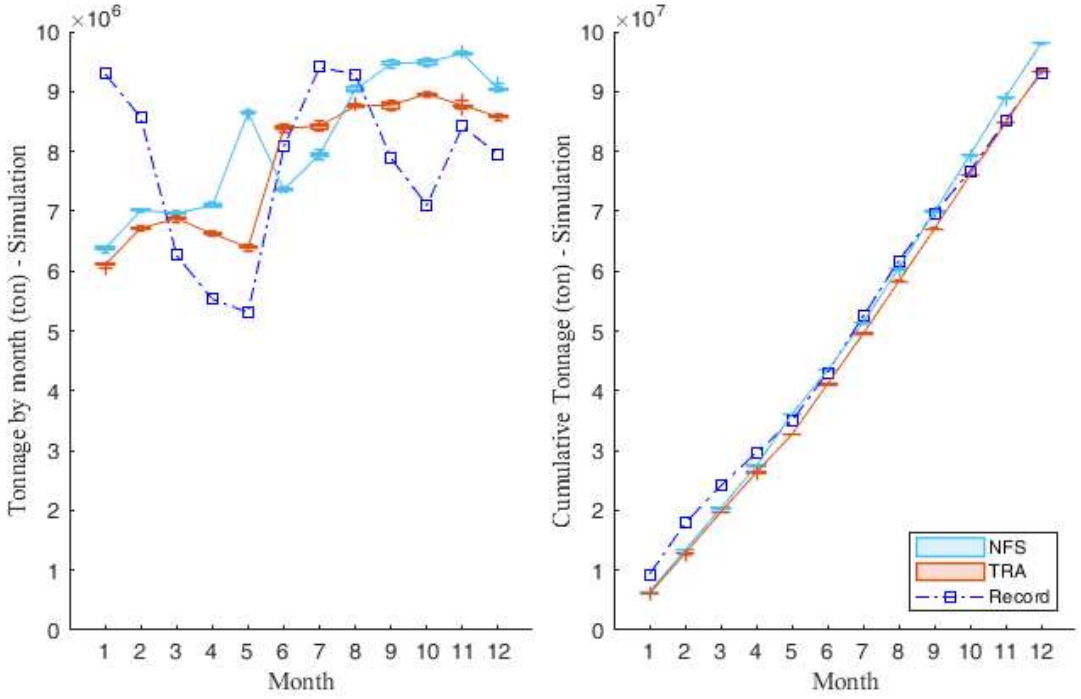


Figure 12 Average monthly production and cumulative production of NFS mining method and traditional mining method compare against record.

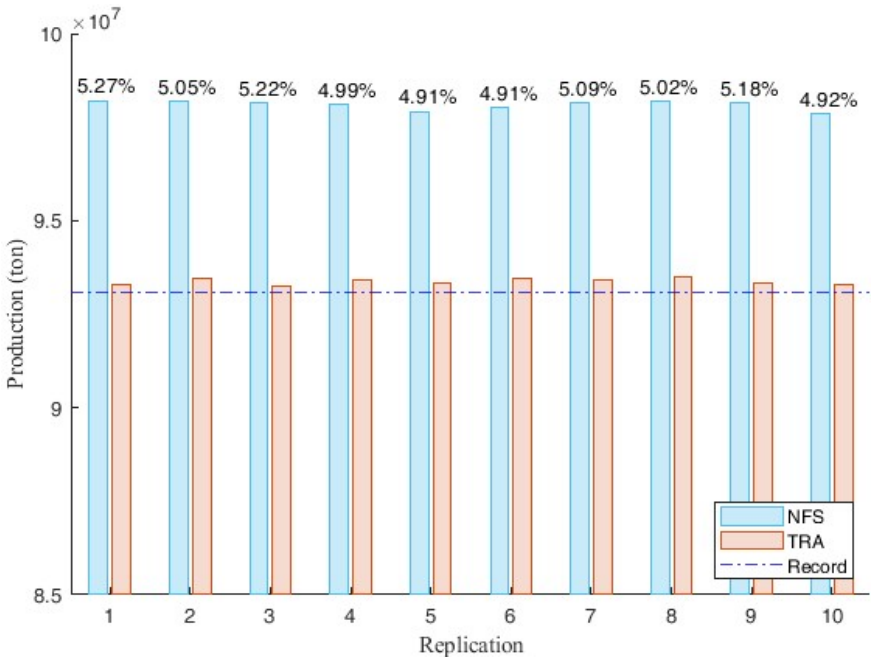


Figure 13 Simulated annual production comparison between NFS mining method and traditional mining method.

In this section, we demonstrate the impact of improved truck efficiency and TPGOH on the tonnage of material transported to the crusher/stockpile per unit of time and ultimately, on production rate. Our results show that with the same number of trucks, the NFS method outperforms the traditional method in terms of production. Figure 12 displays the monthly average and annual production of both methods, indicating that in most months, the NFS method yields higher production and overall cumulative tonnage. The average production results of ten replications are shown in Table 4 and year by year comparison are shown in Figure 13. Our findings indicate that compared to the traditional mining method, the NFS method improves yearly production by 5.06%.

Table 4. Tonnage related simulation data comparison of two methods.

Operational data	Range	Mean	Summation
Average tonnage/truck(ton) - SimTra	470±0	335.15±0.32	93,374,636±189,085
Average tonnage/truck(ton) - SimNfs	470±0	335.31±0.65	98,096,248±270,705
Difference	0.00%	0.05%	5.06%

4.4. Equipment utilization

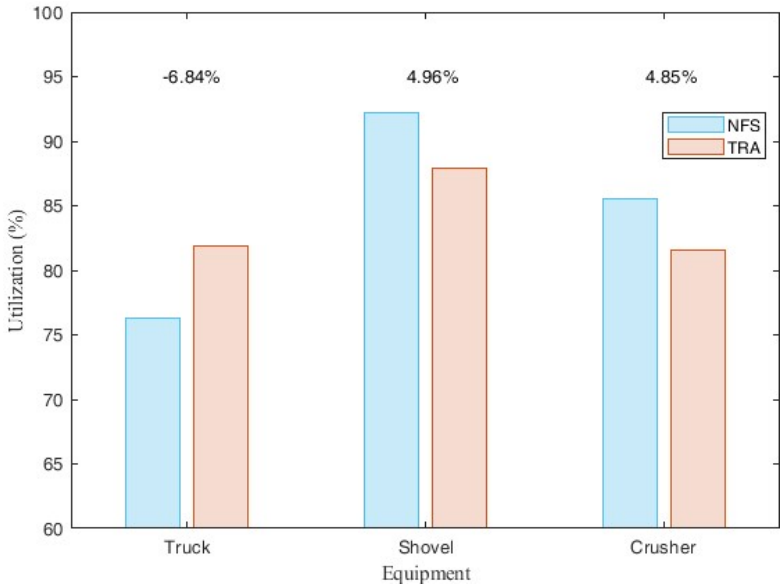


Figure 14 Trucks', shovels', and crusher' utilization comparison between NFS mining method and traditional mining method.

The increase in production can be attributed to the enhanced utilization rates of the crusher and shovels. As shown in Figure 14, demonstrates that the utilization rates of shovels and crusher under the NFS method are elevated by 4.96% and 4.85%, respectively, as compared to the traditional mining method. However, the constant number of trucks used for transportation, coupled with the reduction in the distance covered, has led to an increase in the wait time in queue for trucks. Consequently, there is a decrease of 6.84% in the overall utilization rate of the trucks. It also shows that the NFS method inherits the advantages of IPCC and curtails the demand for trucks. The improved utilization rate of the crusher and shovels can be primarily attributed to the presence of the near-face stockpile. In the traditional method, a fully loaded crusher would result in waiting time for trucks to dump their loads, and if one of the shovels is under maintenance or engaged in mining waste blocks at a specific time, the crusher would remain idle. Although the NFS method cannot entirely eradicate this issue, it has minimized its frequency, thus enhancing the utilization rate of the equipment. Table 5 displays that the average truck waiting time at the crusher/stockpile has reduced by 57.14%. However, the truck wait time at the shovels has increased by 21.05%. Overall, the NFS method has the potential to optimize production efficiency in mining operations while reducing the number of trucks required for transportation.

Table 5. Queue time comparison of two methods.

Operational data	Range	Mean	Summation
Ore Dumping Queue (Min) - SimTra	553±55	1.26±0.06	227,631±9,818
Ore Dumping Queue (Min) - SimNFS	292±532	0.54±0.07	102,180±12,652
Difference	-47.25%	-57.14%	-55.11%
Waste Dumping Queue (Min) - SimTra	3.05±0.88	0.06±0.01	5,458±139
Waste Dumping Queue (Min) - SimNFS	3.12±0.58	0.06±0	5,273±203

Difference	2.30%	0.00%	-3.50%
Queue Time Before Shovel (Min) - SimTra	600±454	5.96±0.07	1,660,660±16,196
Queue Time Before Shovel (Min) - SimNFS	724±562	7.24±0.06	2,117,266±13,539
Difference	17.13%	21.48%	27.50%

5. Summary and conclusion

The NFS mining method is a new mining method that combines IPCC with a pre-crusher stockpile and theoretically has all the advantages of IPCC and stockpile. However, its performance is not verified. To tackle this problem, this paper presents an optimization-simulation based framework that can evaluate a mining method from multiple aspects, in a quantitative and objective manner. Running this framework to evaluate a mining method involves three steps: The first step is to establish and run an optimization model suitable for the target mining method and obtain a practical or even optimal mining schedule. The second step is to create a simulation model suitable for the target method and use the optimized mining schedule as input. Then run the simulation model for multiple replications and quantify the performance of this method. The last step is to compare the simulated results with the benchmark and objectively evaluate the pros and cons of the target method. Specifically, a short-term mining schedule optimization model for the NFS method based on mixed integer linear programming is proposed in this research and. Meanwhile, simulation models for the traditional TS mining method and the NFS method are also built. After that, the established simulation and optimization framework was applied to an oil sand mine, and the validation of the proposed framework was conducted by comparing the simulation results of the traditional mining method with real records. Subsequently, the framework was employed for the NFS mining method, and the simulation results were compared with the benchmark (i.e., the simulation results of the traditional mining method). Through these comprehensive steps, this study provides a novel and quantitative assessment of the NFS method's performance, allowing for the verification of its theoretical advantages.

In comparison to the conventional truck and shovel mining method, the NFS method showcases significant advantages. Notably, it achieves a reduction of 17.87% in the transportation distance covered by trucks, along with a shortened truck cycle time by 16.30%. Consequently, the TPGOH of ore material experiences a substantial increase of 19.79%. Additionally, the NFS method effectively mitigates idle time for shovels and the crusher, resulting in a respective utilization improvement of 4.96% and 4.85%. Simulation results also demonstrate a significant decrease of 57.14% in the dumping queue time preceding the crusher. By enhancing equipment efficiency and utilization, the NFS method ultimately achieves a remarkable production increase of 5.06%.

The findings of this study suggest that the NFS method has significant application value and is worthy of further research. Meanwhile, this research provides important insights into the potential of the NFS method for improving the system’s stability, mining efficiency, and productivity, and highlights the importance of simulation modeling in evaluating and optimizing mining methods.

The current research does not provide verification of quality blending, an essential theoretical advantage of the NFS method. Additionally, the study does not examine the influence of stockpile capacity size and the number of zones on the performance of the NFS method. These aspects hold significant importance in promoting and applying the NFS method, prompting the author to undertake further exploration.

6. Declaration of Competing Interest

None.

7. Reference

[1] Darling P (2011) SME mining engineering handbook. SME

[2] Osanloo M, Paricheh M (2020) In-pit crushing and conveying technology in open-pit mining operations: a literature review and research agenda. Int J Min Reclam Environ 34:430–457

[3] Dean M, Knights P, Kizil MS, Nehring M (2015) Selection and planning of fully mobile in-pit crusher and conveyor systems for deep open pit metalliferous applications. Future Mining, AusIMM, The University of New South Wales, Australia 146:219–225

[4] Yarmuch J, Epstein R, Cancino R, Peña JC (2017) Evaluating crusher system location in an open pit mine using Markov chains. Int J Min Reclam Environ 31:24–37

[5] Osanloo M, Paricheh M (2020) In-pit crushing and conveying technology in open-pit mining operations: a literature review and research agenda. Int J Min Reclam Environ 34:430–457

[6] Ozdemir B, Kumral M (2019) Simulation-based optimization of truck-shovel material handling systems in multi-pit surface mines. Simul Model Pract Theory 95:36–48. https://doi.org/https://doi.org/10.1016/j.simpat.2019.04.006

[7] Gong H, Tabesh M, Moradi Afrapoli A, Askari-Nasab H (2022) Near-face stockpile open pit mining: a method to enhance NPV and quality of the plant throughput. Int J Min Reclam Environ 1–16

[8] Hong S-Y, Bal A, Badurdeen F, Agioutantis Z, Hicks S (2020) Evaluation of bunker size for continuous/discrete flow systems by applying discrete event simulation: A case study in mining. Simul Model Pract Theory 105:102155. https://doi.org/https://doi.org/10.1016/j.simpat.2020.102155

[9] Jupp K, Howard TJ, Everett JE (2013) Role of pre-crusher stockpiling for grade control in iron ore mining. Applied Earth Science 122:242–255

[10] Koushavand B, Askari-Nasab H, Deutsch C V (2014) A linear programming model for long-term mine planning in the presence of grade uncertainty and a stockpile. Int J Min Sci Technol 24:451–459

[11] Smith ML, Wicks SJ (2014) Medium-term production scheduling of the lumwana mining complex. Interfaces (Providence) 44:176–194

[12] Souza F, Chaves LS, Burgarelli H, Nader A, Arroyo C, Alberto L (2018) Direct stockpile scheduling: Mathematical formulation. Dyna (Medellin) 85:296–301

[13] Bley A, Boland N, Froyland G, Zuckerberg M (2012) Solving mixed integer nonlinear programming problems for mine production planning with stockpiling. Optimization Online (http://www optimization-online org/DB_HTML/2012/11/3674 html)

[14] Paithankar A, Chatterjee S, Goodfellow R, Asad MWA (2020) Simultaneous stochastic optimization of production sequence and dynamic cut-off grades in an open pit mining operation. Resources Policy 66:101634

[15] Utley RW (2011) In-pit crushing. SME mining engineering handbook 941–956

[16] Borkovic A (1983) Computer simulation of truck and conveyor haulage at Bougainville Copper Ltd's Panguna mine. University of New South Wales

[17] Basu AJ, Baafi EY (1999) Discrete event simulation of mining systems: current practice in Australia. International Journal of Surface Mining, Reclamation and Environment 13:79–84

[18] Radlowski JK (1988) In-pit crushing and conveying as an alternative to an all truck system in open pit mines

[19] Bernardi L, Kumral M, Renaud M (2020) Comparison of fixed and mobile in-pit crushing and conveying and truck-shovel systems used in mineral industries through discrete-event simulation. Simul Model Pract Theory 103:102100. https://doi.org/https://doi.org/10.1016/j.simpat.2020.102100

[20] Peng S, Zhang D, Xi Y (1988) Computer simulation of a semi-continuous open-pit mine haulage system. International journal of mining and geological engineering 6:267–271

[21] Yilmaz E, Erkayaoglu M (2021) A discrete event simulation and data-based framework for equipment performance evaluation in underground coal mining. Min Metall Explor 38:1877–1891

[22] van Vianen T, Ottjes J, Lodewijks G (2014) Simulation-based determination of the required stockyard size for dry bulk terminals. Simul Model Pract Theory 42:119–128. https://doi.org/https://doi.org/10.1016/j.simpat.2013.12.010

[23] Sturgul JR (1987) How to determine the optimum location of in-pit movable crushers. International journal of mining and geological engineering 5:143–148

[24] Paricheh M, Osanloo M, Rahmanpour M (2017) In-pit crusher location as a dynamic location problem. J South Afr Inst Min Metall 117:599–607

[25] Lizotte Y, Bonates E (1987) Truck and shovel dispatching rules assessment using simulation. Mining Science and Technology 5:45–58

[26] Huerta JR, Silva RS, De Tomi G, da Silva ALMA (2022) A dynamic simulation approach to support operational decision-making in underground mining. Simul Model Pract Theory 115:102458

[27] Tabesh M, Askari-Nasab H, Peroni R (2015) A Comprehensive Approach to Strategic Open Pit Mine Planning with Stockpile Consideration. Application of Computers and Operations Research in the Mineral Industry (APCOM 2015)

[28] Rockwell Automation (2019) Arena

[29] Tabesh M, Askari-Nasab H (2013) Automatic creation of mining polygons using hierarchical clustering techniques. Journal of mining science 49:426–440. https://doi.org/10.1134/S1062739149030106

[30] Tabesh M, Askari-Nasab H, Peroni R (2015) A comprehensive approach to strategic open pit mine planning with stockpile consideration. In: Proceedings of the Thirty-seventh international symposium on applications of computers and operations research in mineral industry. Society for Mining, Metallurgy and Exploration, pp 326–332

[31] The MathWorks Inc. (2018) MATLAB R2018b

[32] CPLEX (2014) IBM ILOG CPLEX Optimization Studio Version 12.6

Pit Optimization Design Considering Minimum Mining Width for the Production Scheduling Problem

Samaneh Moradi Pirbalouti and Hooman Askari-Nasab
Mining Optimization Laboratory (MOL)
University of Alberta, Edmonton, Canada

ABSTRACT

Mine planning leads to prioritizing the extraction of blocks, which covers scheduling, and determining pit limits. Therefore, powerful equipment with substantial space requirements is employed to extract the materials. In recent studies, a main solution is the automatic design of functional sections, known as pushbacks. A practical design considers desirable mining or bench width at the bottom of the mine and between successive pushbacks. Therefore, this paper presents an optimization mathematical model including minimum mining width and constraints based on mixed integer linear programming. The model has two main objectives. The first one is to maximize total profit. The second objective is to decrease greenhouse gas emissions from transportation and production operations in the mine. Simultaneously, the introduced model investigates production scheduling problems for extraction, mining, and processing steps. Also, implemented approaches to solve the programming models from meta-heuristic to exact solution methods have been compared, and based on that, an exact solution methodology in Python using Gurobipy is chosen. For solving the problems on a large scale, a Simulated Annealing metaheuristic algorithm and a Genetic algorithm are applied. After analyzing the results, it is concluded for large-scale problems, the SA algorithm, and for short-scale problems the exact method is more efficient.

Keywords*: Pit optimization, production scheduling, push-back design, minimum mining width*

1. Introduction

In the pit mine design problem, the ore deposit is better to be determined by a three-dimensional array of blocks which has properties such as grade and tonnage. This 3-D array with different properties is named the block model that is the core concept in mining studies. The fundamental data for the mine planning problem is the block model with operational and geotechnical constraints, economic attributes and costs. Based on these initial data, the production scheduling problem is able to be designed for extraction, mining and processing steps. The main objective in all of these problems is to maximize profit and economic value of the project. Therefore, the base of mine planning problems is optimization using the proposed algorithms [1]. To calculate the economic value of the mine, it is necessary to define the final pit and its limitations which can indicate the ore and waste blocks [2].

Decision makers in a mining project should be aware to define extended and developed parts to make shovels operate easier around the mine. The best way is to consider a minimum bottom width and then exclude the lowest width to reach more width in the next levels. Also, this is important for mine planners to determine mining or bench width among distinct pushbacks of the project providing the

ISBN: 978-1-55195-503-2

required access for large shovels and other equipment. There are different tools to propose a mine planning, production scheduling and push-back design problem: Mixed Integer Linear Programming [1, 3, 4], Integer Programming [5], Dynamic Programming [6], Meta-heuristic Algorithms [1, 7-9], Stochastic Optimization [9-11]. This research aims to propose a comprehensive reference to assess and compare the existing studies and applied methods of modeling and solving the related problems on production scheduling and pit optimization which have considered minimum mining width and push-back design. Also, in this study an optimization mathematical model is proposed in which the pit and pushback design constraints are followed and considers minimum mining width limitation. To solve the MILP model in large-scale problems, a maximum flow algorithm is applied with a genetic algorithm. Based on the study of Paithannkar [7], the graph structure for maximum flow is created for multiple periods under uncertainty, and the flow in the arcs is controlled by a genetic algorithm to develop a production schedule. Also, another metaheuristic method of Simulated Algorithm which is used by Christian Both [9] is implemented. The model proposed in this research has two main objective functions. The first one is to maximize total profit which is total income minus capital costs and operational costs. The second objective is to decrease greenhouse gas emissions from transportation and production operations in the mine. Carbon emissions are produced from different sources when extracting, mining, and processing. Also, GHG from facilities such as trucks, and shovels and energy consumption affect the amount of carbon produced in the mine environment [6].

2. Literature Review

In this section, a comprehensive review of the research topic, production scheduling with minimum mining width is proposed and then some of the main studies about pit optimization and pushback design is discussed.

2.1. Production Scheduling with Minimum Mining Width

The minimum mining width is an important constraint that makes mine planning more profitable and practical. For the first time, this concept was introduced by the research of Wharton et al. [12] in which the effect of minimum mining width on net present value was studied. They investigated the application of an automated approach to include minimum mining width for Four-X pit outlines. The final NPV of the project has an optimized value since this reaches a reduction in NPV. The reason for achieving a less NPV is due to the waste stripping inclusion and a space for mining extra in case of a pit development. Pourrahimian et al. [3] developed two distinct mixed integer linear programming models for production scheduling, taking into account various linear constraints such as minimum mining width. The researchers also considered the accessibility and mobility of equipment as part of the problem. In addition, they employed block clustering prior to optimizing the schedule. The outcomes of their study demonstrated that the second model successfully generated a realistic mining schedule, allowing sufficient room for equipment maneuverability and preventing the scattering of excavation sequences within the designated scheduling period. Yarmuch et al. [8] proposed a model focused on maximizing the value of pushbacks in mining operations. In their model, they introduced a closeness factor as a measure of the mineability of a design. The researchers considered that pushbacks should possess sufficient mining width and be composed of connected blocks. Furthermore, each pushback was required to have a ramp connecting its bottom to the surface. Upon solving the model, they concluded that it effectively captured the mineability conditions and provided appropriate guidelines for pushback design. The optimized design achieved through their proposed method exhibited a notable improvement of 15.517 USD million (6.71%) in the net present value (NPV) of the case study.

Another study was conducted by Yarmuch et al. [13] about a novel optimization model for semi-practical pushbacks, taking into consideration operational conditions such as minimum operational width and connectivity among the blocks forming the pushbacks. The primary objective of the model

was to maximize the approximate net present value (NPV) of mining extraction. To address this problem, the researchers proposed an algorithm incorporating a Sliding Window Heuristic, variable bounding, and other preprocessing routines. By utilizing the proposed algorithm, they were able to obtain high-quality solutions within significantly less amount of time compared to directly implementing and solving the model formulation using MILP solvers. Malharkumar et al.[14] conducted a study on an iron deposit, focusing on the uncertainty of ore grade. They formulated a production scheduling problem to evaluate and generate a production schedule for the iron ore deposit. The researchers specifically examined a case study in India. The operational requirements such as minimum mining width at pit bottom and maximum vertical depth are considered for planning the mine project. Their findings indicated that proper planning and production scheduling have the potential to enhance the profitability of iron ore projects by minimizing in-situ grade variability and uncertainty regarding the spatial distribution of ore. Additionally, in the case study, out of the five production scenarios generated, the mining direction towards the north was preferred due to its ability to meet specified quality targets.

Nancel-Penard et al. [1] conducted a study focusing on the minimum mining width, aiming to enhance profitability by considering geospatial and design limitations. Their primary objective was to optimize the pushback design for strategic planning in an open-pit mining scenario. To achieve this, they developed an integer linear programming model to generate optimal ultimate pits based on three designated block models. To solve the model efficiently, they employed a modified Lerchs and Grossman algorithm alongside a preprocessing heuristic approach. The findings of their research indicated that the proposed preprocessing technique reduced computation time by a factor of 14 in one of the block models. Also, Moradi-Afrapoli et al. [15] proposed a study in which advanced analytics for surface mining is investigated. They studied in-pit crushing and equipment selection in their research and applied multi criteria decision-making methods.

2.2. Pit Optimization and Pushback Design

Tabesh et al. [16] put forth a multi-step approach to address the long-term production planning problem in open-pit mining. Their approach encompassed three essential components: controlled optimal phase-design, selective mining-unit characterization, and long-term production scheduling optimization. To tackle this problem, the researchers utilized a combination of a greedy heuristic, a local search algorithm, and a clustering algorithm. The pushback design algorithm they developed provided the mine planner with the ability to regulate the mineralized material and rock tonnage within each pushback. Furthermore, the results obtained from the pushback design procedure exhibited tonnage uniformity. Kaydim et al.[5] introduced an integer programming model aimed at optimizing the long-term production scheduling of open-pit mines by maximizing the net present value (NPV). The model considered both minimum and maximum achievable mining and processing capacity values. By optimizing the model, the researchers were able to maximize the NPV for an eight-year production period, achieving a negligible optimality gap. The results indicated that metal prices were the most influential parameter on the resulting NPV value, even in the optimized production scenario.

Xu et al.[6] presented an optimization problem for production scheduling in open-pit metal mines, considering ecological costs that incorporated the carbon emission cost of energy consumption. The researchers generated a series of geologically optimal pushbacks within the ultimate pit and arranged them using a Dynamic Programming (DP) model to obtain the optimal production schedule. When incorporating ecological costs, the model demonstrated a reduction of 2.8% in the total present value of ecological costs. On the other hand, in scenarios where ecological costs were not considered, the model showcased a 2.5% increase in the overall net present value. Gu et al. [17] introduced a push-back sequencing model to address the production planning problem in open-pit coal mining. The primary objective of their study was to develop a dynamic method for sequencing pushbacks and implementing a moving cone elimination algorithm to optimize coal production and waste stripping

rates. The proposed method also aimed to optimize the mining sequence and mine life of the coal mine. By applying this approach, the researchers obtained the best production schedule with the highest net present value (NPV). This schedule provided information on the optimal quantities of mined coal and waste for each year, the optimal mining zones, and the optimal mine life for the final pit.

Paithankar et al. [7] introduced a production schedule optimization method for open-pit mines, aiming to generate a long-term schedule that maximizes flow in multiple periods while considering uncertainty. Their approach utilized a hybrid of maximum-flow and genetic algorithms to solve the optimization problem. The resulting solution exhibited robustness, with an average gap of less than 6% compared to the upper bound solution, except for one case. The researchers also evaluated the method on deterministic instances and observed that it did not perform as well as certain existing methods. Nevertheless, the method can be easily adapted to handle deterministic models, incorporating various uncertainty modeling approaches, and accommodate additional scheduling constraints.

Pierre Nancel-Penard et al. [1] introduced a recursive time aggregation-disaggregation heuristic for addressing the multi-dimensional and multi-period precedence-constrained knapsack problem. They specifically applied this heuristic to the open-pit mine block sequencing problem to validate its effectiveness in maximizing profit while satisfying minimum and maximum resource consumption constraints. The proposed method utilizes a binary tree structure to recursively aggregate and disaggregate scheduling periods, solving two-period sub-problems sequentially. The researchers implemented sliding time window heuristics, highlighting the challenges encountered when solving scheduling instances with conflicting knapsack constraints. The application of this heuristic provides insights into optimizing resource allocation and scheduling in open-pit mining, considering complex constraints and multi-period considerations.

There are some other important studies on pit-optimization in which quantitative analysis of near-face stockpile mining is proposed. For example, Gong et al. [18] presented a study in which a mixed integer linear programming model was presented for integrated simulation and optimization problem. They implemented the quantitative analysis of near-face stockpile mining. Also, for validation of their model, they applied a case study of oil sand mine. Gong et al. [19] also, used near-face stockpile mining in the other study in which a method was implemented to increase net present value and quality of the plant throughput.

In Table 1, there is a comprehensive summary of the related studies about production scheduling and pushback design problems including minimum mining width assumption. After investigating these studies and their shortcomings, we can propose the most important contributions of the current research.

Table 1. Summary of the related research to minimum mining width in production scheduling and pushback design.

Year/Author	Main goal	Methodology/tools	Main Findings	Future Research
2022/ Nancel-Penard et al. [1]	● Determining the extracted volumes to maximize profit with minimum width at the mine.	● A MILP model ● The modified Lerchs and Grossman ● Preprocessing heuristic approach	● Lower computation time in the preprocessing ● A decrease in NPV between original and practical pushbacks.	● Using a spatial aggregation/disaggregation heuristic approach in Jélvez et al. (2016). ● Using a model able to generate production plans considering minimum width.
2009/ Pourrahimian et al. [3]	● Two alternative MILP production scheduling with minimum mining width ● To maximize the total discounted economic value, or NPV.	TOMLAB/CPLEX optimization solver	● Model 1 with higher discounted economic value and more run time than model 2. ● Model 2 with a practical schedule and enough space for equipment.	–
2021/ Yarmuch, J. L [8]	generate maximum value practical pushbacks with a closeness factor to quantify the design's mine ability.	● Python and Gurobi MIPsolver ● Commercial mine planning software ● Traditional methodology.	● Closeness factor is 89.34% in contrast to the 48.00% obtained from the traditional methodology.	● Aggregation technique to reduce the number of variables. ● Designing the pushbacks sequentially, in a greedy way.
2014/ Tabesh et al. [16]	A multi-step methodology for open-pit mine planning with controlled optimal phase-design, characterization of selective mining-units, and long-term production scheduling optimization.	● A methodology using integer programming (CPLEX). ● A greedy heuristic with a local search algorithm and clustering (MATLAB). ● The Lerchs and Grosmann, parameterization approach (Whittle).	● The push-back design algorithm is to control the mineralized material and rock tonnage in each push-back. ● The results from the pushback design are uniform in terms of tonnage.	-

Year/Author	Main goal	Methodology/tools	Main Findings	Future Research
2022/ Kaydım, H. E. [5]	An integer programming model to optimize the long-term production scheduling of open-pit mines by maximizing the NPV.	AMPL CPLEX module of the NEOS Server.	● Maximizing the NPV of eight-year production with a negligible optimality gap. ● The cost has the least effect on the NPV. ● Metal prices are the most influential parameter on the resultant NPV value.	● The two-dimensional model can be extended to a three-dimensional model. ● Variations in cost and revenue can be evaluated by sensitivity analysis. ● Multi-stockpile option can be included into the model.
2018/ Xu, X. C et al. [6]	● A method of open pit production scheduling to consider ecological costs as internal costs. ● A series of optimum pushbacks is generated and sequenced using a Dynamic Programming (DP) to obtain the best production schedule.	● The moving cone exclusive method. ● The method of generating geologically optimum pushbacks. ● The opportunity cost method to estimate the economic value of conserving soil.	● The schedule with ecological costs has lower production rates and a longer mine life than that without ecological costs. ● A reduction in NPV of ecological costs when using ecological costs and a gain in NPV in cases without ecological costs.	-
2011/ Gu, X. W. [17]	A dynamic sequencing method to optimize the coal production rate, waste stripping rate, mining sequence, and mine life of an open-pit coal mine.	● Dynamic pushback sequencing ● A moving cone elimination algorithm.	The highest NPV in the best production schedule, with the best quantities of coal and waste, the best zone to be mined in each year, and the best number of years to mine the entire final pit.	● Post-processing to adjust to the optimum solution. ● Solid programming
2020/ Malharkumar, P. et al. [14]	The production schedule for an iron ore deposit in India.	Lerchs and Grossmann algorithm (Geovia Surpac software and Whittle software)	● To increase the profitability of iron ore projects by minimizing in-situ grade variability and uncertainty. ● Significant quantity of overburden is dumped into the internal dump of the mine to reduce re-handling of overburden during the reclamation.	-

Year/Author	Main goal	Methodology/tools	Main Findings	Future Research
2019/ Paithankar, A. et al.[7]	The long-term production schedule for maximum flow in multiple periods under uncertainty.	The maximum flow algorithm with a genetic algorithm.	The method can be adapted to solve a deterministic model or any uncertainty modeling.	● Adding other sources of uncertainty, additional operational constraints, multiple destinations, introducing stockpiles and cut-off grade optimization.
2021/ Yarmuch, J. L et al. [13]	● A new optimization model for semi practical pushbacks with minimum operational width and connectivity within the blocks. ● To maximize NPV of the mining extraction.	An algorithm using Sliding Window Heuristic, variable bounding, and other preprocessing routines.	To obtain solutions with less than 10% optimality gap for mining instances ranging between 30,000 to 50,000 blocks.	● A general approach to model mining width to generalize rectangular templates to different shapes. ● The root relaxation offers a good approach to the final integer solution for large-size instances.
2020/Aref Alipour [20]	● A 3D Genetic Algorithm array is employed to reflect the 3D feature of the real mine block model. ● To maximize the NPV under sequencing and capacity constraints.	● Genetic Algorithm. ● The penalty and normalization methods ● SimSched commercial package.	● The computational time of GA was short in relation to the complexity of the OPPS[1] problem. ● GA could produce better solutions rather than SimSched DBS.	● Considering a more direct integration of block economic values and other operational constraints' uncertainty.
2021/ Gonzalo Nelis [21]	● propose an optimization mathematical model for operational issues.	● cut-off grade approach ● incorporate horizontal precedence constraints to ensure the existence of a feasible path from the bench access to each block.	● The model was able to generate mining cuts and an extraction sequence fulfilling mining, processing and operational constraints. ● The mining cut design captured most of the profit.	● Study the best location of the representative SMUs and their influence on production schedule. ● Appling heuristic algorithms ● Considering uncertainty in the parameters

[1] Open-Pit Production Scheduling

According to the previous studies and their shortcomings, the contributions and objectives of this work are as follows:

1. We develop a mixed integer linear programming mathematical model in which production scheduling constraints and optimizing the objective functions are investigated simultaneously.
2. We consider one important assumption, minimum mining width and related constraints in the mathematical model.
3. The proposed model includes two goals. The first objective function is to maximize the net present value. The second objective function is to decrease greenhouse gas emission from the operations in the mine.
4. In addition to production scheduling problems, the model aims at designing pushbacks, which is to digitize pushback considering the ramps and roads within the specified bench height, width and batter angle.

3. Mathematical Formulation (MILP)

In this section, we want to describe the mathematical optimization model which is used for production scheduling problem- with minimum mining width. Before introducing the model, we have presented the indices, parameters and variables.

3.1. Indices

T	The scheduling periods set
N	The set of blocks which are scheduled
K	The set of mining cuts which are scheduled

3.2. Parameters

gu^t	Maximum acceptable average head grade of ore being transported to the mill during time period "t".
gl^t	Minimum acceptable average head grade of ore being transported to the mill during time period "t".
g_k	Ore grade average within mining cut "k".
Ot_k	Amount of ore extracted in mining section "k"
W_k	Quantity of waste material in mining cut "k".
${PC_{max}}^t$	Maximum limit on the capacity for processing ore during time period "t
${PC_{min}}^t$	Minimum limit on the capacity for processing ore during time period "t
${MC_{max}}^t$	Maximum limit on the capacity for mining ore during time period "t
${MC_{min}}^t$	Minimum limit on the capacity for mining ore during time period "t
q_k^t	Discounted cost of mining all the material in mining cut k as waste and in the period t

v_k^t Net present value of revenue obtained from selling the end product within mining section "k" during period "t," subtracting the discounted additional expenses of extracting all material from mining cut "k" as ore and subsequently processing it.

α Pollution factor for extraction operation

β Pollution factor for processing operation

3.3. Variables

s_k^t The proportion of mining cut "k" to be extracted as ore and subjected to processing during time period "t."

y_k^t The proportion of mining cut k intended for mining during period t.

X_n^t The sequence of extraction of blocks, equal to 1 if block n is to be mined in period t, otherwise 0.

b_k^t A binary variable that indicates the priority of extracting mining cut k in period t.

The production scheduling with minimum mining width model (PSMW) in this problem has two objective functions. The first one is maximization of total profit which is total revenue minus total costs. The second one is minimization of total greenhouse gas emission from mining and processing operations. The PSMW model developed from pourrahmanian et al. [3] is formulated by merging concepts from Caccetta et al. [22] and Boland et al. [23]. In this model, both mining and processing are operated on the mining-cut level. Before optimizing the schedule, the blocks are categorized into clusters, and two continuous variables present ore processing and mining activities. Within the mining bench, blocks are grouped into clusters, considering their attributes, spatial coordinates, rock composition, and grade distribution.

The PSMW model is proposed as below:

$$\sum_t \sum_k v_k^t \times s_k^t - q_k^t \times y_k^t \tag{1}$$

$$\sum_t \sum_k (\beta \times s_k^t - \alpha \times y_k^t) \tag{2}$$

Equations (3) through (5) manage constraints related to grade blending, processing capacity, and mining capacity on the mining-cut level while considering fractional extraction from mining cuts.

$$gl^t \leq \frac{\sum_k g_k \times Ot_k \times s_k^t}{\sum_k Ot_k \times s_k^t} \leq gu^t \qquad \forall t \in \{1, \dots, T\} \tag{3}$$

$$PC_{min}{}^t \leq \sum_k Ot_k \times s_k^t \leq PC_{max}{}^t \qquad \forall t \in \{1, \dots, T\} \tag{4}$$

$$MC_{min}{}^t \leq \sum_k (Ot_k \times W_k) \times y_k^t \leq MC_{max}{}^t \qquad \forall t \in \{1, \dots, T\} \tag{5}$$

Equation (6) guarantees that the quantity of ore extracted and processed from a specific mining cut during any given period remains equal to or less than the amount of rock extracted from that same mining cut.

$$s_k^t \leq y_k^t \qquad \forall t \in \{1, \dots, T\} \quad \forall k \in \{1, \dots, K\} \tag{6}$$

Equations (7) and (8) verify the group of directly preceding cuts that need to be extracted before mining cut k can be extracted.

$$\sum_i y_k^i - b_k^t \leq 0 \qquad \forall t \in \{1, \dots, T\} \quad \forall k \in \{1, \dots, K\} \tag{7}$$

$$b_k^t - b_k^{t+1} \leq 0 \qquad \forall t \in \{1, \dots, T-1\} \quad \forall k \in \{1, \dots, K\} \tag{8}$$

$$0.4(\text{Int (m)}) X_{Wb}^t - \sum_{n=1}^{m} X_n^t \leq 0 \qquad \forall t \in \{1, \dots, T\} \quad \forall Wb \in \{1, \dots, N\} \tag{9}$$

Equation (9) indicates binary and continuous variables in the model.

$$b_k^t, X_n^t \in \{0, 1\}, \qquad s_k^t \geq 0 \quad y_k^t \geq 0 \tag{10}$$

4. Problem Solution

In this section, the suggested solution methods are presented. Since the problem is presented as a mixed integer multi-objective optimization model, the exact epsilon-constraint method is used to solve the small numerical experiments and is solved in Python software. Then, to solve the model with medium and large-scale numerical examples, the meta-heuristic algorithm of simulated annealing (SA) and genetic optimization of non-dominant ranking (NSGA-II) are used.

When working with meta-heuristic algorithms, setting the parameters of the algorithms is very important. These parameters are performed through numerical experiments. There are different methods to design the numerical experiments. One of the methods is to adjust the parameters by Taguchi including a series of experiments with a fractional factor. According to Taguchi [24], the factors affecting parameter setting are generally divided into two groups of controllable factors and uncontrollable factors. In this method, the objective is to reach optimal levels of controllable factors and reducing the effects of uncontrollable factors. This is necessary to measure the qualitative characteristics of the tests as S/N ratio. Where S represents the value of the signal and N represents the noise. This ratio indicates deviations in the response variable (objective function). In this way, each algorithm is parameterized based on the target value of the problem. The parameter setting is performed two times.

After setting the parameters of algorithms, we compare the performance of two non-dominant genetic algorithms and simulated annealing. We use the method of relative performance increase, which is defined as the following formula.

$$RPI_s = \frac{f_s - f_b}{f_b} \times 100 \tag{11}$$

In the above relation, f_s means the value of the objective function, calculated by the applied algorithm. f_b is equal to the most optimal objective value obtained from the algorithms. To ensure more efficiency of the algorithms, each numerical example should be solved at least10 times. Based on the result and RPI calculated of each objective function, this is expected that the meta-heuristic algorithms have the higher performance for large-scale problems (n>17). Also, for small-scale problems, this is expected that the exact solution method has more efficiency.

Figure 1 and 2 show that for numerical examples with scale<17, exact solution method is capable to obtain optimal solutions and less running time, while for problems with scale>17, meta-heuristic algorithms are able to give more efficiency and less running time.

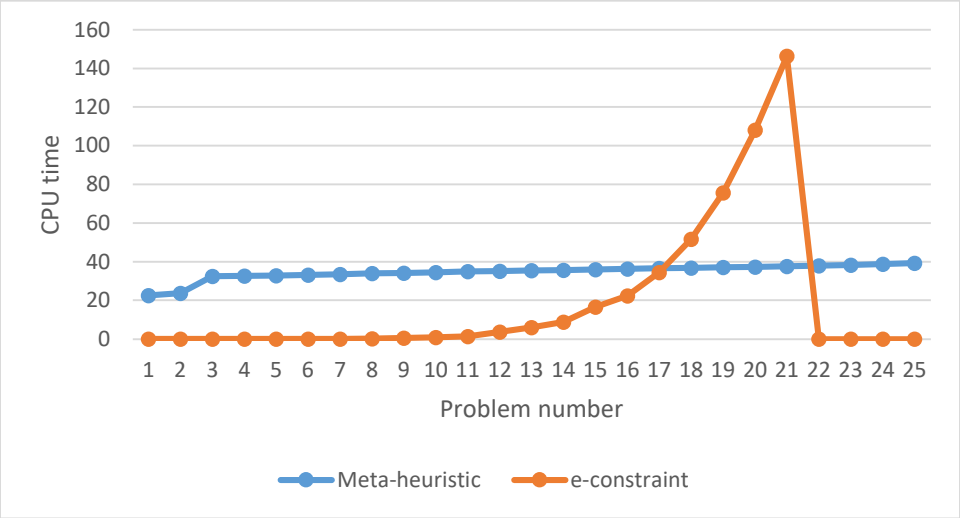


Figure 1. Running time for two solution methods.

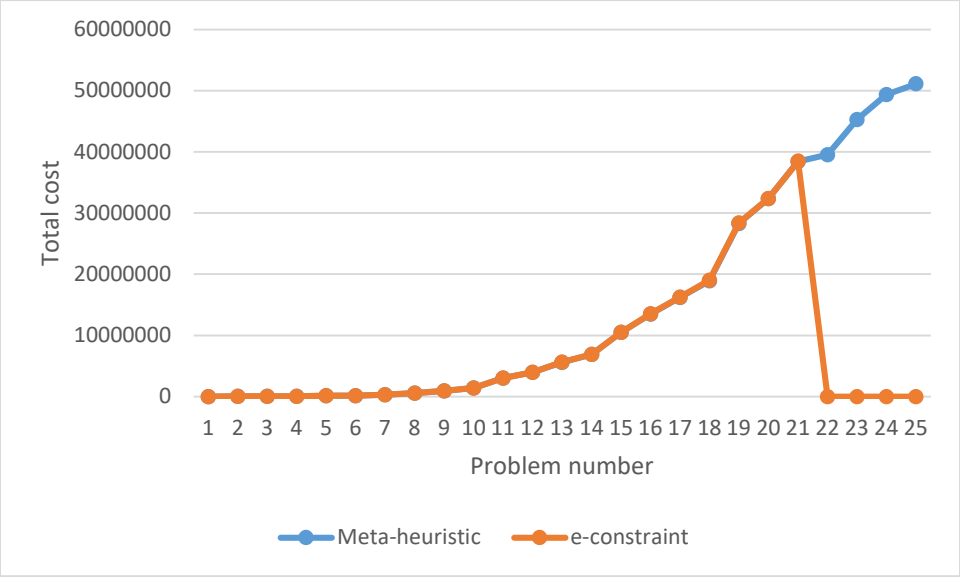


Figure 2. The efficiency of two solution methods.

5. Conclusion

The mixed-integer linear programming formulation for the PSMW problem was introduced in the mathematical formulation section. This model aims to control extraction, processing, and the sequence operations of blocks at the mining-cut level, offering a more efficient problem size and computational time. The proposed model was evaluated using block model data in the studied problem of Nancel-Penard et al. [1]. The PSMW model has two main objective functions. The first one is to maximize total profit which is total income minus investment and operational costs. The second objective is to decrease greenhouse gas

emissions from transportation and production operations in the mine. Simultaneously, the introduced model investigates production scheduling problems for extraction, mining and processing steps. The MILP is applied for a case study to indicate the validation and ability of the model in generating practical solutions. Also, implemented approaches to solve the programming models from meta-heuristic to exact solution methods have been compared, and based on that, an exact solution methodology for pit design to solve the mathematical mixed integer linear programming model with the exact solution method in Python using Gurobipy is chosen. For solving the problems on a large scale, a Simulated Annealing metaheuristic algorithm and a Genetic algorithm are applied. After analyzing the final solutions from different methods, it is concluded that for large-scale problems SA and NSGA-II algorithms and for short-scale problems the exact method (epsilon-constraint) is more efficient in terms of running time, efficiency and optimal solutions.

6. References

[1] Nancel-Penard, P. and N. Morales, Optimizing pushback design considering minimum mining width for open pit strategic planning. Engineering Optimization, 2022. 54(9): p. 1494-1508.

[2] Dagdelen, K. Open pit optimization-strategies for improving economics of mining projects through mine planning. in 17th International Mining Congress and Exhibition of Turkey. 2001.

[3] Pourrahimian, Y., H. Askari-Nasab, and D. Tannant, Production scheduling with minimum mining width constraints using mathematical programming. 2009.

[4] Jélvez, E., N. Morales, and H. Askari-Nasab, A new model for automated pushback selection. Computers & Operations Research, 2020. 115: p. 104456.

[5] Kaydım, H.E., Long-Term Production Scheduling Optimization for A Polymetallic Open Pit Mine. 2022, Middle East Technical University.

[6] Xu, X.-c., et al., Production scheduling optimization considering ecological costs for open pit metal mines. Journal of cleaner production, 2018. 180: p. 210-221.

[7] Paithankar, A. and S. Chatterjee, Open pit mine production schedule optimization using a hybrid of maximum-flow and genetic algorithms. Applied Soft Computing, 2019. 81: p. 105507.

[8] Yarmuch, J.L., et al., A mathematical model for mineable pushback designs. International Journal of Mining, Reclamation and Environment, 2021. 35(7): p. 523-539.

[9] Both, C. and R. Dimitrakopoulos, Joint stochastic short-term production scheduling and fleet management optimization for mining complexes. Optimization and Engineering, 2020. 21(4): p. 1717-1743.

[10] Huang, S., et al., A stochastic mixed integer programming framework for underground mining production scheduling optimization considering grade uncertainty. IEEE Access, 2020. 8: p. 24495-24505.

[11] Tabesh, M. and H. Askari-Nasab, Clustering mining blocks in presence of geological uncertainty. Mining Technology, 2019.

[12] Wharton, C. and J. Whittle, The effect of minimum mining width on NPV, in Optimizing with Whittle. 1997, Whittle Programming Pty. Ltd Perth, Western Australia. p. 173-178.

[13] Yarmuch, J.L., et al., A model for open-pit pushback design with operational constraints. Optimization and Engineering, 2021: p. 1-17.

[14] PALEI, S.K. and S. CHOUDHURY, Production scheduling of an iron deposit under ore grade uncertainty. Journal of Mines, Metals & Fuels, 2020. 68(3).

[15] Moradi-Afrapoli, A. and H. Askari-Nasab, Advanced Analytics for Surface Extraction, in Advanced Analytics in Mining Engineering: Leverage Advanced Analytics in Mining Industry to Make Better Business Decisions. 2022, Springer. p. 181-203.

[16] Tabesh, M., C. Mieth, and H. Askari–Nasab, A multi–step approach to long–term open–pit production planning. International Journal of Mining and Mineral Engineering, 2014. 5(4): p. 273-298.

[17] Gu, X.W., et al., A push-back sequencing model for production planning in open-pit coal mining. Applied Mechanics and Materials, 2011. 88: p. 219-224.

[18] Gong, H., A.M. Afrapoli, and H. Askari-Nasab, Integrated Simulation and Optimization Framework for Quantitative Analysis of Near-face Stockpile Mining. Simulation Modelling Practice and Theory, 2023: p. 102794.

[19] Gong, H., et al., Near-face stockpile open pit mining: a method to enhance NPV and quality of the plant throughput. International Journal of Mining, Reclamation and Environment, 2023. 37(3): p. 200-215.

[20] Alipour, A., et al., Production scheduling of open-pit mines using genetic algorithm: A case study. International Journal of Management Science and Engineering Management, 2020. 15(3): p. 176-183.

[21] Nelis, G. and N. Morales, A mathematical model for the scheduling and definition of mining cuts in short-term mine planning. Optimization and Engineering, 2021: p. 1-25.

[22] Caccetta, L. and S.P. Hill, An application of branch and cut to open pit mine scheduling. Journal of global optimization, 2003. 27: p. 349-365.

[23] Boland, N., et al., LP-based disaggregation approaches to solving the open pit mining production scheduling problem with block processing selectivity. Computers & Operations Research, 2009. 36(4): p. 1064-1089.

[24] Mitra, A., The taguchi method. Wiley Interdisciplinary Reviews: Computational Statistics, 2011. 3(5): p. 472-480.

Optimizing Green Truck Dispatch in an Open Pit Mine through a Multi-Objective Simulation and Optimization Framework with Fuel Consumption Consideration

Mohammadreza Kazemi Ashtiani[a], Ali Moradi Afrapoli[b], John Doucette[c] and Hooman Askari-Nasab[a]

Mining Optimization Laboratory (MOL)

[a] University of Alberta, Edmonton, Canada

[b] Université Laval, Québec City, Canada

[c] Department of Mechanical Engineering, University of Alberta, Edmonton, Canada

ABSTRACT

In open pit mining, trucks play a vital role in transporting materials. By optimizing truck dispatching strategies, both productivity and sustainability principles can be effectively enhanced. This research focuses on developing a new framework for green truck dispatching, aiming to accomplish four specific objectives: minimizing the deviations from target production rates set by strategic plans, reducing shovel idle time, minimizing truck wait time, and minimizing truck fuel consumption. The significant contribution of this study lies in the inclusion of Greenhouse Gas (GHG) mitigation by considering fuel consumption reduction as an objective, which brings direct economic and environmental benefits. To account for uncertainty in open-pit mining operations, a discrete event simulation using Arena software is employed. Different scenarios are examined based on objective weights. The case study conducted at Gol-E-Gohar mines in Iran, an iron ore mine, demonstrates that the developed framework successfully reduced fuel consumption by 4.88% per ton of production. In absolute terms, this equates to a total reduction of over 12,000 liters of fuel. By prioritizing fuel consumption, a potential reduction of up to 6% in fuel consumption per tonne of production is attainable, potentially leading to a significant overall decrease of up to 20,000 liters in fuel consumption.

Keywords*: Truck dispatching, Open-pit mine, Discrete Event Simulation, Real-Time Decision Making, Fuel Consumption, Multi-objective optimization*

1. Introduction

The mining industry, vital for the global economy and population growth, faces challenges due to its energy consumption and emissions. Approximately 8% of global greenhouse gas emissions stem from the mining industry (Rahnema et al., 2023). Energy efficiency improvement is crucial for environmental sustainability, but research in this area, especially related to energy-intensive activities like haulage in open-pit mines, is lacking. Both the industry and academia recognize the challenge of inadequate energy efficiency in mining, underscoring the importance of advancing environmental sustainability (Patterson et al., 2017). Certain mining projects, such as iron, bauxite, and coal ventures, attribute 41% to 66% of energy consumption and 37% to 54% of greenhouse gas emissions to mineral loading and hauling activities (Feng et al., 2022). Apart from the substantial

ISBN: 978-1-55195-503-2

environmental impact, the mining haulage system entails noticeable operational costs. Haulage expenses constitute a significant portion of mining operational costs, around 50-60% (Alarie and Gamache, 2002; Moradi-Afrapoli et al., 2021; Moradi Afrapoli et al., 2019; Moradi Afrapoli and Askari-Nasab, 2017; Upadhyay and Askari-Nasab, 2019).

The truck fleet transports materials from shovels to plants or waste dumps depending on the type of the material. The process of dynamically assigning a truck first to a shovel and then to an unloading point is referred to as truck dispatching. Efficient truck dispatching is vital for optimizing productivity, profitability, and sustainability. This research addresses truck dispatching in open-pit mining, proposing an innovative approach that considers factors like truck capacity, distances, extraction rates, and plant capacity. The goal is a solution that meets operational needs, enhances productivity, reduces costs, and contributes to sustainability by reducing greenhouse gas emissions. This study examines truck dispatching in open-pit mines, where trucks aren't locked to specific areas. Instead, they're assigned based on real-time factors such as shovel availability and production rates. To achieve this, a multi-objective stochastic simulation and optimization framework is developed, utilizing mathematical models and simulations to optimize truck dispatching, with a primary focus on minimizing fuel consumption and carbon emissions. In summary, effective truck dispatching enhances open-pit mining success by improving productivity, cost-efficiency, and environmental impact. This research develops a framework considering the dynamic nature of mining, aiming to provide practical, optimized solutions that adapt to operational changes.

In the subsequent sections, after a brief literature review, the benchmark methods for dispatching trucks will be introduced, and then the new framework applied in this research will be presented. This will be followed by a detailed explanation of the case study, including key performance indicators (KPIs) and different operational scenarios. Moving on to the results, the paper will analyze how well the framework performed in the case study, comparing it to the benchmark methods. Finally, in the last section, the paper will have a thorough discussion of the results, drawing conclusions, and suggesting areas for future research.

2. **Literature Review**

Truck dispatching in open-pit mines is a critical aspect of mining operations. It involves determining the optimal allocation and routing of trucks to transport materials from mining sites to dump sites for further processing. Truck dispatching decisions have direct impact on production rate, operational cost, fuel consumption, and subsequently GHG emissions. Efficient truck dispatching strategies can lead to satisfy the target production requirement, as well as reducing the operational cost, and GHG emissions. Therefore, well-coordinated truck dispatching plays a crucial role in balancing production needs with environmental considerations. Cost-efficient dispatching methods are a priority for industrial companies, while sustainable dispatching methods align with the preferences of governments and communities. Past research has employed three distinct approaches including, operations research, queuing theory, and simulation techniques to optimize decision-making in this context (Upadhyay, 2013). In the upcoming sections, a range of studies focusing on truck dispatching, routing, and allocation problems are reviewed and categorized based on their methodologies and underlying objectives. These perspectives are organized into two primary viewpoints: the economical perspective and the environmental perspective.

2.1. Economical Perspective

Ataeepour and Baafi (1999) applied a simulation model using Arena simulation software to examine the impact of truck dispatching on mine productivity by ensuring optimal utilization of available trucks and shovels, with the trucks being identical in their scenario. Topal and Ramazan (2010) introduced mixed integer programming model to meet production targets and optimize the truck schedule considering the truck maintenance cost in an open-pit mine. Souza et al. (2010) introduced a hybrid algorithm combining greedy randomized adaptive search procedure (GRASP) and general

variable neighborhood search (GVNS) metaheuristics for dynamic truck allocation in an open-pit mine. Their approach aimed to minimize truck usage while meeting production and quality goals. Zhang and Xia (2015) employed integer programming to optimize open-pit mine truck dispatching, resulting in cost reduction and production objectives satisfaction. Matamoros and Dimitrakopoulos (2016) presented a new method to optimize truck fleet allocation. Their method handled input parameter uncertainties and improved allocation efficiency resulting in cost savings in a multi-element iron mine case study. Fadin and Moeis (2017) applied a "look-ahead algorithm" approach (Jang et al., 2001) to solve open-pit mine truck dispatching. Combining simulation and optimization models with real data, the approach aimed to optimize truck routes and schedules, boosting production, and reducing operational costs. Utilizing discrete event simulation, the research tested multiple dispatching scenarios. Shishvan and Benndorf (2019) investigated optimizing material dispatch in coal mines, particularly focusing on safe placement of diverse overburden types. Their approach considered equipment factors like capacity, performance, and availability to make dispatch decisions. Alexandre et al. (2019) developed two Multi-objective Genetic Algorithms (MOGAs) to efficiently and dynamically allocate trucks in an open-pit mine. The goals were to maximize production and minimize costs within operational constraints. Wang et al. (2023) addressed real-time truck dispatching challenges in open-pit mines, optimizing full and empty truck stages. Unlike prior methods, the model splits into full and empty truck dispatching, aiming to minimize waiting times, path flow deviations, and transportation costs with adjustable weights. To gain a deeper understanding of truck dispatching, it would be beneficial to explore two comprehensive review studies on the subject. Newman et al. (2010) reviewed mine planning operations, including open-pit truck dispatching, categorizing strategies and analyzing their mathematical basis. Moradi Afrapoli and Askari-Nasab (2017) conducted a comprehensive assessment of fleet management methods, addressing path determination, production optimization, and real-time dispatching. They examined various allocation techniques like queuing theory, linear programming, goal programming, and stochastic programming.

2.2. Environmental Perspective

As global warming concerns grow, most of the large organizations are investing more resources and effort into reducing energy consumption and emissions of pollutants (Ganji et al., 2020). In spite of efforts to reduce energy consumption, numerous mines find it difficult to reduce their energy consumption (Awuah-Offei, 2016). The literature extensively covers green vehicle routing problems in various industries, emphasizing sustainability and environmental factors. However, the mining sector's exploration of green vehicle routing is comparatively limited. Awuah-Offei (2016) reviewed previous studies regarding energy efficiency in loading and hauling activities within the mining industry. Yu et al. (2016) used mixed integer programming to optimize shovel production plans and truck allocations, reducing costs, fuel consumption, and emissions. They also considered equipment failure uncertainties with a multi-scenario approach. Gonzalez et al. (2017) presented a simulation-based approach to determine the optimal balance between carbon emissions and operational costs in underground mining projects. Mohtasham et al. (2021) used mixed integer linear programming to optimize truck scheduling in open-pit mines, aiming to maximize production, minimize deviations in head grade, and tonnage, and minimize fuel consumption. In a follow-up study, Mohtasham et al. (2022) addressed fleet cycle time uncertainty using a multi-stage approach involving simulation-based optimization and a novel heuristic algorithm for real-time truck scheduling decision-making in open-pit mines, targeting production loss and fuel consumption reduction. Mirzaei-Nasirabad et al. (2023) presented a multi-stage approach that optimizes real-time dispatching and determines fleet size. The technique in their study, assessed through a case study in a copper ore mine. Anaraki and Afrapoli (2023) introduced a mathematical multi-objective model that aims to minimize transportation costs and carbon emissions associated with truck travel in open pit mines. The model takes into account various types of trucks with different age groups, recognizing their impact on carbon emissions. Huo et al. (2023) Utilized reinforcement learning in order to improve truck fleet dispatching efficiency in open-pit mining. Their primary objective was to develop a smart fleet

management system and decrease greenhouse gas emissions. This study differs from previous research by introducing a real-time decision-making framework that integrates economic, environmental, and uncertainty considerations. The approach simultaneously addresses emissions, economic goals, and operational objectives, providing benefits to both economy and environment.

3. **Methodology**

This chapter delves into the theoretical foundations of an integrated simulation and optimization framework for open-pit mine truck dispatching. By introducing a new multi-objective mixed integer goal programming (MOMIGP) model, this chapter focuses on enhancing production efficiency through the reduction of shovel idle time, truck wait time, deviations from target production rates, and greenhouse gas (GHG) emissions arising from truck fuel consumption. Notably, the MOMIGP model adeptly manages dispatching decisions in the face of uncertain factors.

Within this chapter, there are two sections. The first section presents optimization models, while another section introduces the integrated simulation and optimization framework. Divided into three subsections, the optimization models section introduces three distinct truck dispatching optimization approaches: Modular Mining Dispatch (MODULAR MINING) by White and Olson (1993; 1986), Tri-Objective model by Moradi Afrapoli et al. (2019), and Quad-Objective model, which is the central model of this research.

3.1. Optimization Models

3.1.1. Modular Mining Dispatch

The Modular Mining Dispatch stands as one of the mining industry's most extensively utilized truck dispatching systems for open-pit mines. This system offers real-time dispatching, a crucial factor in optimizing mining operations. Within the Modular Mining Dispatch model, truck dispatching relies on the prioritization in two main lists: "needy shovels" and "available trucks." The first list encompasses shovels requiring trucks, ranked by urgency, while the second list ranks available trucks by their next availability. Dispatching entails assigning the foremost available truck to the top-listed shovel, a process repeated until all trucks are dispatched. Thanks to its effectiveness and widespread application, Modular Mining Dispatch has emerged as the dominant fleet dispatching system in the mining market. Given its extensive industry usage, the Modular Mining Dispatch model serves as one of benchmark models for comparison in evaluating the Quad-Objective dispatch model of this research. This choice stems from its established reputation as an efficient solution for mining fleet dispatching. This model also served as the benchmark in the study by Moradi Afrapoli et al. (2019).

3.1.2. Tri-Objective Model

To facilitate real-time truck dispatching in open-pit mines, Moradi Afrapoli et al. (2019) developed a Tri-Objective dispatching model that concurrently minimizes shovel idle times, truck wait times, and deviations from planned production rates. This model efficiently managed diverse fleets of varying sizes and types, operating autonomously to maintain the target production rate. The model is executed whenever a new truck assignment is needed including when the truck starts working, and when the truck dumps its load. Their model accounted for operational factors like stripping ratios, truck capacity, plant throughput, and shovel dig rates. Impressively, their Tri-Objective model achieved maximum plant capacity with 14% fewer trucks than the Modular Mining Dispatch model, utilizing just 86% of the intended fleet size while meeting production needs. Meeting the predefined production rate, this model holds the status of an additional benchmark in this context.

3.1.3. Quad-Objective Model

This study introduces a Quad-Objective mathematical optimization model designed for real-time truck dispatching. An exceptional aspect of this model is its incorporation of an extra objective function dedicated to minimizing overall trucks' fuel consumption, thus addressing carbon emissions

and environmental concerns. The model is employed whenever a truck requires a new assignment, triggered by events like the initiation of a truck's operation, truck dumping, shovel breakdowns before loading, and the restart of a truck's operation after downtime. Numerous indices, parameters, and decision variables are available within the optimization model. The indices are listed below:

t	Index for set of trucks: $t = \{1, \dots, T\}$
s	Index for set of shovels: $s = \{1, \dots, S\}$
d	Index for set of dumping points: $d = \{1, \dots, D\}$
d'	Index for set of locations where trucks are required to dump their load before traveling to the new shovel: $d' = \{1, \dots, D\}$
w	Index for set of weights assigned to individual goals: $w = \{1, 2, 3, 4\}$
g	index for the group of trucks that are currently waiting in a queue of the shovel: $g = \{1, \dots, NTWS\}$

The decision variables are listed below:

x_{tsd}	Binary variable equals to 1 if truck t assigns to the path of shovel s to dumping point d , and 0 otherwise
y_{sd}^{-}	Negative deviation of the met path flow rate and the desired path flow rate for the path between shovel s and dumping point d
y_{sd}^{+}	Positive deviation of the met path flow rate and the desired path flow rate for the path between shovel s and dumping point d

The parameters are listed below:

IT_{tsd}	Idle time for shovel s if truck t is assigned to transport material from shovel s to the dumping point d
WT_{tsd}	Wait time for truck t if it is assigned to transport material from shovel s to the dumping point d
N_w	Normalized weights of individual goals based on priority
AF	A factor balancing available trucks with the required capacity of plants
PC_d	Capacity of the plant d: $d = \{1, \dots, P\} \subset \{1, \dots, \mathrm{D}\}$
SC_s	Production capacity of shovel s
MP_{sd}	Path flow rate for the path from shovel s to the dumping point d that the production operation has met so far
TC_t	Actual capacity of truck t (tonne)
NTC_t	Nominal capacity of truck t (tonne)

P_{sd}	Path flow rate for the path from shovel s to the dumping point d
TR_{tsd}	Next time truck t reaches shovel s, if truck t is assigned to transport material from shovel s to the dumping point d
SA_{tsd}	Next time shovel s is available to serve truck t, if truck t is assigned to transport material from shovel s to the dumping point d
TNOW	Current time of the operation/simulation
$LD_{td'}$	The distance truck t must travel to reach the dumping point d' to dump its load
$ED_{td's}$	The distance truck t must travel from the dumping point d' to the next expected shovel s
ALT_t	Average loading time of truck t
APL_t	Average payload of truck t
$LV_{td's}$	Average loaded velocity of truck t traveling to dumping point d' and will travel to shovel s after dumping its load
$EV_{td's}$	Average empty velocity of truck t traveling from dumping point d' to the next expected shovel s
$DQ_{td'}$	Queue time for truck t in the queue of the dumping point d'
$DT_{td'}$	Dump time for truck t to dump its material in dumping point d'
$NTWS_s$	Number of trucks waiting in queue at shovel s
ST_g	Spotting time for the truck g in the queue
LT_g	Loading time for the truck g in the queue
α_t	Intercept of truck t for the fuel consumption
β_t	Payload coefficient of truck t for the fuel consumption
γ_t	Loading time coefficient of truck t for the fuel consumption
τ_t	Idle time coefficient of truck t for the fuel consumption
ω_t	Empty traveling time coefficient of truck t for the fuel consumption
φ_t	Loaded traveling time coefficient of truck t for the fuel consumption
SIT_{tsd}	Shovel idle time coefficient, by assigning truck t to the path of shovel s to dumping point d

TWT_{tsd} Truck wait time coefficient, by assigning truck t to the path of shovel s to dumping point d

F_{tsd} Truck fuel consumption coefficient, by assigning truck t to the path of shovel s to dumping point d

In order to determine the arrival time of each truck to be loaded by shovel, Eq. (1) is used. To calculate the shovel availability, Eq. (2) is used, which represents the next time the shovel will be available to load the truck. The coefficients for three objectives within the optimization problem can be calculated using Eqs. (3), (4) and (5). Accordingly, these coefficients correspond to the objective functions associated with shovel idle time, truck wait time, and fuel consumption, respectively.

$$TR_{tsd} = TNOW + \frac{LD_{td'}}{LV_{td's}} + DQ_{td'} + DT_{td'} + \frac{ED_{td's}}{EV_{td's}} \quad (1)$$
$$\forall t \in \{1, \dots, T\} \,\&\, \forall s \in \{1, \dots, S\} \,\&\, \forall d \in \{1, \dots, D\} \,\&\, \forall d' \in \{1, \dots, D\}$$

$$SA_{tsd} = TNOW + \sum_{g=1}^{NTWS_s} \left(ST_g + LT_g\right) \quad (2)$$
$$\forall t \in \{1, \dots, T\} \,\&\, \forall s \in \{1, \dots, S\} \,\&\, \forall d \in \{1, \dots, D\}$$

$$SIT_{tsd} = \max\left(0, TR_{tsd} - SA_{tsd}\right) \quad (3)$$
$$\forall t \in \{1, \dots, T\} \,\&\, \forall s \in \{1, \dots, S\} \,\&\, \forall d \in \{1, \dots, D\}$$

$$TWT_{tsd} = \max\left(0, SA_{tsd} - TR_{tsd}\right) \quad (4)$$
$$\forall t \in \{1, \dots, T\} \,\&\, \forall s \in \{1, \dots, S\} \,\&\, \forall d \in \{1, \dots, D\}$$

$$F_{tsd} = \alpha_t + \beta_t \times APL_t + \gamma_t \times ALT_t + \tau_t \times TWT_{tsd} + \omega_t \frac{ED_{td's}}{EV_{td's}} + \varphi_t \frac{LD_{td'}}{LV_{td's}} \quad (5)$$
$$\forall t \in \{1, \dots, T\} \,\&\, \forall s \in \{1, \dots, S\} \,\&\, \forall d \in \{1, \dots, D\} \,\&\, \forall d' \in \{1, \dots, D\}$$

The optimization model comprises four distinct objectives, each with a specific purpose. The initial objective focuses on minimizing active shovel idle time, calculated using Eq. (6). The second objective aims to reduce truck wait time during operation, computed through Eq. (7). The third objective adopts a goal programming approach to minimize deviations from path flow rates, as determined by Eq. (8). Lastly, the fourth objective function aims to minimize total fuel consumption by active trucks using Eq. (9). These objectives possess differing scales and varying degrees of influence on the system. The model is categorized as a Mixed Integer Linear Programming (MILP) model, necessitating a non-preemptive mixed integer linear weighted sum goal programming approach for resolution. Following are the objective functions of the model:

$$f_1 = \sum_{t=1}^{T} \sum_{s=1}^{S} \sum_{d=1}^{D} SIT_{tsd} x_{tsd} \quad (6)$$

$$f_2 = \sum_{t=1}^{T} \sum_{s=1}^{S} \sum_{d=1}^{D} TWT_{tsd} x_{tsd} \quad (7)$$

$$f_3 = \sum_{s=1}^{S}\sum_{d=1}^{D}(y_{sd}^{-} + y_{sd}^{+}) \tag{8}$$

$$f_4 = \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{d=1}^{D} F_{tsd}x_{tsd} \tag{9}$$

To achieve the model's solution, the four objectives are converted into dimensionless forms through the application of Nadir and Utopia points, a concept proposed in (Grodzevich and Romanko, 2006). Within this method, Utopia defines lower boundaries for each objective, while Nadir establishes upper limits. By determining these points, a range is set for the objective functions within the Pareto optimal set. When considering a single objective, optimization directs towards the Utopia point, yielding minimal values. Conversely, upper limits are determined using components derived from the Nadir point. The process of normalization is achieved by employing Nadir and Utopia points, thereby scaling objectives within a range of 0 to 1 by Eq. (10). To establish the necessary priority weights for the weighted sum method, each component of the objective function outlined in Eq. (11) represents a weighted and normalized version of an individual objective from Eqs. (6) to (9).

$$\bar{f_i} = \frac{f_i - U_i}{N_i - U_i} \qquad \forall i \in \{1,2,3,4\} \tag{10}$$

$$f = N_1\bar{f_1} + N_2\bar{f_2} + N_3\bar{f_3} + N_4\bar{f_4} \tag{11}$$

Following are the constraints of the model:

$$\sum_{s=1}^{S}\sum_{d=1}^{D} TC_t x_{tsd} \le NTC_t \qquad \forall t \in \{1,\dots,T\} \tag{12}$$

$$\sum_{t=1}^{T}\sum_{s=1}^{S} TC_t x_{tsd} \ge AF \times PC_d \qquad \forall d \in \{1,\dots,P\} \tag{13}$$

$$\sum_{t=1}^{T}\sum_{d=1}^{D} TC_t x_{tsd} \le SC_s \qquad \forall s \in \{1,\dots,S\} \tag{14}$$

$$\sum_{t=1}^{T} TC_t x_{tsd} + MP_{sd} + y_{sd}^{-} - y_{sd}^{+} = P_{sd} \qquad \forall s \in \{1,\dots,S\} \,\&\, \forall d \in \{1,\dots,D\} \tag{15}$$

$$x_{tsd} \in \{0,1\} \qquad \forall t \in \{1,\dots,T\} \,\&\, \forall s \in \{1,\dots,S\} \,\&\, \forall d \in \{1,\dots,D\} \tag{16}$$

$$y_{sd}^{-} \ge 0 \qquad \forall s \in \{1,\dots,S\} \,\&\, \forall d \in \{1,\dots,D\} \tag{17}$$

$$y_{sd}^{+} \ge 0 \qquad \forall s \in \{1,\dots,S\} \,\&\, \forall d \in \{1,\dots,D\} \tag{18}$$

$$AF = \frac{\sum capacity\ of\ available\ trucks}{\sum required\ flow\ rate\ at\ paths} \tag{19}$$

In order to ensure the system's efficient operation, a number of constraints are placed on it. According to constraint (12), the amount of tonnage that a truck can transport in one payload is limited to its nominal capacity. For constraint (13) it is considered that the material hauled to the processing plants using all the trucks must meet the processing target determined by each plant in AF times the percentage. AF, or the adjustment factor, is calculated using Eq. (19), and it is used to adjust the amount of material required for each processing plant. This means that only the AF portion of the plant's requirements can be met. It is indicated by constraint (14) that the total haulage capacity directed to a shovel will be limited to the nominal digging rate for that shovel. Constraint (15) calculates the deviation of the path flow rate from the desired path flow rate for each path connecting a source to a destination. Finally, constraint (16) ensures that the first set of decision variables are binary, and constraints (17) and (18) ensure that the goal programming variables are not negative. After the model has been solved, trucks will be dispatched to shovels in order to ensure that the system operates efficiently.

3.2. Integrated Simulation and Optimization Framework

The simulation segment of the framework follows a structured procedure, outlined in Figure 1. Initially, the model identifies active trucks awaiting assignment to suitable shovels and destinations. Subsequently, the multi-objective optimization model takes charge, efficiently assigning unassigned trucks to their respective tasks, ensuring optimal utilization. Throughout the simulation, the optimization model is recurrently executed upon specific events, such as a truck commencing work, completing a dump, or reactivating after a failure. These events trigger a reevaluation of the optimal truck assignment decision. The optimization process for truck assignments persists throughout the simulation runtime until the designated time period is reached.

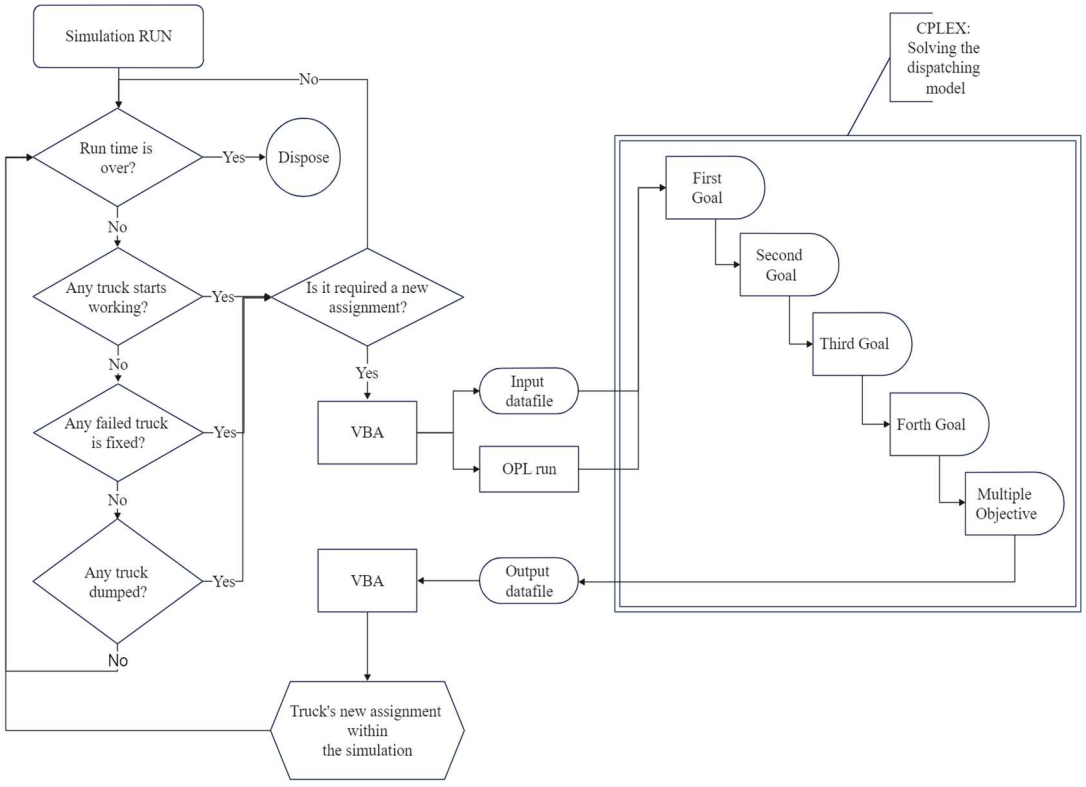


Figure 1. An overview of the simulation and optimization integration process.

4. **Design of Experiments and Results**

The assessment of the developed model in this study is carried out using a case study based on historical data from the Gol-E-Gohar iron ore open-pit mine in Iran. Figure 2 illustrate the layout of loading and dumping points, along with the operational road network. Five shovels are active at the loading points, with two assigned for ore extraction and three for waste. Trucks have three destinations: two processing plants and a waste dump.

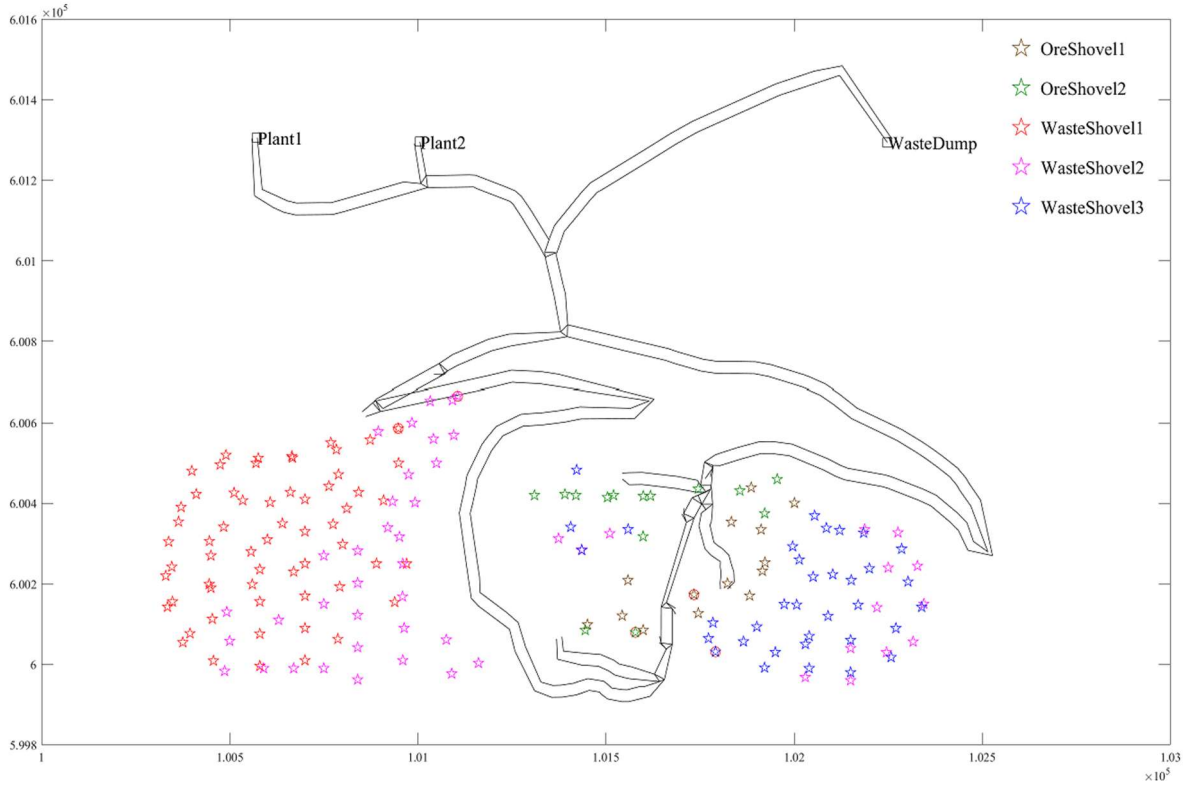


Figure 2. Gol-E-Gohar iron ore mine network.

The ore shovels utilized are Hitachi EX2500, while waste shovels 1 and 2 are Hitachi EX5500, and waste shovel 3 is a Hitachi EX2500. The available fleet comprises 30 CAT 785C trucks.

Fuel consumption for each CAT 785C truck is computed using the regression formula derived from (Dindarloo and Siami-Irdemoosa, 2016) specific to the CAT 785C truck type. The formula is depicted in Eq. (20):

$$F\left(\frac{l}{cycle}\right) = 1.37071 + 0.00483 \times PL + 0.00398 \times LT + 0.00499 \times ES + 0.01471 \times ETR + 0.00278 \times LS + 0.0519 \times LTR \quad (20)$$

The equation's variables signify the following quantities: fuel consumption (F) in liters per cycle, payload (PL) in metric tons, loading time (LT) in seconds, empty idle time (ES) in seconds, empty travel time (ETR) in seconds, loaded idle time (LS) in seconds, and loaded travel time (LTR) in seconds.

The simulation was conducted over a span of 10 days, operating for 12 hours each day. The runtime and the quantity of replications are pivotal for precise and dependable outcomes, as multiple simulation iterations diminish randomness and enhance resilience, particularly for intricate systems or uncertain conditions. The targeted ore and waste material productions for the planned 10-day

mining operations are 552, and 718 kilotonnes respectively. The input data comprises deterministic and stochastic information, with stochastic input distributions calibrated using historical data through the Arena Input Analyzer tool (Rockwell Automation, 2019).

Key Performance Indicators (KPIs) introduced below (Table 1) are essential variables within the fleet management system of an open-pit mine, exerting a substantial influence on operational efficiency and overall performance. KPIs are crucial when comparing different models, as they provide a basis for evaluating performance and making informed decisions.

Table 1. Key Performance Indicators.

Key Performance Indicator (KPI)	**Significance**
Shovel's Utilization	Measures efficiency and productivity
Truck's Waiting Time	Indicates operational flow
Truck's Fuel Consumption	Displays environmental impact
Production of Ore and Total Tonnages	Shows the efficiency of production planning and resource utilization
Ore Tonne Per Gross Operating Hour (OTPGOH)	Quantifies the efficiency of ore production per hour of operation, the mining productivity and resource utilization

Selecting appropriate weights for multi-objective optimization is vital and requires understanding of the problem domain and objectives. Sensitivity analysis helps determine weights, reflecting stakeholder preferences and trade-offs among objectives. Table 2 presents scenarios with different objective's weights and

Table 3 showcases corresponding KPIs for each scenario.

Table 2. Weights of the objective functions.

Scenario	W1(SIT)	W2(TWT)	W3(PD)	W4(FC)
S1	0.1	0.25	0.55	0.1
S2	0.3	0.1	0.5	0.1
S3	0.1	0.2	0.5	0.2
S4	0.1	0.1	0.4	0.4
S5	0.1	0.3	0.4	0.2
S6	0.2	0.3	0.4	0.1
S7	0.25	0.25	0.25	0.25
S8	0.1	0.1	0.7	0.1
S9	0.1	0.1	0.2	0.6
S10	0.6	0.1	0.2	0.1
S11	0.1	0.6	0.2	0.1
S12	0.1	0.35	0.55	0
S13	1	0	0	0
S14	0	1	0	0
S15	0	0	1	0
S16	0	0	0	1

Table 3. Weighted scenarios' KPIs.

Scenario	Util. Ore (%)	Util. Waste (%)	Queue Time (mins)	Fuel Cons. (kl)	Ore Tonnage (kt)	Total Tonnage (kt)	Ore TPGOH (t)
S1	81.2	56.0	3.66	416	552	1273	4602
S2	81.2	56.1	3.73	414	552	1273	4603
S3	81.2	56.2	3.75	413	552	1278	4601
S4	81.1	56.4	3.66	415	552	1279	4602
S5	81.2	56.2	3.68	415	552	1278	4603
S6	81.3	56.2	3.71	414	552	1276	4602
S7	81.2	56.2	3.66	416	552	1277	4603
S8	81.0	56.3	3.66	415	552	1277	4604
S9	81.2	56.2	3.85	410	552	1278	4603
S10	81.3	56.2	3.61	417	552	1277	4602
S11	81.2	56.3	3.62	416	552	1278	4603
S12	81.2	55.9	3.62	417	552	1271	4603
S13	81.2	56.2	3.64	416	552	1275	4603
S14	81.2	55.3	3.59	420	552	1263	4603
S15	81.2	51.0	4.16	417	552	1205	4603
S16	81.1	55.7	4.18	403	552	1269	4603

Most KPIs remain stable despite weight adjustments, except Total Tonnage and Fuel Consumption. The fuel consumption weight (W4) strongly negatively correlates (-0.91) with total fuel consumption. Other weights also correlate with their KPIs. Notably, Total Fuel Consumption and Average Queue Time negatively correlate (-0.63). To achieve minimal fuel consumption and acceptable production in 10 days, weight scenario 9 is chosen for further comparison with benchmarks. Figure 3, and Figure 4 depict Total production, Average truck queue time, and total fuel consumption across all scenarios.

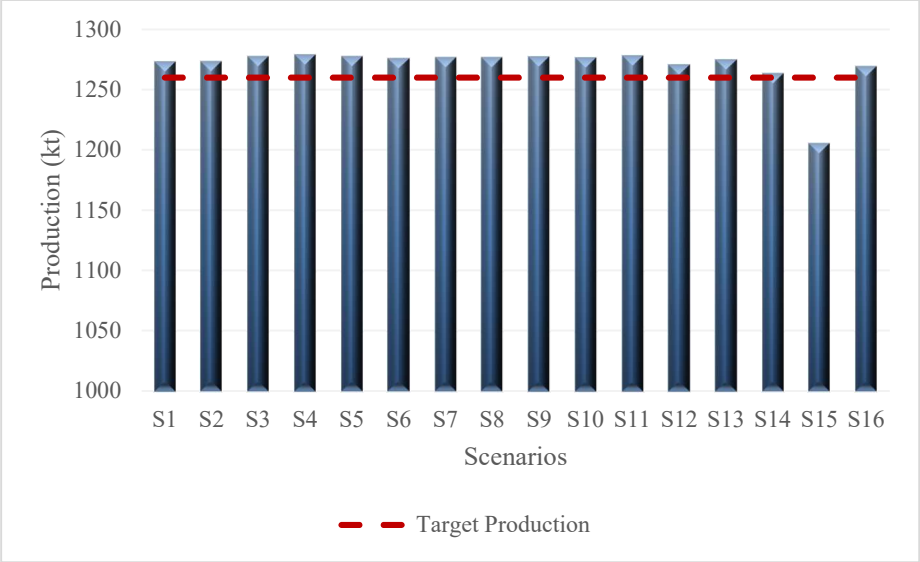


Figure 3. Production for different scenarios.

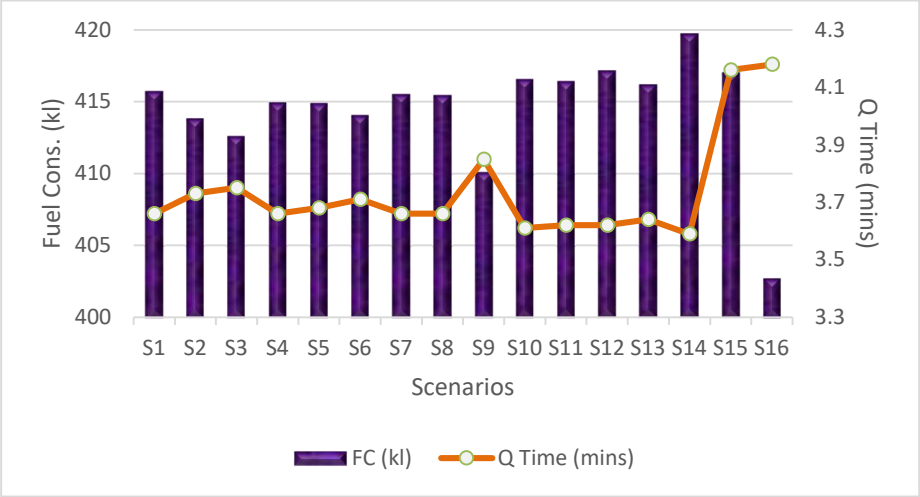


Figure 4. Each scenario's fuel consumption and queue time.

4.1. Comparison

The comparison of the Quadratic Objective (Quad-Obj.) model (designated as model number 3) introduced in this study against the Modular Mining Dispatch model (model number 1) and the Tri-Objective (Tri-Obj.) model (model number 2) extracted from the work of Moradi Afrapoli et al. (2019) is shown by various figures below. This comparison involves the assessment of multiple significant Key Performance Indicators (KPIs).

For Plant 1, the Quad-Obj. and Tri-Obj. models transported about 16% more material on average than the Modular Mining Dispatch model. Similarly, for Plant 2, both models outperformed the Modular Mining Dispatch model by approximately 11%. Figure 5 reveals material quantities transported to the plants and the waste dump across all models. The Modular Mining Dispatch model moved more waste, yielding a higher stripping ratio (SR). However, this model couldn't meet the target ore production. In contrast, both Tri-Obj. and Quad-Obj. models succeeded. However, the Quad-Obj. model had a higher SR than Tri-Obj., moving more waste by 3.7%, equivalent to 26.2 kt. Figure 6 presents the daily average TPGOH along with their corresponding confidence levels. The Tri-Obj. and Quad-Obj. models demonstrate higher TPGOH values when contrasted with the

Modular Mining Dispatch model. Furthermore, the average TPGOH levels remain fairly constant across all days for all models.

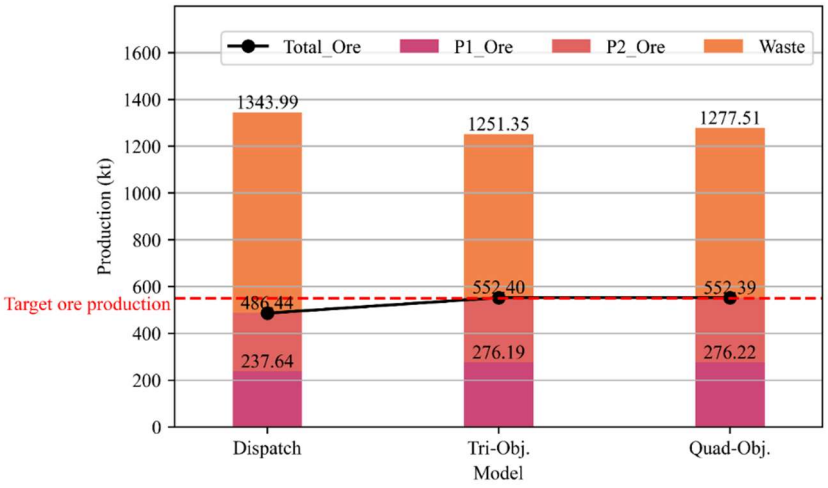


Figure 5. Tonnage Statistics for Plant1, Plant2, and Waste Dump for all models.

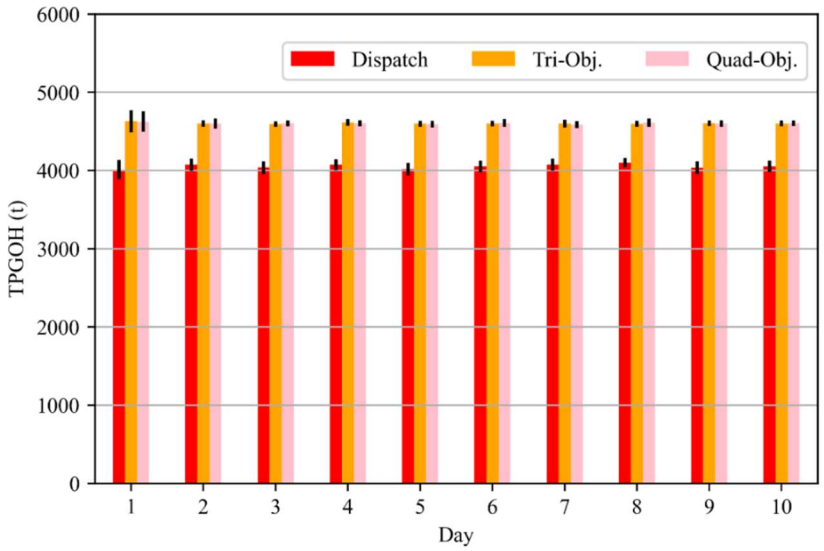


Figure 6. Average TPGOH in each day for each model.

Figure 7 highlights the consistent waste delivery superiority of the Quad-Obj. model over the Tri-Obj. model every day. Notably, the Modular Mining Dispatch model surpasses both models in waste delivery, yet it falls short in meeting required ore tonnage delivery for each plant.

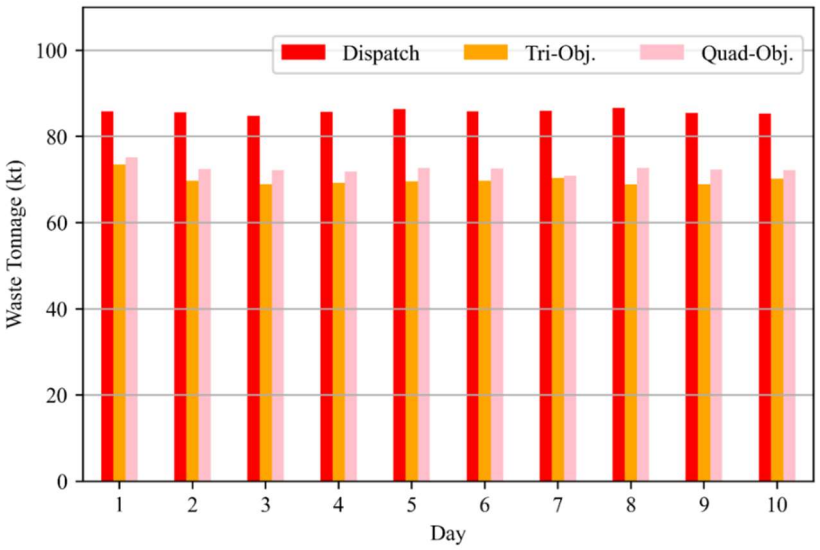


Figure 7. Average Waste tonnage in each day for each model.

Figure 8 presents the fuel consumption details for generating 1000 tonnes of ore for each model, along with a total fuel consumption bar chart. Notably, the Quad-Obj. model consumes 12190 liters less fuel than the previous Tri-Obj. benchmark model. The Modular Mining Dispatch model boasts the lowest fuel consumption due to its focus on selecting shortest paths for trucks and prioritizing waste materials over ores. This choice is influenced by shorter distances between waste polygons and the waste dump compared to those between ore polygons and plants. The Quad-Obj. model shines with the lowest fuel consumption per tonne of ore, yielding a 2.88% reduction, equivalent to roughly 22050 liters saved, compared to the Tri-Obj. model. The reduction increases to 4.88% when total production, including waste, is considered.

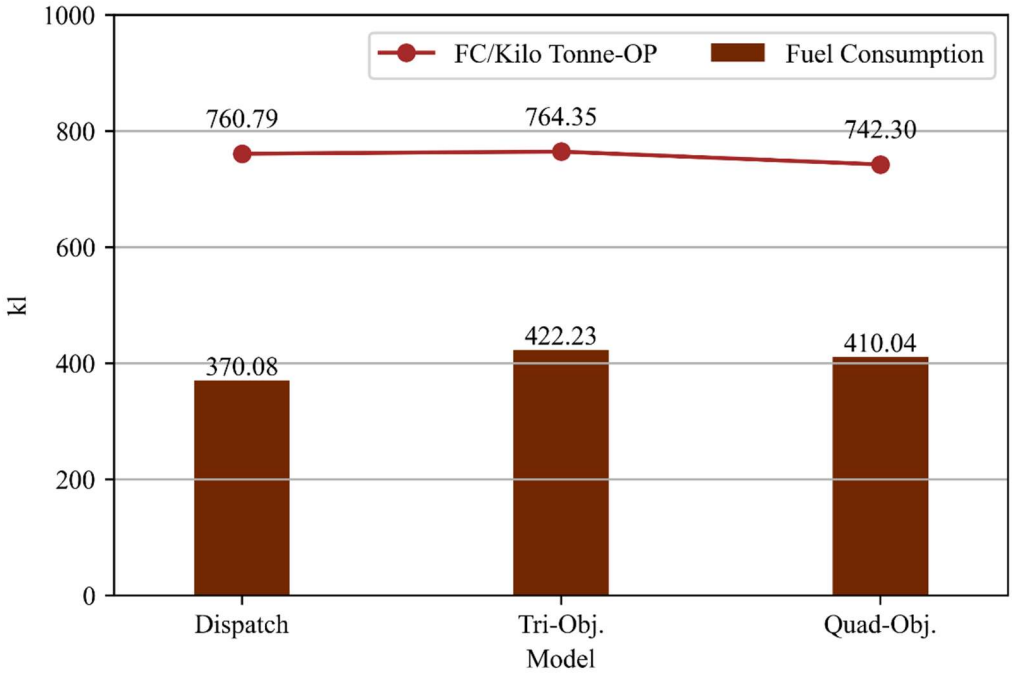


Figure 8. Fuel consumption per a kilotonne ore production.

Figure 9 depicts shovel utilization across models. The Modular Mining Dispatch model shows lower ore shovel utilization but higher waste shovel utilization. Quad-Obj. and Tri-Obj. models exhibit similar utilizations, differing only in waste shovel 4, where Quad-Obj. model surpasses Tri-Obj. model.

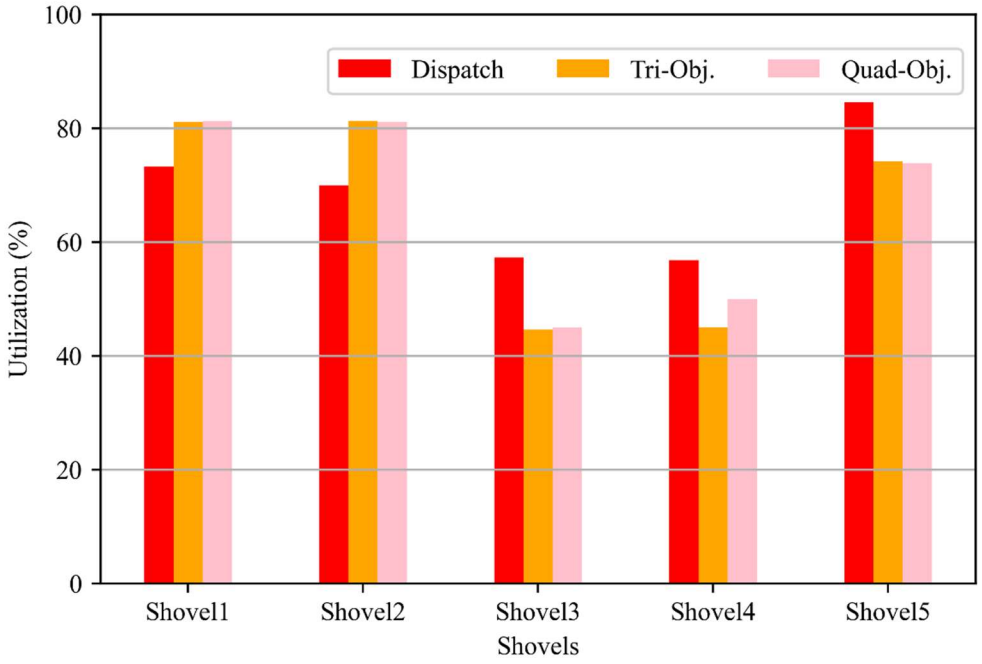


Figure 9. Shovels Utilization.

In Figure 10, and Figure 11 the truck average waiting time for each model is shown. The first figure shows the waiting time for shovels, and the second figure shows the waiting time in processing plants. Among the models, the Modular Mining Dispatch model has the shortest queue times for ore shovels while experiencing the longest queue times for waste shovels, with waste shovel 5 showing a notable variation. Concerning queue times at destinations, waste dumps exhibit no queue time due to multiple available dumping points. Additionally, the Modular Mining Dispatch model avoids processing plant queues by assigning more trucks to the waste dump. Another important observation is that, across both processing plants, the Quad-Obj. model demonstrates lower average queue times compared to the Tri-Obj. model.

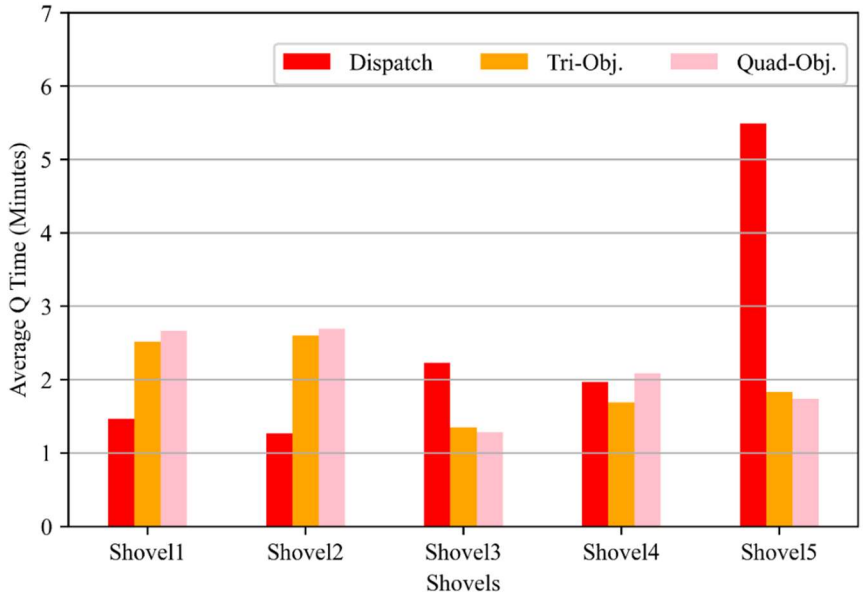


Figure 10. Trucks Average Queue Time at Each Shovel (Minutes).

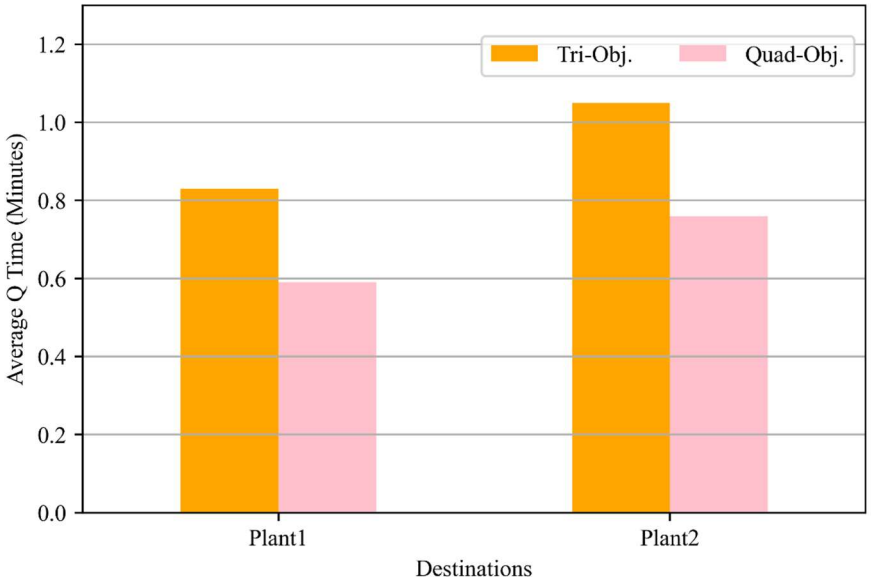


Figure 11. Destinations Average Queue Time (Minutes).

Finally, the S16 scenario (within objective's weight scenarios), as the most fuel-efficient scenario, is evaluated against the Tri-Obj. benchmark model in Figure 12. Notably, implementing the Quad-Obj. model within the S16 scenario resulted in a 4.6% reduction in total fuel consumption, a 1.4% increase in total production, and a 6% decrease in fuel consumption per tonne of production.

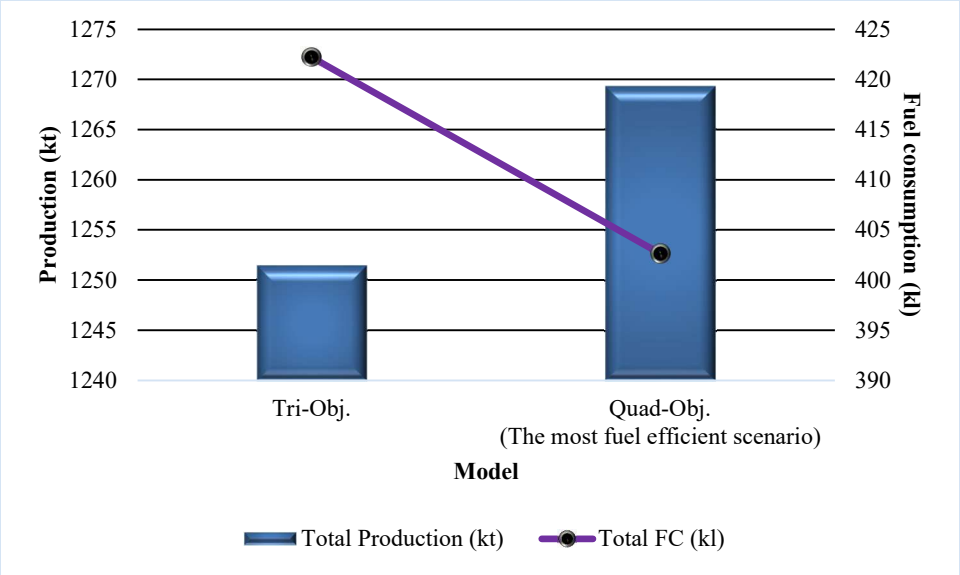


Figure 12. Production and fuel consumption of the most fuel-efficient scenario and Tri-Obj. models.

5. **Conclusions**

This study primarily focuses on optimizing truck dispatching. The developed framework aims to minimize path flow rate deviations, shovel idle time, truck wait time, and fuel consumption. A notable contribution of the study is the integration of fuel consumption reduction as an objective in the dispatching model, yielding economic and environmental advantages. To address the uncertainty in open-pit mining, a discrete event simulation model was developed using Arena software (Rockwell Automation, 2019). Scenarios with varied objective weights were explored, with application in the Gol-E-Gohar iron ore mine as a case study. The Quad-Objective model yielded a 4.88% reduction in fuel consumption per tonne of production compared to the Tri-Objective benchmark, saving over 12,000 liters. Prioritizing fuel consumption led to a potential 6% reduction per tonne, corresponding to a noticeable 20,000 liters overall decrease. The model-maintained production rates while increasing waste extraction by 3.74%, equivalent to about 26.2 kilotonnes over ten operational days.

In future studies, it will be important to consider the age of trucks when developing simulation and optimization models. Truck age significantly impacts performance, including speed, fuel use, and emissions. Integrating age data can yield insights into efficiency, costs, and environmental effects, informing maintenance and replacement strategies. Moreover, applying In-pit crushing and conveying (IPCC) in mine haulage systems is worth investigating. IPCC involves crushing ore in the pit and conveying it using belts, reducing costs, energy consumption, GHG emissions, and truck transport requirements.

6. **References**

[1] Alarie, S., Gamache, M., 2002. Overview of solution strategies used in truck dispatching systems for open pit mines. Int. J. Surf. Mining, Reclam. Environ. 16, 59–76. https://doi.org/10.1076/ijsm.16.1.59.3408

[2] Alexandre, R.F., Campelo, F., Vasconcelos, J.A., 2019. Multi-objective evolutionary algorithms for the truck dispatch problem in open-pit mining operations. Learn. Nonlinear Model. 17, 53–66. https://doi.org/10.21528/lnlm-vol17-no2-art5

[3] Anaraki, M.G., Afrapoli, A.M., 2023. Sustainable open pit fleet management system: integrating economic and environmental objectives into truck allocation. Min. Technol. 1–11.

[4] Ataeepour, N., Baafi, E.Y., 1999. ARENA simulation model for truck-shovel operation in despatching and non-despatching modes. Int. J. Surf. Mining, Reclam. Environ. 13, 125–129. https://doi.org/10.1080/09208119908944228

[5] Awuah-Offei, K., 2016. Energy efficiency in mining: A review with emphasis on the role of operators in loading and hauling operations. J. Clean. Prod. 117, 89–97. https://doi.org/10.1016/j.jclepro.2016.01.035

[6] Dindarloo, S.R., Siami-Irdemoosa, E., 2016. Determinants of fuel consumption in mining trucks. Energy 112, 232–240. https://doi.org/10.1016/j.energy.2016.06.085

[7] Fadin, A.Y.F., Moeis, A.O., 2017. Simulation–Optimization Truck Dispatch Problem Using Look–Ahead Algorithm in Open Pit Mines. GEOMATE J. 13, 80–86.

[8] Feng, Y., Liu, Q., Li, Y., Yang, J., Dong, Z., 2022. Energy efficiency and CO2 emission comparison of alternative powertrain solutions for mining haul truck using integrated design and control optimization. J. Clean. Prod. 370, 133568. https://doi.org/10.1016/j.jclepro.2022.133568

[9] Ganji, M., Kazemipoor, H., Hadji Molana, S.M., Sajadi, S.M., 2020. A green multi-objective integrated scheduling of production and distribution with heterogeneous fleet vehicle routing and time windows. J. Clean. Prod. 259, 120824. https://doi.org/10.1016/j.jclepro.2020.120824

[10] Gonzalez, M., Navarrete, I., Arroyo, P., Azúa, G., Mena, J., Contreras, M., 2017. Sustainable decision-making through stochastic simulation: Transporting vs. recycling aggregates for Portland cement concrete in underground mining projects. J. Clean. Prod. 159, 1–10. https://doi.org/10.1016/j.jclepro.2017.05.012

[11] Huo, D., Sari, Y.A., Kealey, R., Zhang, Q., 2023. Reinforcement Learning-Based Fleet Dispatching for Greenhouse Gas Emission Reduction in Open-Pit Mining Operations. Resour. Conserv. Recycl. 188, 106664. https://doi.org/10.1016/j.resconrec.2022.106664

[12] Jang, J., Suh, J., Park, N., Liu, R., 2001. A Look-Ahead Routing Procedure for Machine Selection in a Highly Informative Manufacturing System. Int. J. Flex. Manuf. Syst. 13, 287–308. https://doi.org/10.1023/A:1011199619582

[13] Matamoros, M.E.V., Dimitrakopoulos, R., 2016. Stochastic short-term mine production schedule accounting for fleet allocation, operational considerations and blending restrictions. Eur. J. Oper. Res. 255, 911–921. https://doi.org/10.1016/j.ejor.2016.05.050

[14] Mirzaei-Nasirabad, H., Mohtasham, M., Askari-Nasab, H., Alizadeh, B., 2023. An optimization model for the real-time truck dispatching problem in open-pit mining operations. Optim. Eng. 1–25.

[15] MODULAR MINING [WWW Document], n.d. URL https://www.modularmining.com

[16] Mohtasham, M., Mirzaei-nasirabad, H., Askari-nasab, H., 2022. Multi-stage optimization framework for the real- time truck decision problem in open-pit mines : a case study on Sungun copper mine. Int. J. Mining, Reclam. Environ. 36, 461–491. https://doi.org/10.1080/17480930.2022.2067709

[17] Mohtasham, M., Mirzaei-nasirabad, H., Askari-nasab, H., 2021. A multi-objective model for fleet allocation schedule in open-pit mines considering the impact of prioritising objectives on transportation system performance. Int. J. Mining, Reclam. Environ. 35, 709–727. https://doi.org/10.1080/17480930.2021.1949861

[18] Moradi-Afrapoli, A., Upadhyay, S., Askari-Nasab, H., 2021. Truck dispatching in surface mines-Application of fuzzy linear programming. J. South. African Inst. Min. Metall. 121, 505–512.

[19] Moradi Afrapoli, A., Askari-Nasab, H., 2017. Mining fleet management systems: a review of models and algorithms. Int. J. Mining, Reclam. Environ. 33, 42–60. https://doi.org/10.1080/17480930.2017.1336607

[20] Moradi Afrapoli, A., Tabesh, M., Askari-Nasab, H., 2019. A multiple objective transportation problem approach to dynamic truck dispatching in surface mines. Eur. J. Oper. Res. 276, 331–342. https://doi.org/10.1016/j.ejor.2019.01.008

[21] Newman, A.M., Rubio, E., Caro, R., Weintraub, A., Eurek, K., 2010. A review of operations research in mine planning. Interfaces (Providence). 40, 222–245.

[22] Olson, J.P., Vohnout, S.I., White, J., 1993. On improving truck/shovel productivity in open pit mines. CIM Bull. 86 (973), 43–49.

[23] Patterson, S.R., Kozan, E., Hyland, P., 2017. Energy efficient scheduling of open-pit coal mine trucks. Eur. J. Oper. Res. 262, 759–770. https://doi.org/10.1016/j.ejor.2017.03.081

[24] Rahnema, M., Amirmoeini, B., Moradi Afrapoli, A., 2023. Incorporating Environmental Impacts into Short-Term Mine Planning: A Literature Survey. Mining. https://doi.org/10.3390/mining3010010

[25] Rockwell Automation, 2019. Arena, Version 19.

[26] Shishvan, M.S., Benndorf, J., 2019. Simulation-based optimization approach for material dispatching in continuous mining systems. Eur. J. Oper. Res. 275, 1108–1125. https://doi.org/10.1016/j.ejor.2018.12.015

[27] Souza, M.J.F., Coelho, I.M., Ribas, S., Santos, H.G., Merschmann, L.H.C., 2010. A hybrid heuristic algorithm for the open-pit-mining operational planning problem. Eur. J. Oper. Res. 207, 1041–1051. https://doi.org/10.1016/j.ejor.2010.05.031

[28] Topal, E., Ramazan, S., 2010. A new MIP model for mine equipment scheduling by minimizing maintenance cost. Eur. J. Oper. Res. 207, 1065–1071. https://doi.org/10.1016/j.ejor.2010.05.037

[29] Upadhyay, S.P., 2013. Dissertation Proposal: Hybrid Simulation-Optimization Approach for Production Scheduling & Truck-Shovel Allocation Optimization. University of Alberta, Edmonton, Canada.

[30] Upadhyay, S.P., Askari-Nasab, H., 2019. Dynamic shovel allocation approach to short-term production planning in open-pit mines. Int. J. Mining, Reclam. Environ. 33, 1–20. https://doi.org/10.1080/17480930.2017.1315524

[31] Wang, X., Dai, Q., Bian, Y., Xie, G., Xu, B., Yang, Z., 2023. Real-time truck dispatching in open-pit mines. Int. J. Mining, Reclam. Environ. 1–20.

[32] White, J.W., Olson, J.P., 1986. Computer-based dispatching in mines with concurrent operating objectives. Min. Eng.(Littleton, Colo.);(United States) 38.

[33] Yu, H., Solvang, W.D., Sun, X., 2016. A Decision-Support Model for Operational Planning of Surface Coal Mining Considering Equipment Failure. https://doi.org/10.1109/sims.2016.7802905

[34] Zhang, L., Xia, X., 2015. An integer programming approach for truck-shovel dispatching problem in open-pit mines. Energy Procedia 75, 1779–1784.

Appendix

LIST OF ABBREVIATIONS:

CAT	Caterpillar
HIT	Hitachi
TPGOH	Tonne Per Gross Operating Hours
OTPGOH	Ore Tonne Per Gross Operating Hours
SR	Stripping Ratio
Q	Queue
SIT	Shovel Idle Time
TWT	Truck Wait Time
PD	Production Deviation
FC	Fuel Consumption
Min	Minutes
Hrs	Hours
t / kt	Tonnes / Kilo Tonnes
l / kl	Liters / Kilo Liters
Tph	Tonne Per Hour

An Innovative Optimization Model for Long-term Production Scheduling of Sublevel Caving Mines Using Mixed Integer Linear Programming

Soroush Khazaei and Yashar Pourrahimian
Mining Optimization Laboratory (MOL)
University of Alberta, Edmonton, Alberta, Canada

ABSTRACT

As a factory-like mining method, sublevel caving includes a range of activities such as development, stockpiling, and production, each occurring independently on different levels. In order to achieve more reliable production scheduling, it is essential to consider the coordination of operations from the development phase to the plant. This research paper introduces a mixed-integer linear programming (MILP) framework designed for the long-term production scheduling optimization of sublevel caving mines. The primary objective of this framework is to maximize the net present value while addressing various operational constraints such as development activities, mining and processing capacities, continuous mining, the allowable number of active mining units, grade blending, and vertical and horizontal sequencing. We have developed a Jupyter Notebook-based model to implement this framework and employed the powerful CPLEX solver to obtain efficient solutions. The proposed MILP model offers systematic schedules of all development activities, including vertical shaft and its ventilation, man-way-raises and ventilations, orepasses, and operational developments while ensuring optimal sequences of ore extraction and maximizing the operation's profitability in the scope of long-term planning. The efficacy of the proposed model is demonstrated through the implementation of the model on an illustrative sublevel caving case study. The results highlight the ability of the framework to generate robust schedules that account for the simultaneous occurrence of development activities and ore production throughout the mine life.

1. Introduction

The mining sector is currently focused on finding more cost-effective extraction methods and enhancing the efficiency of existing underground mining techniques [20]. Consequently, sublevel caving (SLC) methods have become increasingly popular in mining hard rock masses due to their potential for high production rates and economical operation [7]. Notably, significant progress in drilling and blasting techniques has led to a remarkable reduction in the development-to-production ratio within SLC mines [6].

As a caving mining method, SLC relies on the gravity flow of materials, resulting in a random and irregular flow pattern. Moreover, this unpredictability is further compounded by various factors, including mine layout, the chaotic material flow, blasting performance, hang-ups, fleet size, number of active production faces, multiple-level ore recovery, rate of cave propagation, and surface subsidence. Consequently, the intricate interplay of these factors makes the design of an SLC mine a considerably complex task.[21].

The advancements and complexities of SLC require a well-designed mine plan that improves overall performance and considers essential SLC components. A high-performance SLC mine plan is one

ISBN: 978-1-55195-503-2

that has a holistic view and aligns all operations with a strategic approach. As a critical component of mine planning, production scheduling determines the most beneficial mining sequence over the life of the mine. Developing a schedule that meets all mining aspects can substantially reduce costs and increase profitability. Therefore, providing an exhaustive mathematical model that can integrate all activities, including development, mining, and processing, simultaneously increases the model's practicality and strength [10; 4].

Underground production scheduling is subject to several discrete and continuous decisions that indicate the location, destination, extraction time, and mining units' extraction portion over the mine's life, along with vertical and horizontal precedence relations [20; 3]. A production schedule aims to define the most profitable extraction sequence of the material that produces the desired market specification while meeting the demanded quantities of run-of-mine ore at each period and satisfying a set of physical and operational constraints [15; 18]. Compared to the manual and heuristic methods, the exact algorithms created by mathematical programming models would be an excellent alternative to provide an operationally optimal multi-time-period schedule in mines [19; 11].

Although linear- and mixed-integer programming models have significant potential for optimizing production scheduling in both open-pit and underground mines, they often overlook the pre-extraction material flow [1; 3]. In the context of SLC mining, development activities are not fully integrated into the optimization models. This paper presents a mathematical programming framework based on mixed-integer linear programming (MILP) formulation for long-term SLC production scheduling. The MILP model maximizes the operation's NPV. The model's primary goal is to integrate the schedules of all development activities, including the capital, ventilation, orepass, and operational developments, into the mining and processing schedules. The model further controls the mining and processing capacities, continuous mining, the allowable number of active production areas, grade blending, and vertical and horizontal sequencing. The provided model is more comprehensive and includes more details than previous models, which only focus on the extraction sequences in SLC production scheduling.

2. Relevant Literature Review

Only a few studies have been conducted on SLC production scheduling, with the Kiruna mine in northern Sweden being the primary focus of successive efforts in this area. Khazaei and Pourrahimian [9] presented a comprehensive review and summarized the researchers' attempts in the SLC production scheduling optimization field, which mainly focused on the extraction sequencing of mining units.

Almegren [2] presented a long-term production scheduling of Kiruna mines using the application of Lagrangian relaxation, but this method was not used in the final formulation due to the gap phenomenon and the assumption of complete mining of blocks in each time period. Topal [23] formulated a combined model that solved one-year sub-problems with a monthly resolution to provide a five-year schedule. Deglegen et al. [5] set up a model to minimize the deviation from planned quantities by breaking the whole model into one-year sub-problems to achieve production plans for a seven-year time horizon. Kutcha et al. [12] used the aggregation method and the earliest and the latest start date to improve the tractability of their MILP model. However, more robust methods required to determine the latest start date for each machine placement were still required.

Newman et al. [16] designed a heuristic-based algorithm to directly solve the production scheduling problem of the Kiruna mine both at the machine placement level and production block level. Despite reducing the solution time as well as deviations from planned production quantities, it can only be applied for time horizons of 2 years or fewer. Newman et al. [17] reduced deviations in the total demand by developing an optimization-based decomposition heuristic. The formulation incorporates both short- and long-term production scheduling decisions to align production and demanded

quantities. Shenavar et al. [22] optimized the stope boundary and applied the IP model to formulate the long-term production scheduling for a 2D representation of a real SLC mine.

The problem of obtaining an optimal mine plan for large-scale surface mining projects is often computationally challenging due to complex sequencing constraints and ore quality requirements. As a result, metaheuristics and intelligent computing methods have been widely used to approximate good solutions within a reasonable amount of time for the open-pit scheduling problem Mousavi et al. [14]. A review of metaheuristic approaches for the specific problem of long-term open-pit planning is provided by Franco-Sepulveda et al. [8].

Although metaheuristics techniques are popular in the mining industry due to their adaptability and the short time required to find good quality sub-optimal solutions, the exact methods are more reliable because of the ability to obtain the true optimal solution than metaheuristic techniques. Furthermore, there has been no holistic-viewed schedule that simultaneously considers all activities like development, mining, and processing. All existing SLC schedules focus on the extraction sequencing of ore material. This paper's primary focus is to provide a comprehensive model that integrates development activities into the production sequencing in SLC mines.

3. Problem Definition

Manual planning methods and heuristic algorithms found in commercial software do not ensure achieving an optimal schedule in SLC mining. Thus, a mathematical programming model offers a promising approach to generating an operationally feasible multi-time-period schedule for the SLC mine. This paper leverages operations research applications to optimize production scheduling using a MILP model.

In an SLC mine, the production schedule specifies the extracted tonnage and grades of scheduling units over the life of the mine to achieve a strategic objective. The proposed model generates the long-term production schedule at a mining unit level. A mining unit is where the Load-Haul-Dump unit (LHD) operates, which contains one production drift mining starts from the end of the drift and continues backward (Figure 1). Each mining unit consists 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, processing capacities, continuous mining of scheduling units, restrictions on the allowable number of active production faces, grade blending, and vertical and horizontal sequencing.

At the mining unit level, the schedule of each mining unit is controlled by the completion of the development activities in the production area and the level that the mining unit is located while considering the vertical and horizontal precedence relationships among mining units. The mine planner also controls the number of new mining units that need to be started in each period to meet the mining and processing plant capacities, the allowable number of active mining units, and the average production grade sent to the processing plant in each period.

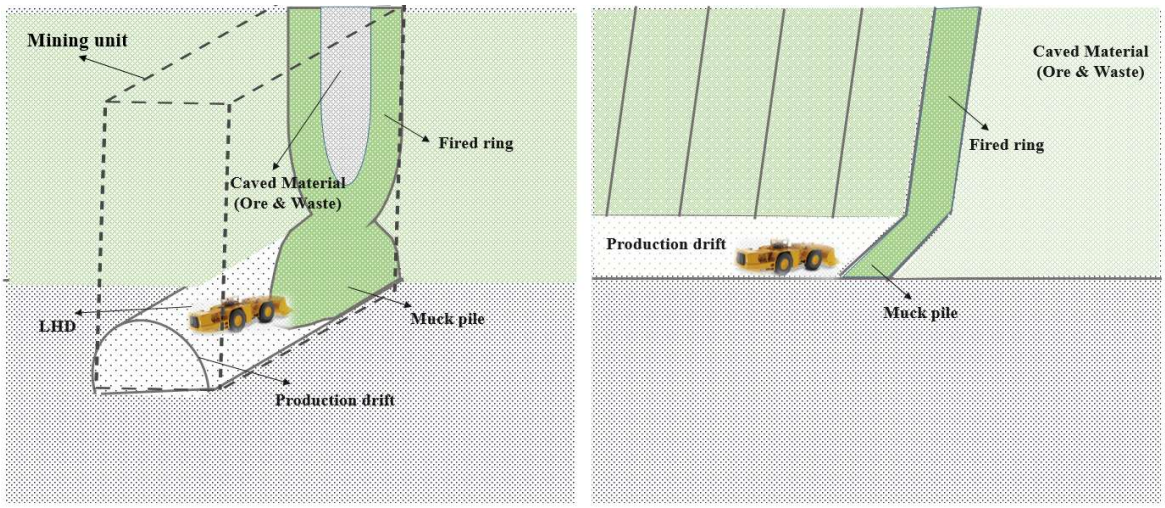


Figure 1. Typical view of mining unit in an SLC mine.

Figure 2 illustrates the schematic layout used to develop the model. The vein-like deposit with stable surrounding rock that caves in a controlled manner after drilling and blasting operations contributes to the use of the SLC mining method. On the largest scale, the mine is divided into a number of production areas, each of which includes horizontal sublevels, two orepasses, and one man-way-raise. Miners first drill vertical shafts, haulage level drift, and access routes driven along the strike of the orebody and provide access to all production areas. The development plan for each specific production area consists of capital development (man-way-raise), orepass development, and operational development (perimeter drifts and production drifts). A man-way-raise is extracted due to transferring workers and ventilation installations to supply fresh air in each sublevel. In addition, two orepasses are drilled for transferring material from each active sublevel to the haulage level. Finally, operational developments, including perimeter and production drifts, are mined to create horizontal sublevels for mining operations, including drilling, blasting, and loading extracted material from drawpoints to the orepasses. A perimeter drift in a sublevel is driven along to the strike of the orebody and is offset from the ore–waste contact on the footwall side. The perimeter drift's role is to provide access to the production drifts for ore transportation, services, and ventilation. The production drifts are staggered between the levels to provide optimal coverage for drilling and allow for the downward flow of caved material. Fan-shaped rings are drilled from the production drifts. In each sublevel, the ore is drilled and blasted in mining units. Depending on the regularity of the orebody, train systems or tuck haulages are utilized to transport ore from the orepasses to the haulage level. Then the ore is hoisted to the surface through the vertical shaft.

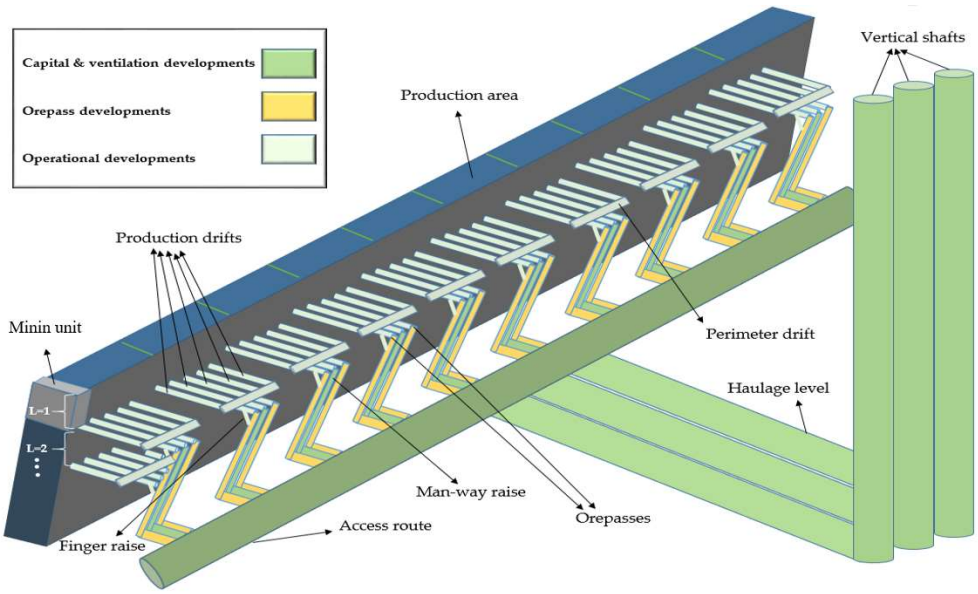


Figure 2. Schematic layout of Sublevel caving developments.

Figure 3 shows the considered mining and development activities in the model. The development activities are divided into four categories, including vertical shaft development, ventilation facilities, man-way-raise development, and ventilation requirements, in addition to orepass and operational developments. SLC is generally used as the primary mining method in mechanized mines with independent unit operations. All unit operations, including drilling, charging, blasting, loading, and transportation, are performed separately, resulting in a standardized procedure and safe operation [13].

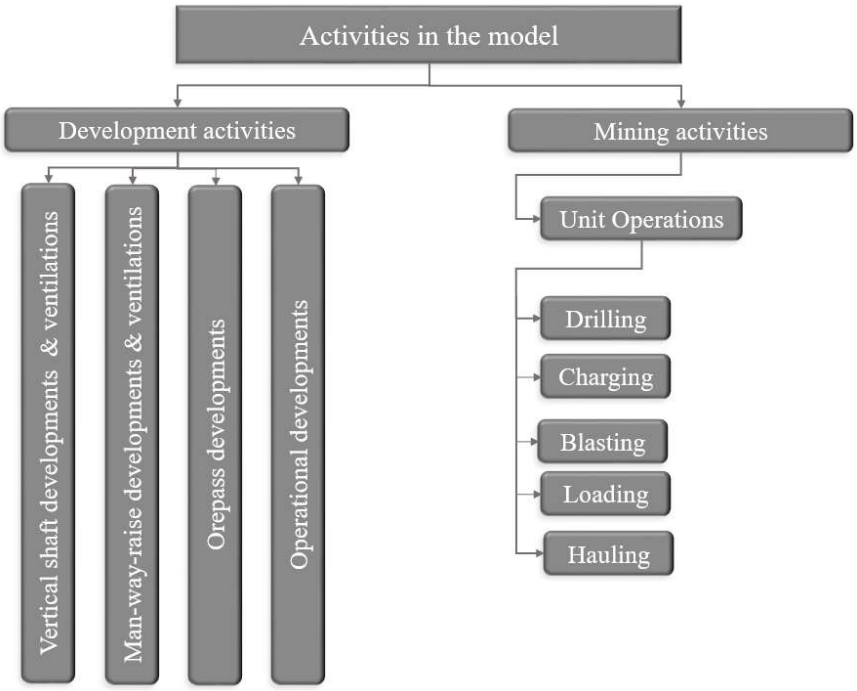


Figure 3. Mining and development activities in the SLC model.

4. Preliminary Mathematical Model for SLC Long-Term Production Scheduling

The initial model focuses on long-term decisions and constraints at the mining unit level, serving as the central scheduling unit. The formulated model aims to harmonize all development schedules with mining and processing schedules. It also manages the number of active mining units, extraction proportions per period, continuous mining, and the mining duration throughout the mine's life. Continuous decision variables track development activities and mined material for each mining unit in each period, while binary variables govern the order of development activities and whether a mining unit initiates extraction in a specific period, t.

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.

4.1. Sets

S_{M_v} Set of mining units m s in the production area v.

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

$S_{M_{v,l}}$ Set of mining units in the production area v on the level l.

$S^V_{M_m}$ Set of mining units whose start period is restricted vertically by mining unit m.

$S^H_{M_m}$ Set of mining units whose start period is forced by adjacency to mining unit m.

4.2. Decision Variables

$x^t_m \in [0,1]$ Continuous variable representing the portion of the mining unit to be mined at period t.

$x^t_{m,p} \in [0,1]$ Continuous variable representing the portion of mining unit m sending directly to the processing plant at period t.

bs^t_m Binary integer variable equals one if mining of mining unit m is started at period t; otherwise, it is zero.

as^t_m Binary integer variable equals one if mining unit m is active at period t; otherwise, it is zero.

$b_{sd_l}{}^t \in \{0,1\}$ Binary integer variable controlling the precedence of vertical shafts developments. It is equal to one if vertical shaft development on level l has started by or in period t; otherwise, it is zero.

$b_{vds_l}{}^t \in \{0,1\}$ Binary integer variable controlling the precedence of ventilation development in vertical shafts.

$b_{mwr_{v,l}}{}^t \in \{0,1\}$ Binary integer variable controlling the precedence of man-way-raise development in each production area. It is equal to one if man-way-raise development in production area v on level l has started by or in period t; otherwise, it is zero.

$b_{vd_{v,l}}^{t} \in \{0,1\}$ Binary integer variable controlling the precedence of ventilation development in man-way-raise in each production area.

$b_{opd_{v,l}}^{t} \in \{0,1\}$ Binary integer variable controlling the precedence of orepass development in each production area.

$b_{od_{v,l}}^{t} \in \{0,1\}$ Binary integer variable controlling the precedence of operational developments in each production area.

$d_{sd_{l}}^{t} \in [0,1]$ Continuous variable represents the vertical shaft development activities to be completed on level l at period t.

$d_{vds_{l}}^{t} \in [0,1]$ Continuous variable represents the ventilation development activities in vertical shafts to be completed on level l at period t.

$d_{mwr_{v,l}}^{t} \in [0,1]$ Continuous variable represents the man-way-raise development activities to be completed in production area v on level l at period t.

$d_{vd_{v,l}}^{t} \in [0,1]$ Continuous variable represents the ventilation development activities in the man-way-raise to be completed in production area v on level l at period t.

$d_{opd_{v,l}}^{t} \in [0,1]$ Continuous variable represents the orepass development activities to be completed in production area v on level l at period t.

$d_{od_{v,l}}^{t} \in [0,1]$ Continuous variable represents the operational development activities to be completed in production area v on level l at period t.

4.3. Parameters

csd_{l}^{t} Variable cost per length of vertical shafts development on level l at period t.

$cvds_{l}^{t}$ Variable cost per length of ventilation development in vertical shafts on level l at period t.

$cmwr_{v,l}^{t}$ Variable cost per length man-way-raise development in production area v on level l at period t.

$cvd_{v,l}^{t}$ Variable cost per length of ventilation development in man-way-raise in production area v on level l at period t.

$copd_{v,l}^{t}$ Variable cost per length of orepass development in production area v on level l at period t.

$cod_{v,l}^{t}$ Variable cost per length of operational development in production area v on level l at period t.

o_{m} Ore tonnage in mining unit m.

g_{m} Average grade of ore in mining unit m.

dil_{m} Mining dilution of mining unit m.

r_m	Mining recovery of mining unit m.
rp^t	Processing recovery: the portion of mineral recovered in mining unit m at period t.
sp^t	Selling price in present value terms obtainable per unit of the mineral commodity at period t.
sc^t	Selling cost in present value terms obtainable per unit of mineral commodity.
ec_m^t	Mining and processing cost per ton of ore extracted from mining unit m at period t.
p^t	Penalty cost per ton associated with tonnage deviations at period t.
l_a	The uppermost level in each production area assumed the same for all of them $(l=1)$.
l_v	The lowest level in each production area assumed the same for all of them $(l=L)$.
dl_{sd_l}	Vertical shaft development length on the level l.
dl_{vds_l}	The length of ventilation development in the vertical shaft on the level l.
$dl_{mwr_{v,l}}$	The length of the man-way-raise development in the production area v on the level l.
$dl_{vd_{v,l}}$	The length of ventilation development in man-way-raise in production area v on the level l.
$dl_{opd_{v,l}}$	Orepass development length in production area v on the level l.
$dl_{od_{v,l}}$	Operational development length in production area v on the level l.
$\underline{Dev_{sd}^t}$	Lower bound on vertical shaft development at period t.
$\overline{Dev_{sd}^t}$	Upper bound on vertical shaft development at period t.
$\underline{Dev_{vds}^t}$	Lower bound on ventilation development in vertical shafts at period t.
$\overline{Dev_{vds}^t}$	Upper bound on ventilation development in vertical shafts at period t.
$\underline{Dev_{mwr}^t}$	Lower bound on man-way-raise development for all production areas at period t.
$\overline{Dev_{mwr}^t}$	Upper bound on man-way-raise development for all production areas at period t.

$\underline{Dev^t_{vdv}}$ Lower bound on ventilation development in man-way-raise for all production areas at period t.

$\overline{Dev^t_{vdv}}$ Upper bound on ventilation development in man-way-raise for all production areas at period t.

$\underline{Dev^t_{opd}}$ Lower bound on orepass development for all production areas at period t.

$\overline{Dev^t_{opd}}$ Upper bound on orepass development for all production areas at period t.

$\underline{Dev^t_{od}}$ Lower bound on operational development for all production areas at period t.

$\overline{Dev^t_{od}}$ Upper bound on operational development for all production areas at period t.

$\underline{Ton^t}$ Lower bound on mining capacity at period t.

$\overline{Ton^t}$ Upper bound on mining capacity at period t.

$\underline{Ton^t_p}$ Lower bound on ore processing capacity at period t.

$\overline{Ton^t_p}$ Upper bound on ore processing capacity at period t.

$\underline{g^t_p}$ Lower bound on an acceptable average grade by processing plant at period t.

$\overline{g^t_p}$ Upper bound on an acceptable average grade by processing plant at period t.

4.4. 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.

$$Max\left[\sum_{t=1}^{T}\sum_{m=1}^{M}\frac{([o_m\times g_m\times r_m\times rp^t\times(sp^t-sc^t)-o_m\times(1+dil_m)\times ec^t_m]\times x^t_{m,p})}{(1+i)^t}\right]$$
$$-\left[\begin{array}{l}\sum_{t=1}^{T}\sum_{l=1}^{L}\frac{(csd^t_l\times dll_{sd_l})\times d_{sd_l}{}^t+(cvds^t_l\times dll_{vds_l})\times d_{vds_l}{}^t}{(1+i)^t}\\+\\\sum_{t=1}^{T}\sum_{v=1}^{V}\sum_{l=1}^{L}\frac{(cmrw^t_{v,l}\times dll_{mwr_{v,l}})\times d_{mwr_{v,l}}{}^t+(cvd^t_{v,l}\times dll_{vd_{v,l}})\times d_{vd_{v,l}}{}^t+(copd^t_{v,l}\times dll_{opd_{v,l}})\times d_{opd_{v,l}}{}^t+(cod^t_{v,l}\times dll_{od_{v,l}})\times d_{od_{v,l}}{}^t}{(1+i)^t}\end{array}\right] \quad (1)$$

4.5. Capital Development Constraints

Capital development is divided into two phases of vertical shafts and man-way-raises. That is developed in production areas. Eq. (2) defines the vertical shaft development capacity. The inequality ensures that the total length of capital development required in each period is within the stated lower and upper limits of the whole available equipment capacity for developing the mine. Eqs. (3) to (5) control the precedence relation between the sections of vertical shaft developments and the

ventilation developments on each level. Eq. (6) ensures that the ventilation development on the level l_a starts after completing the vertical shaft developments on the lowest level.

$$\underline{Dev_{sd}^{t}} \le \sum_{l=1}^{L} (dl_{sd_l} \times d_{sd_l}^{\ t}) \le \overline{Dev_{sd}^{t}} \qquad \forall t \in \{1,2,...,T\} \tag{2}$$

$$b_{sd_{l+1}}^{\ t} - \sum_{t' \le t} d_{sd_l}^{\ t'} \le 0 \qquad \forall l \in \{1,2,...,L-1\}, t \in \{1,2,...,T\} \tag{3}$$

$$\sum_{t' \le t} d_{sd_l}^{\ t'} - b_{sd_l}^{\ t} \le 0 \qquad \forall l \in \{1,2,...,L\}, t \in \{1,2,...,T\} \tag{4}$$

$$b_{sd_l}^{\ t} - b_{sd_l}^{\ t+1} \le 0 \qquad \forall l \in \{1,2,...,L\}, t \in \{1,2,...,T-1\} \tag{5}$$

$$b_{vds_{l_a}}^{\ t} - \sum_{t' < t} d_{sd_{l_v}}^{\ t'} \le 0 \qquad \forall l \in \{1,2,...,L\}, t \in \{1,2,...,T\} \tag{6}$$

Eq. (7) defines the man-way-raise development capacity constraint for the mine. Eqs. (8) to (10) control the precedence relation between the sections of man-way-raise developments on each level within a production area. Eq. (11) and (12) prevent man-way-raise ventilation and orepass development on the level l_v before completing the man-way-raise developments on the top level in the production area v.

$$\underline{Dev_{mwr}^{t}} \le \sum_{v=1}^{V} \sum_{l=1}^{L} (dl_{mwr_{v,l}} \times d_{mwr_{v,l}}^{\ t}) \le \overline{Dev_{mwr}^{t}} \qquad \forall t \in \{1,2,...,T\} \tag{7}$$

$$b_{mwr_{v,l}}^{\ t} - \sum_{t' \le t} d_{mwr_{v,l+1}}^{\ t'} \le 0 \qquad \begin{array}{l} \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L-1\}, \\ t \in \{1,2,...,T\} \end{array} \tag{8}$$

$$\sum_{t' \le t} d_{mwr_{v,l}}^{\ t'} - b_{mwr_{v,l}}^{\ t} \le 0 \qquad \begin{array}{l} \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L\}, \\ t \in \{1,2,...,T\} \end{array} \tag{9}$$

$$b_{mwr_{v,l}}^{\ t} - b_{mwr_{v,l}}^{\ t+1} \le 0 \qquad \begin{array}{l} \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L\}, \\ t \in \{1,2,...,T-1\} \end{array} \tag{10}$$

$$b_{vd_{v,l_v}}^{\ t} - \sum_{t' < t} d_{mwr_{v,l_a}}^{\ t'} \le 0 \qquad \forall v \in \{1,2,...,V\}, t \in \{1,2,...,T\} \tag{11}$$

$$b_{opd_{v,l_v}}^{\ t} - \sum_{t' < t} d_{mwr_{v,l_a}}^{\ t'} \le 0 \qquad \forall v \in \{1,2,...,V\}, t \in \{1,2,...,T\} \tag{12}$$

4.6. Ventilation Development Constraints

Ventilation development consists of two phases of ventilation installation in both vertical shaft and man-way-raises in production areas. Eq. (13) defines the ventilation development capacity constraint for the mine. Eqs. (14) to (16) control the precedence relation between the sections of ventilation developments and the ventilation developments on each level. Eq. (17) ensures that no man-way-raise development can start before completing the ventilation development in the vertical shaft on the level l_v.

$$\underline{Dev_{vds}^{t}} \le \sum_{l=1}^{L} (dl_{vds_l} \times d_{vds_l}^{\ t}) \le \overline{Dev_{vds}^{t}} \qquad \forall t \in \{1,2,...,T\} \tag{13}$$

$$b_{vds_{l+1}}^{t} - \sum_{t' \le t} d_{vds_l}^{t'} \le 0 \qquad \forall l \in \{1,2,...,L-1\}, t \in \{1,2,...,T\} \tag{14}$$

$$\sum_{t' \le t} d_{vds_l}^{t'} - b_{vds_l}^{t} \le 0 \qquad \forall l \in \{1,2,...,L\}, t \in \{1,2,...,T\} \tag{15}$$

$$b_{vds_l}^{t} - b_{vds_l}^{t+1} \le 0 \qquad \forall l \in \{1,2,...,L\}, t \in \{1,2,...,T-1\} \tag{16}$$

$$b_{mwr_{v,l_v}}^{t} - \sum_{t' < t} d_{vds_{l_v}}^{t'} \le 0 \qquad \forall v \in \{1,2,...,V\}, t \in \{1,2,...,T\} \tag{17}$$

Eq. (18) checks the man-way-raise development capacity for the mine. Eqs. (19) to (21) dictate the precedence relationships between the stages of ventilation facility installation in man-way-raise developments on each level within a production area. Eq. (22) enforces the operational development on the uppermost level in the production area v to complete the man-way-raise ventilation developments on that level and production area.

$$\underline{Dev_{vdv}^{t}} \le \sum_{v=1}^{V} \sum_{l=1}^{L} (dl_{vd_{v,l}} \times d_{vd_{v,l}}^{t}) \le \overline{Dev_{vdv}^{t}} \qquad \forall t \in \{1,2,...,T\} \tag{18}$$

$$b_{vd_{v,l}}^{t} - \sum_{t' \le t} d_{vd_{v,l+1}}^{t'} \le 0 \qquad \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L-1\}, t \in \{1,2,...,T\} \tag{19}$$

$$\sum_{t' \le t} d_{vd_{v,l}}^{t'} - b_{vd_{v,l}}^{t} \le 0 \qquad \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L\}, t \in \{1,2,...,T\} \tag{20}$$

$$b_{vd_{v,l}}^{t} - b_{vd_{v,l}}^{t+1} \le 0 \qquad \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L\}, t \in \{1,2,...,T-1\} \tag{21}$$

$$b_{od_{v,l_a}}^{t} - \sum_{t' < t} d_{vd_{v,l_a}}^{t'} \le 0 \qquad \forall v \in \{1,2,...,V\}, t \in \{1,2,...,T\} \tag{22}$$

4.7. Orepass Development Constraints

Eq. (23) dictates the total orepass development length between the lower and upper bounds of the total available equipment capacity. Eqs. (24) to (26) control the precedence relationships between the stages of orepass developments on each level within a production area. Eq. (27) enforces the operational development on the uppermost level in each production area to complete orepass developments on level l_a.

$$\underline{Dev_{opd}^{t}} \le \sum_{v=1}^{V} \sum_{l=1}^{L} (dl_{opd_{v,l}} \times d_{opd_{v,l}}^{t}) \le \overline{Dev_{opd}^{t}} \qquad \forall t \in \{1,2,...,T\} \tag{23}$$

$$b_{opd_{v,l}}^{t} - \sum_{t' \le t} d_{opd_{v,l+1}}^{t'} \le 0 \qquad \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L-1\}, t \in \{1,2,...,T\} \tag{24}$$

$$\sum_{t' \le t} d_{opd_{v,l}}^{t'} - b_{opd_{v,l}}^{t} \le 0 \qquad \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L\}, t \in \{1,2,...,T\} \tag{25}$$

$$b_{opd_{v,l}}^{t} - b_{opd_{v,l}}^{t+1} \le 0 \qquad \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L\}, t \in \{1,2,...,T-1\} \tag{26}$$

$$b_{od}{}^{t}_{v,l,a} - \sum_{t'<t} d_{opd}{}^{t'}_{v,l,a} \le 0 \qquad \forall v \in \{1,2,...,V\}, t \in \{1,2,...,T\} \tag{27}$$

4.8. Operational Development Constraints

If a mining unit is scheduled to be mined in a period, a set of operational development must be ready ahead or in that period. Eq. (28) defines the operational development capacity constraints. Eqs. (29) to (31) control the lateral precedence relation of the operational development required for mining each mining unit. Eq. (32) ensures that the operational developments in the production area v, and on level l must be completed before any of the mining units in that production area, and on that level starts being mined.

$$\underline{Dev^{t}_{od}} \le \sum_{v=1}^{V}\sum_{l=1}^{L}(dl_{od_{v,l}} \times d_{od}{}^{t}_{v,l}) \le \overline{Dev^{t}_{od}} \qquad \forall t \in \{1,2,...,T\} \tag{28}$$

$$b_{od}{}^{t}_{v,l+1} - \sum_{t'\le t} d_{od}{}^{t'}_{v,l} \le 0 \qquad \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L-1\}, t \in \{1,2,...,T\} \tag{29}$$

$$\sum_{t'\le t} d_{od}{}^{t'}_{v,l} - b_{od}{}^{t}_{v,l} \le 0 \qquad \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L\}, t \in \{1,2,...,T\} \tag{30}$$

$$b_{od}{}^{t}_{v,l} - b_{od}{}^{t+1}_{v,l} \le 0 \qquad \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L\}, t \in \{1,2,...,T-1\} \tag{31}$$

$$bs^{t}_{m} - \sum_{t'\le t} d_{od}{}^{t'}_{v,l} \le 0 \qquad \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L\}, t \in \{1,2,...,T\}, m \in S_{M_{v,l}} \tag{32}$$

4.9. Mining and Processing Capacity

Eq. (33) enforces the mining capacity, using continuous decision variable x^{t}_{m}, between the acceptable lower and upper limits of the total available equipment capacity in each period. Eq. (34) controls the quantity of mill feed using continuous decision variable $x^{t}_{m,p}$.

$$\underline{Ton^{t}} \le \sum_{m=1}^{M}\left[(o_m \times (1+dil_m) \times x^{t}_{m}\right] \le \overline{Ton^{t}} \qquad \forall t \in \{1,2,...,T\} \tag{33}$$

$$\underline{Ton^{t}_{p}} \le \sum_{m=1}^{M}(o_m \times (1+dil_m) \times x^{t}_{m,p}) \le \overline{Ton^{t}_{p}} \qquad \forall t \in \{1,2,...,T\} \tag{34}$$

4.10. Active Mining Units Constraints

Crew and LHD availability limit the number of active mining units in each period. LHD restrictions in each level, each production area, and each period within all production areas are controlled by Eq. (35) to Eq. (37), respectively.

$$\sum_{m\in S_{M_l}} as^{t}_{m} \le LHD_l \qquad \forall l \in \{1,2,...,L\}, t \in \{1,2,...,T\} \tag{35}$$

$$\sum_{m\in S_{M_v}} as^{t}_{m} \le LHD_v \qquad \forall v \in \{1,2,...,V\}, t \in \{1,2,...,T\} \tag{36}$$

$$\sum_{m=1}^{M} as_m^t \le LHD_t \qquad \forall t \in \{1,2,...,T\} \tag{37}$$

4.11. Continuous Mining Constraints

Each mining unit must be continuously extracted after opening until closing. Eq. (38) forces variable as_m^t to be zero if no portion of the mining unit m is extracted at period t, while Eq. (39) changes the value as_m^t to 1 when a portion of the mining unit m is extracted at period t. Eq. (40) 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. (41) 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.

$$as_m^t \le M \times x_m^t \qquad \forall t \in \{1,2,...,T\}, m \in \{1,2,...,M\} \tag{38}$$

$$x_m^t \le as_m^t \qquad \forall t \in \{1,2,...,T\}, m \in \{1,2,...,M\} \tag{39}$$

$$as_m^t - as_m^{t-1} \le bs_m^t \qquad \forall m \in \{1,2,...,M\}, t \in \{2,...,T\} \tag{40}$$

$$as_m^1 - bs_m^1 \le 0.5 \qquad \forall m \in \{1,2,...,M\} \tag{41}$$

4.12. Processing Plant Grade Control Constraint

Eq. (42) meets the ore quality specification of the processing plant within the predefined limits.

$$\underline{g_p^t} \le \left[\frac{\sum_{m=1}^{M} (g_m \times o_m \times (1+dil_m) \times x_{m,p}^t)}{\sum_{m=1}^{M} (o_m \times (1+dil_m) \times x_{m,p}^t)} \right] \le \overline{g_p^t} \qquad \forall t \in \{1,2,...,T\} \tag{42}$$

4.13. Vertical and Horizontal Sequencing Constraints

Some strict operational rules must be satisfied when extracting the ore body using the SLC method. Figure 4 illustrates six mining units. Considering the operational rules, vertical sequencing requires MU5 to start being mined only after MU2 is returned to a safe distance. Furthermore, horizontal sequencing dictates that MU2 starts being mined once after MU1 retreats past enough its neighbour on the same level. Eqs. (43) and (44) enforce vertical and horizontal sequencing between mining units modelled with the long-term resolution, respectively. These operational rules are satisfied using two sets of $S_{M_m}^V$ and $S_{M_m}^H$ the required extraction percentage for the predecessor mining units, which is assumed constant for all mining units δ_m.

$$bs_m^t - \sum_{t'=1}^{t} x_{m'}^{t'} \le \delta_m \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T\}, m' \in S_{M_m}^V \tag{43}$$

$$bs_m^t - \sum_{t'=1}^{t} x_{m'}^{t'} \le \delta_m \qquad \forall m \in \{1,2,...,M\}, t \in \{1,2,...,T\}, m' \in S_{M_m}^H \tag{44}$$



Figure 4. A depiction of six mining units.

4.14. Variable Control Constraints

Eq. (45) enforces the extracted material from each mining unit to be sent to the processing plant in each period. Eq. (46) to Eq. (47) ensure that the total fraction of material mined and sent to the processing plant is less than one over the scheduling periods. Eq. (48) to Eq. (53) ensure that all developments will be completed once over the life of the mine. Eq. (54) prevents a mining unit from being mined more than once. Eq. (55) ensures that all continuous decision variables in the model are between zero and one. Eq. (56) guarantees that all binary variables are non-negative and integers.

$$x_{m,p}^{t} = x_{m}^{t} \qquad \forall t \in \{1,2,...,T\}, m \in \{1,2,...,M\} \tag{45}$$

$$\sum_{t=1}^{T} x_{m}^{t} \le 1 \qquad \forall m \in \{1,2,...,M\} \tag{46}$$

$$\sum_{t=1}^{T} x_{m,p}^{t} \le 1 \qquad \forall m \in \{1,2,...,M\} \tag{47}$$

$$\sum_{t=1}^{T} d_{sd_{l}}^{t} \le 1 \qquad \forall l \in \{1,2,...,L\} \tag{48}$$

$$\sum_{t=1}^{T} d_{vds_{l}}^{t} \le 1 \qquad \forall l \in \{1,2,...,L\} \tag{49}$$

$$\sum_{t=1}^{T} d_{mwr_{v,l}}^{t} \le 1 \qquad \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L\} \tag{50}$$

$$\sum_{t=1}^{T} d_{vd_{v,l}}^{t} \le 1 \qquad \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L\} \tag{51}$$

$$\sum_{t=1}^{T} d_{opd_{v,l}}^{t} \le 1 \qquad \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L\} \tag{52}$$

$$\sum_{t=1}^{T} d_{od_{v,l}}^{t} \le 1 \qquad \forall v \in \{1,2,...,V\}, l \in \{1,2,...,L\} \tag{53}$$

$$\sum_{t \in T_m} bs_{m}^{t} \le 1 \qquad \forall m \in \{1,2,...,M\} \tag{54}$$

$$x_{m}^{t}, x_{m,p}^{t}, d_{sd_{l}}^{t}, d_{vds_{l}}^{t}, d_{mwr_{v,l}}^{t}, d_{vd_{v,l}}^{t}, d_{opd_{v,l}}^{t}, d_{od_{v,l}}^{t} \in [0,1] \tag{55}$$

$$bs_m^t, as_m^t, b_{sd_l}^t, b_{vds_l}^t, b_{mwr_{v,l}}^t, b_{vd_{v,l}}^t, b_{opd_{v,l}}^t, b_{od_{v,l}}^t \in \{0,1\} \quad (56)$$

5. Implementation of the MILP Model on an Illustrative Example

The effectiveness of the proposed models was assessed by evaluating NPV, mining production, and the practicality of the resulting schedules. The objective is to maximize NPV at a 15% discount rate while ensuring all constraints are met throughout the mine's lifespan. Additionally, the model assumes zero dilution for all mining units.

The proposed formulation is tested using a small-scale illustrative case. The orebody, resembling a vein, is situated 300 meters beneath the surface and comprises 18 mining units, each measuring 25×25×50. The mining activities occur at depths between 300 and 375 meters, distributed across three distinct levels, with each level having a height of 25 meters. The SLC mine is organized into three production areas, each spanning 50 meters and including three horizontal sublevels. Additionally, two vertical orepasses and one man-way-raise provide access to the sublevels, which are progressively deeper cuts in the earth's surface. Within each sublevel, the blasted ore is loaded and hauled by LHDs from the production face to the ore passes, where it is then directly transported to the main haulage level.

This paper relies on several key assumptions in the MILP formulations. The vertical shafts are considered the primary exit point for all materials, and a first-in-first-out approach is used with no material mixing. Development activities in production areas begin only after the vertical shaft development and its ventilation installations are completed. To avoid potential damage, orepasses and man-way-raise are not allowed to be mined simultaneously. As a result, man-way-raise is drilled first before commencing orepass mining in each production area. Furthermore, no operational developments are permitted to begin until man-way-raise ventilation and orepass developments in each production area are completed.

The ore extracted from the mine is sent directly to the surface-based processing plant. To mitigate stress and explosive damage on neighboring mining units, a predetermined number of LHDs operate simultaneously. This approach also prevents congestion and potential damage resulting from LHDs' operation. Once an LHD starts mining a mining unit, it must continue until completion; otherwise, the unit will be closed. According to the vertical and horizontal sequencing rules, at least 50% of a mining unit should be mined before starting to mine units below and adjacent to it.

All the development activities boundaries that are applied to the model are provided in Table 1. These annual boundaries have been assumed the same throughout the mine life.

Table 1. Development activities boundaries (m) over the life of mine (LB: Lower bound, UB: Upper bound).

Vertical Shaft		**Vertical Shaft Ventilation**		**Man Way Raise**		**Man Way Raise Ventilation**		**Orepass**		**Operational**	
LB	**UB**	**LB**	**UB**	**LB**	**UB**	**LB**	**UB**	**LB**	**UB**	**LB**	**UB**
0	250	0	500	0	300	0	300	0	300	0	600

Figure 5 provides a schematic layout of production areas, levels, mining units, and development activities through two cross-sections (i) along the strike of the orebody and (ii) along the dip of the orebody. Figure 6 shows the tonnage and the average grade of each mining unit. In Figure 6, the available tonnage of each mining unit, along with their average grade, is provided. In the horizontal axis, mining units are recognized based on their location (the production area and the level). For instance, MU9 and MU 10 are in Level 2 and Production Area 2.

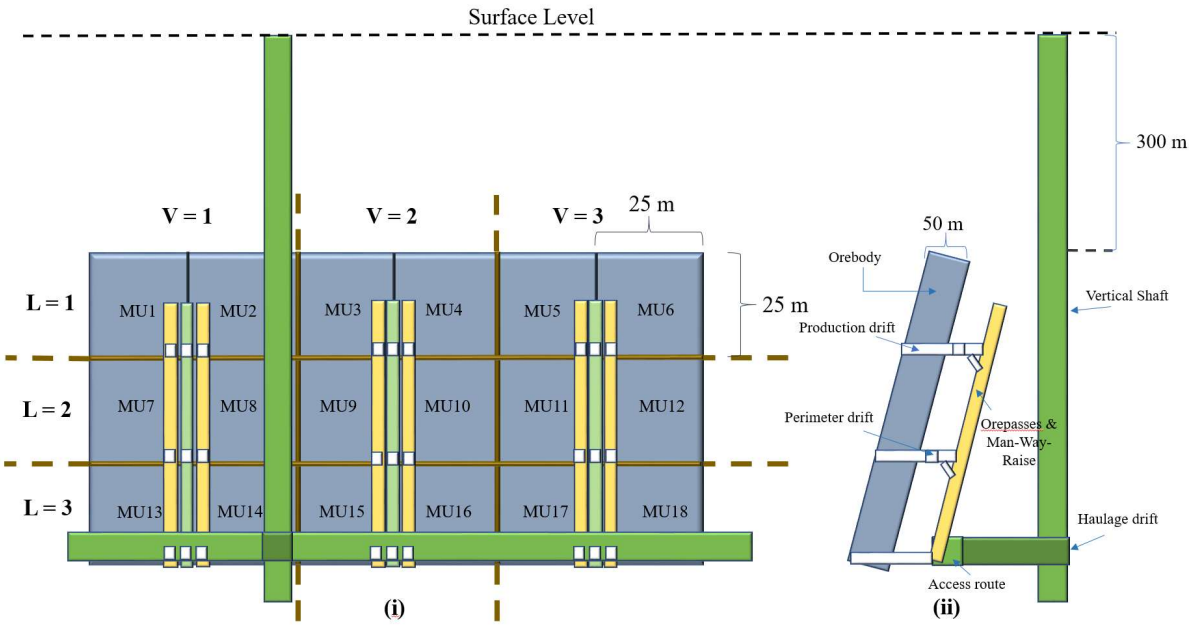


Figure 5. A schematic representation of production areas, levels, mining units, and development layout: (i) is a cross-section along the strike of the orebody, and (ii) is a cross-section along the dip of the orebody.

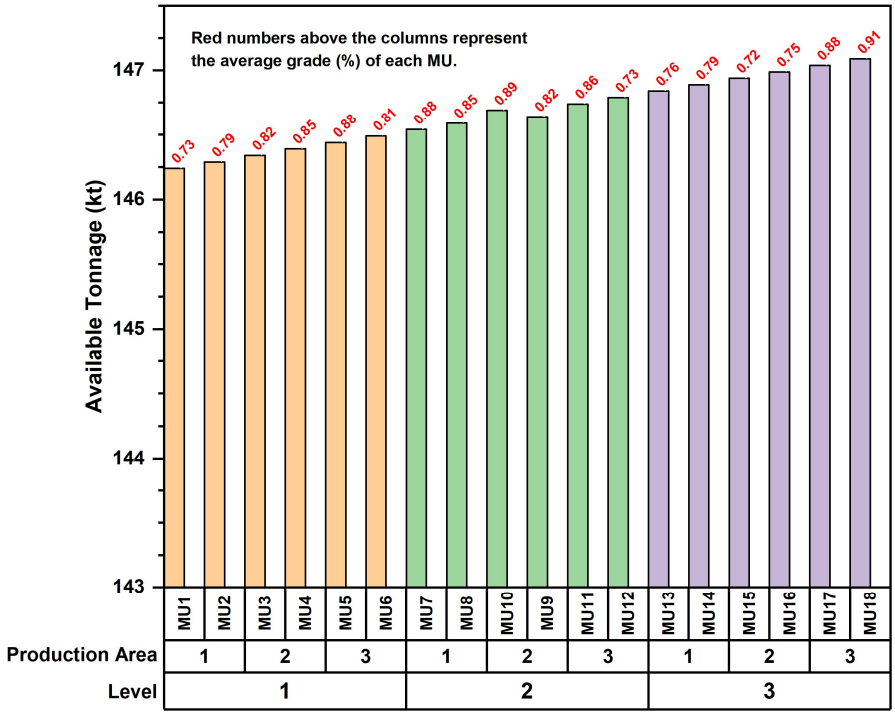


Figure 6. Summary of the tonnage and average grade of mining units in different levels and production areas.

6. Results and Discussion

Table 2 shows the components of the model. Figure 7 represents the development activities' schedules obtained from the model.

Table 2. Mathematical model components.

Model components	Number
Sets	7
Binary decision variables	1248
Continuous decision variables	1248
Constraints	4568

Figure 8 illustrates the annual mine production and processing plant feed, as well as the headgrade of the processing plant. It can be seen that the processing plant capacity limits production each year. Also, the first production takes place in year 7, which indicates that the vertical shaft and its ventilations, as well as all the developments in the first production area, including the man-way-raise and its ventilations, the orepass, and the operational development, need to be completed before commencing any ore extraction. Figure 9 shows the active periods and the extracted portion of each mining unit over the life of the mine. It can be seen that from MU12 to MU18, only 90% of them are extracted.

The developed model has been coded in Jupyter notebook while taking advantage of CPLEX Python API to solve and optimize the model on a PC Intel Core i7, 2.60 GHz, with 16 GB of RAM, running Windows 11. The gap tolerance is considered zero while running the model.

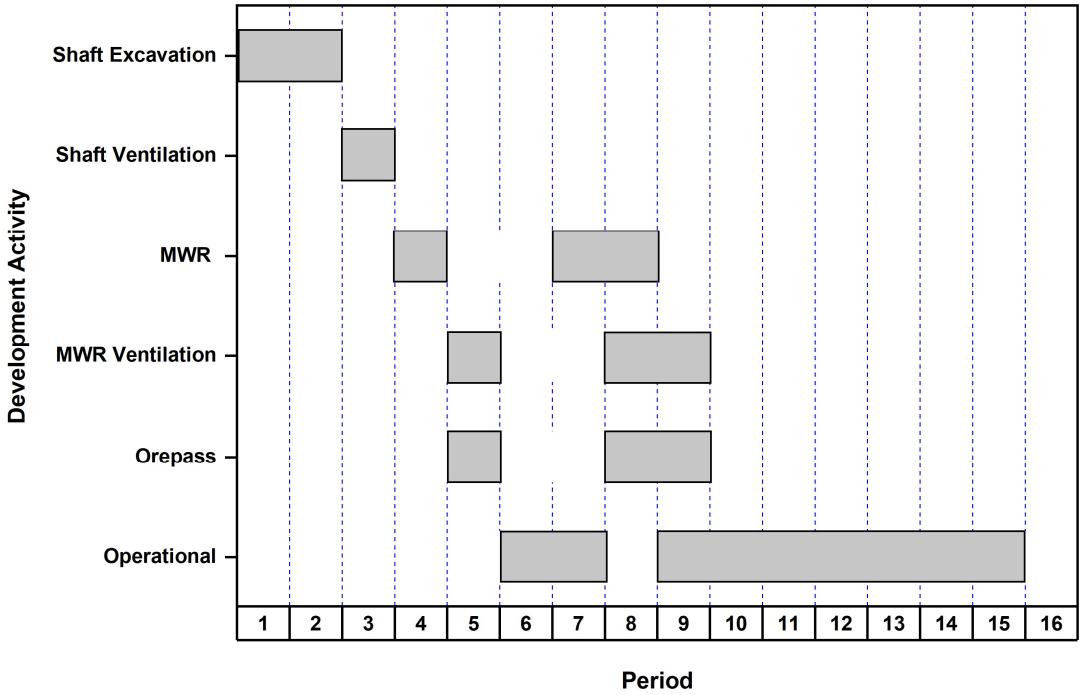


Figure 7. Development activities over the life of mine.

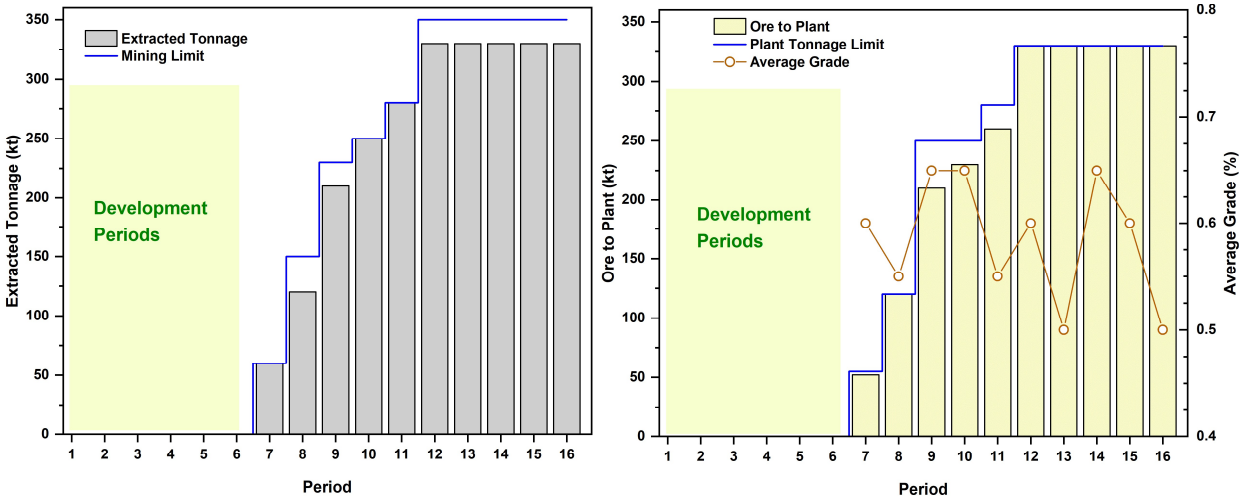


Figure 8. Mine extraction and processing plant feed over the life of mine.

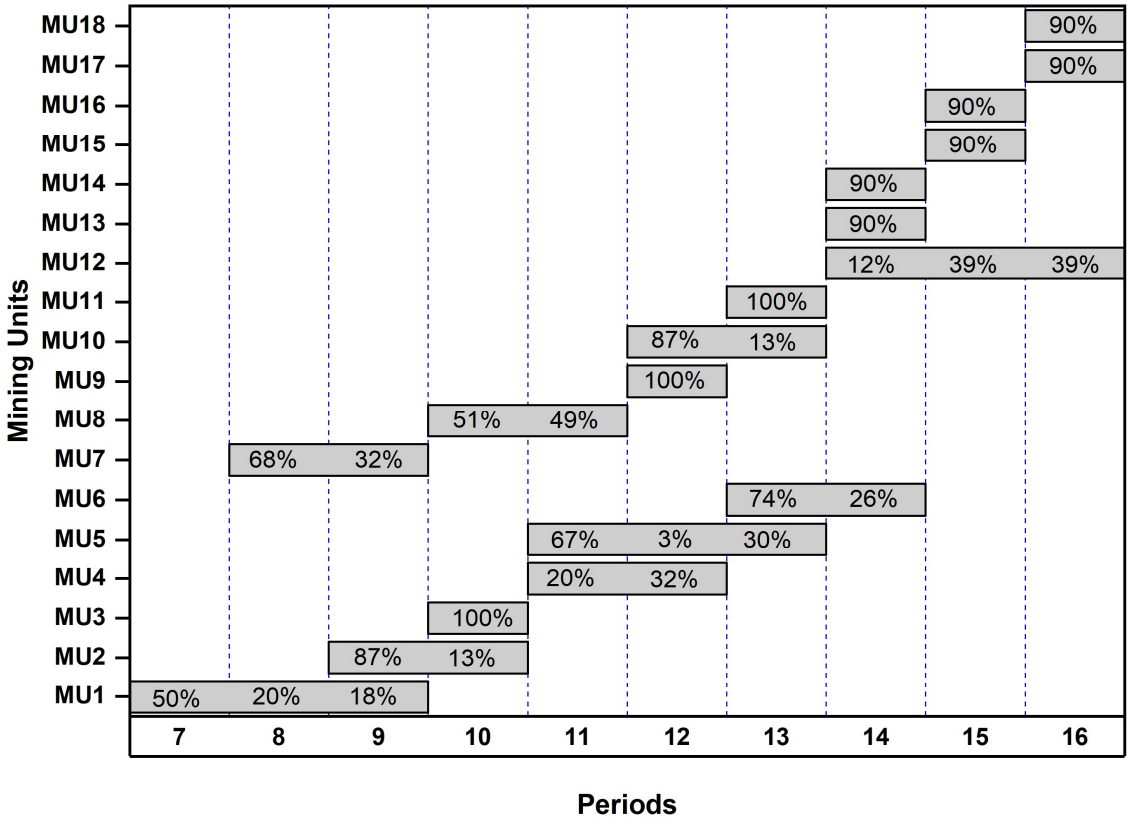


Figure 9. Mining units scheduling (extraction start time, duration, and portion (%) of each mining unit).

To examine the influence of the number of mining units on the running time of the model, it was evaluated for three different quantities of mining units, specifically 18, 36, and 54, resulting in respective running times of 11.9, 98.38, and 768.63 seconds. To ensure a constant mine life, the mine production and processing plant capacities were increased in proportion to the number of mining units. The outcomes indicate an exponential increase in the running time with the addition of mining units. It is noteworthy to mention that our analysis was performed on a schematic SLC mine, and the subsequent phase of our research will involve applying the model to an actual case study.

7. Conclusion and future works

This paper introduces a comprehensive mathematical model aimed at optimizing sublevel caving (SLC) production scheduling to maximize NPV. The model utilizes a mixed-integer-linear programming formulation implemented in the Jupyter Notebook with the CPLEX Python API for solving and optimization. The scheduling of each mining unit is governed by the completion of development activities in the production area and the respective level while considering vertical and horizontal precedence relationships between mining units. It also manages the number of new mining units to be mined in each period to meet production requirements, the active mining unit count per period, and the average production grade. Additionally, the model integrates pre-extraction material flow and development activities into mining unit schedules.

Future research will focus on adapting the model to handle post-extraction material flow, which involves incorporating a stockpiling system to manage processing plant capacity and material flows from the mine to a stockpile, mine to plant, and stockpile to plant. Based on mining unit schedule results, more detailed scheduling at the production ring level will be explored since each mining unit encompasses multiple production rings across the orebody's width, resulting in a 3D-dimensional plan. Moreover, efficient mathematical techniques will be investigated to reduce the number of decision variables and execution time for large-scale SLC production scheduling.

8. References

[1] Afum, B. O., Ben-Awuah, E., and Askari-Nasab, H. (2020). A mixed integer linear programming framework for optimising the extraction strategy of open pit–underground mining options and transitions. International Journal of Mining, Reclamation and Environment, 34 (10), 700-724.

[2] Almgren, T. (1994). An approach to long range production and development planning with application to the Kiruna Mine, Sweden.Thesis, Luleå tekniska universitet, Lulea, Sweden,

[3] Appianing, E. J. A., Ben-Awuah, E., and Pourrahimian, Y. (2023). Life-of-mine optimization for integrated open stope development and production scheduling using a mixed-integer linear programming framework. Mining Technology, 132 (2), 106-120.

[4] Campeau, L.-P. and Gamache, M. (2020). Short-term planning optimization model for underground mines. Computers & Operations Research, 115 104642.

[5] Dagdelen, K., Topal, Erkan and Kuchta, Mark (2002). Linear programming model applied to scheduling of iron ore production. Mine Planning and Equipment Selection 2000,

[6] Darling, P. (2011). SME MINING ENGINEERING HANDBOOK. Vol. 1, Society for Mining, Metallurgy, and Exploration, Inc., Third Edition ed.

[7] Eremenko, A. A., Filippov, V. N., Konurin, A. I., Khmelinin, A. P., Baryshnikov, D. V., and Khristolyubov, E. A. (2018). Drilling and blasting parameters in sublevel caving in Sheregesh mine. in Proceedings of IOP Conference Series: Earth and Environmental Science,

[8] Franco-Sepulveda, G., Del Rio-Cuervo, J. C., and Pachón-Hernández, M. A. (2019). State of the art about metaheuristics and artificial neural networks applied to open pit mining. Resources Policy, 60 125-133.

[9] Khazaei, S. and Pourrahimian, Y. (2021). Mathematical Programming Application in Sublevel Caving Production Scheduling. Mining, 1 (2), 180-191.

[10] Khodayari, F. and Pourrahimian, Y. (2019). Long-term production scheduling optimization and 3D material mixing analysis for block caving mines. Mining Technology, 128 (2), 65-76.

[11] Khodayari, F. a. P., Yashar (2015). Mathematical programming applications in block-caving scheduling: a review of models and algorithms. International Journal of Mining and Mineral Engineering, 6 (3), 234-257.

[12] Kuchta, M., Newman, A., and Topal, E. (2004). Implementing a production schedule at LKAB's Kiruna Mine. Interfaces, 34 (2), 124-134.

[13] Laubscher, D., Guest, A., and Jakubec, J. (2017). Guidelines on Caving Mining Methods- The University Concepts. W.H. Bryan Mining and Geology Research Centre, Brisbane, St Lucia, Queensland 4072, Australia.

[14] Mousavi, A., Kozan, E., and Liu, S. Q. (2016). Open-pit block sequencing optimization: A mathematical model and solution technique. Engineering Optimization, 48 (11), 1932-1950.

[15] Mousavi, A. and Sellers, E. (2019). Optimisation of production planning for an innovative hybrid underground mining method. Resources Policy, 62 184-192.

[16] Newman, A. M. a. K., Mark (2007). Using aggregation to optimize long-term production planning at an underground mine. European Journal of Operational Research, 176 (2), 1205-1218.

[17] Newman, A. M. a. M., Michael A. (2011). A solution approach for optimizing long- and short-term productionscheduling at LKAB's Kiruna mine. European Journal of Operational Research, 211 184-197.

[18] Noriega, R., Pourrahimian, Y., and Ben-Awuah, E. (2022). Optimisation of life-of-mine production scheduling for block-caving mines under mineral resource and material mixing uncertainty. International Journal of Mining, Reclamation and Environment, 36 (2), 104-124.

[19] Pourrahimian, Y. and Askari-Nasab, H. (2014). An application of mathematical programming to determine the best height of draw in block-cave sequence optimisation. Mining Technology, 123 (3), 162-172.

[20] Pourrahimian, Y., Askari–Nasab, Hooman and Tannant, Dwayne (2012). Mixed–Integer Linear Programming formulation for block–cave sequence optimisation. International Journal of Mining and Mineral Engineering, 4 (1), 26-49.

[21] Shekhar, G., Gustafson, A., Boeg-Jensen, P., Malmgren, L., and Schunnesson, H. (2018). Draw control strategies in sublevel caving mines — A baseline mapping of LKAB's Malmberget and Kiirunavaara mines. Journal of the Southern African Institute of Mining and Metallurgy, 118 (7), 723-733.

[22] Shenavar, M., Ataee-pour, M., and Rahmanpour, M. (2020). A New Mathematical Model for Production Scheduling in Sub-level Caving Mining Method. Journal of Mining and Environment.

[23] Topal, E. (1998). Long and short term production scheduling of the Kiruna iron ore mine. Kiruna, Sweden, Master of Science thesis, Colorado School of Mines, Golden, Colorado.

A Stochastic Mixed Integer Linear Programming Framework for Open Stope Mine Production Scheduling Optimization Considering Grade Uncertainty and Stockpiling Strategy

Emmanuel John Andrew Appianing, Obinna Mbadozie and Eugene Ben-Awuah
Mining Optimization Laboratory (MOL)
Laurentian University, Sudbury, Canada

ABSTRACT

The use of traditional geostatistical estimation methods such as ordinary kriging for mine planning have been identified to be biased and introduce smoothing effect which results in unrealistic mine production schedules. The introduction and development of simulation methods where equiprobable orebody realizations are used as input in the mine planning process greatly helps in measuring and managing the associated risk due to grade uncertainty. Often, the outcome of the uncertainty related to orebody modelling is crucial and affects the resultant performance of stope designs and stope production. This is directly linked to the failure to meet set production targets and expected project financial outcomes during the mine-life. Uncertainty-based solutions in underground mine production scheduling optimization helps to minimize the variations between planned and actual production key performance indicators. To incorporate grade uncertainty into the strategic mine plan, a stochastic mixed integer linear programming (SMILP) framework was developed to optimize open stope underground mining production schedules. The objective of the model is to maximize the Net Present Value (NPV) of the mining project while minimizing the associated risk of deviation from the set production targets based on simulated orebody realizations.

1. Introduction

There are two approaches of conducting mine planning, namely, deterministic approach, and stochastic approach. Deterministic mine planning uses historical data collected from previous mine production activities and assumes that this trend will continue in future processes. Conversely, stochastic mine planning can be described as a premeditated course of action based on data collected from historical mine production figures incorporating uncertainty into the modelling processes. Deterministic approaches are known to ignore variations; thus, stochastic mine planning is promoted because it incorporates variations considering that mine production activities are erratic in nature and not static. 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 [27; 37]. Researchers like Ramazan and Dimitrakopoulos [42]; Grieco and Dimitrakopoulos [14]; Leite and Dimitrakopoulos [24]; Carpentier et al. [4]; Malaki [28]; MacNeil and Dimitrakopoulos [25]; Huang et al. [15] have investigated, evaluated, and 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. The authors 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.

ISBN: 978-1-55195-503-2

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 [6; 9; 23], orebody uncertainty, in situ grade and geological uncertainty [9; 8; 10; 12; 47], geological and market uncertainty [46] and NPV [43] 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 [14; 38; 37].

Grieco and Dimatrakopoulos [14] developed and explored a new probabilistic Mixed Integer Programming (MIP) model to optimize stope designs, including size, location, and number of stopes under consideration of grade uncertainty and predefined levels of acceptable risk. The model was applied on data from Kidd Creek Mine, Ontario, Canada to demonstrate its practicality. The application exhibited aspects including risk quantification for contained ore tons, grade, and economic potential. The authors reported that unlike any conventional stope optimization approach, the stope designs generated based on the concept of acceptable risk gives the mine planner control over the final stope layout and its potential future performance while considering grade uncertainty. The application of the proposed approach is based on the ability to stochastically simulate equally probable representations of the deposit.

Martinez [30] gives a classic presentation on why accounting for uncertainty and risk leads to an improvement in decision making so far as mine evaluation is concerned. He introduced a new mine evaluation framework; the Integrated Valuation Optimization Framework (IVOF). He presented this as an alternative tool for mine project evaluation where uncertainty and risk are incorporated in the evaluation process. His paper highlights two main objectives; i) what problems can arise when single estimated values are substituted for a distribution of values when evaluating a mine project in the face of uncertainty and ii) how the ability to deal with uncertainty and risk in mine project evaluation can have a significant impact on the owners' and stakeholders' investment decision-making. 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, such as metal prices, metal grades, costs, schedules, quantities, and environmental issues, among others, which are not known with absolute certainty. He identifies the main sources of uncertainty that arise at the commencement of a mine project evaluation to be uncertainty in orebody modelling, uncertainty in metal prices and costs, and uncertainty and risk in mine planning and design.

Dimitrakopoulos and Grieco [7] adopted risk-based concepts developed in open pit mining to the underground stoping environment and shows examples employing data from Kidd Creek Mine. This example illustrates how conventional technologies cannot quantify risk since they are unable to foresee a significant upside potential and/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. They further outlined a new probabilistic mathematical formulation that optimizes the size, location, and number of stopes in the presence of grade uncertainty with an additional constraint introduced as the minimum acceptable risk allowed in a design. The model was applied to demonstrate the advantages of a user-defined level of acceptable risk. It is worth mentioning, that the authors recommended that further developments of the work could be to include: i) the formulation of a stope optimization formulation that replaces the probability of grades above cutoff with the direct use of all available simulated orebodies, integrating more geological information; ii) consider sequencing and thus accommodating risk management and/or geological risk discounting as part of the stope design process; and iii) extend to integrate geotechnical uncertainties starting from over-breaking and under-breaking.

Dimitrakopoulos [5] proposed a risk-based Stochastic Integer Programming (SIP) optimization model which incorporates uncertainties from both the geological and economic factors while

minimizing cost. The model integrates two elements: stochastic simulation and stochastic optimization. These elements provide 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%. Case studies also show that stochastic optimal designs i) can be about 15% larger in terms of total tonnage when compared to the conventional design, while ii) adding about 10% of NPV comparing to the traditional scheduling using a determined averaging orebody model design. Results suggest a potential new contribution to the sustainable utilization of natural resources. However, Magagula [27] reports that the author indicated the difficulties surrounding creating such planning process.

To integrate ore/metal uncertainty into the optimization of mine production scheduling, a SIP formulation was proposed and tested at a copper deposit by Leite and Dimitrakopoulos [24]. The stochastic solution maximizes the economic value of a project and minimizes deviations from production targets in the presence of ore/metal uncertainty. Unlike the conventional approach, the SIP model accounts and manages risk in ore supply, leading to a mine production schedule with a 29% higher NPV than the schedule obtained from the conventional, industry-standard optimization approach, thus contributing to improving the management and sustainable utilization of mineral resources.

Macneil [26] used stochastic mine planning methods to identify the optimal open pit to underground mining transition depth by identifying a series of candidate scenarios where it is feasible to make an OP-UG transition. The author evaluated the economic viability of each member of the set of candidate transition depths by producing uncertainty-based life-of-mine production plans that were used to outline expected yearly cash flows. The benefits of using stochastic mine planning to provide well-informed long-term strategic decision-making criteria are observed. Results of the application of the stochastic approach produced operational schedules with an increase NPV compared to the corresponding deterministic framework. An application of the proposed method at Geita gold mine in Eastern Africa indicate that future ore production is forecasted to fall well below the mill's capacity, and to supplement this deficiency a transition from open pit to underground mining was considered. Interestingly, results of the analysis from the proposed stochastic framework reflect that the most profitable decision favored continuing production through solely open pit mining for the foreseeable future. Valuable insights towards the risk associated with the proposed mine design are gained through stochastic risk analysis.

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 by these new methods to incorporate more decisions and flexibility to the mining optimization of a mining complex. However, they either ignore uncertainties associated with the mining project or consider decisions taken before optimization [34]. A method that optimizes mining complexes comprised of multiple open-pits, underground operations and processing destinations was presented by Montiel et al., [34]. The proposed method simultaneously optimizes mining, blending, processing, and transportation decision variables while accounting for geological uncertainty. The method employs a simulated annealing model at different decision levels to generate a stochastic-based extraction sequence and processing policies. An application based on a case study shows the method's ability to generate a higher NPV while facing a reduced amount of risk when compared to traditional optimization methods.

Malaki [28] employs the application of grade uncertainty in block cave mining. The author presents a methodology to find the best extraction level and the optimum sequence of extraction for that level under grade uncertainty. The work uses stochastic sequential simulation to address this problem by modelling a set of simulated realizations of the average mineral grade. The Mixed Integer Linear Programming (MILP) model was formulated to obtain the maximum NPV given some constraints such as mining capacity, grade, extraction rate and precedence. Finally, risks associated with grade

uncertainty are investigated and analyzed, considerably helping the decision makers in better understanding of various cases and conditions. The author concludes among other things that more uncertain attributes other than grade should be added to the optimization problem. Hence, the MILP model should be extended to take stochastic variables into account during optimization.

A new SIP model incorporating geological uncertainty to optimize long-term scheduling of an underground project extension was introduced by Carpentier et al., [4]. To represent a deposit integrating the uncertainty, they stochastically generated a set of simulations and placed them in the optimization model. The results show that the schedule generated has a higher expected value when considering and managing grade risk. They also demonstrated the benefits of risk control, allowed by the approach.

MacNeil and Dimitrakopoulos [25] provided an approach to determine an optimal depth at which a mine should transition from open pit to underground mining, based on managing technical risk. The proposed approach is tested on a gold deposit. This work aims to improve on previous attempts to solve this problem by jointly considering geological uncertainty and effectively describing the optimal transition depth in 3-D. Results show the benefits of managing geological uncertainty in long-term strategic decision-making frameworks. The stochastic result produces a 9% increase in NPV over a similar deterministic formulation. The risk-managing stochastic framework also produces operational schedules that reduce a mining project's susceptibility to geological risk. The authors direct future studies to aim at improving the method by considering more aspects of financial uncertainty such as inflation and mining costs.

Huang et al. [15] presented a Stochastic Mixed integer Programming (SMIP) framework to evaluate the effect of grade uncertainty for a gold deposit and to integrate consideration of grade uncertainty in the optimization of the long-term production schedule for underground cut-and-fill mining. The authors reported that conventional mine planning approaches use an estimated orebody model as input to generate optimal production schedules. The smoothing effect of some geostatistical estimation methods causes most of the mine plans and production forecasts to be unrealistic and incomplete. With the development of simulation methods, the risks from grade uncertainty in ore reserves can be measured and managed through a set of equally probable orebody realizations. Thus, a set of equally probable orebody realizations were used as input in the strategic mine plan and to generate a more profitable and risk-based optimized production schedule. The SMIP model showed the ability to minimize risk and improve financial profitability. The model was able to manage geological risk more effectively compared with the conventional method by directly incorporating grade uncertainty into the integrated model formalism. Results from the implemented case study demonstrated a 2-9% improvement in the expected NPV by the SMIP model, and the ability to control the geological risk when compared to the conventional approach.

1.1. 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. 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 [21; 18]. Bley et al. [3] modelled the Long-term open-pit production planning (LTOPP) incorporating stockpiling. The authors added non-linear constraints and proposed a problem-specific solution method. The model presented a formulation which helps to track material flow from aggregate to stockpile and plant.

Gholamnejad and Kasmaee [11] presented a goal programming model for an Iron ore processing plant blending requirement. 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, their proposed model did not include decisions on material flow from the mine and stockpile but solely focused on reclamation decisions. Ramazan and Dimitrakopoulos [44] proposed a production scheduling model with uncertain supply that includes stockpiling. Their model uses 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.

Smith and Wicks [48] presented a MIP for medium-term production planning with stockpiling in a copper mine. 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. Koushavand et al. [20] introduced the cost of uncertainty in a long term mine production plan of a mixed integer linear programming model 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. However, the presence of a stockpile in the model allows optimization to extract extra ore at early stages of the mine-life which helps reduce the chance of short falls at later years.

Tabesh et al, [50] presented a multi-step approach to long-term open-pit production planning by using different resolutions for making mining and processing decisions. They further determined the pushbacks based on a hybrid binary programming-heuristic method and used the intersections of pushbacks and mining benches as mining units. Afterwards, they divided the bench-phases into smaller units with similar rock type and grade using an agglomerative hierarchical clustering algorithm. These units were then used as processing units. They presented a mathematical model to solve the LTOPP problem with the aggregated units and finally, introduced stockpiling to the model with non-linear and linear objective functions and constraints. The idea of piecewise linearization was used to modify the model to be able to solve it with mixed integer linear programming solvers.

Mousavi et al. [36] also considered stockpiling with a predetermined grade and used a non-exact approach to deal with the problem. They compared their results against solutions obtained via exact method and showed how close to the optimum solution their solutions were. However, they did not study the errors caused by assuming a fixed reclamation grade for the stockpile and their largest case study had 2,500 blocks which is a relatively small number. Tabash and Askari-Nasab [49] proposed a mathematical formulation that uses aggregated units for making mining, processing and stockpiling decisions while respecting various mining and processing constraints. They first propose a non-linear model that estimates stockpile grade and controls the head grade of material sent to the processing plants. Next, they use the idea of piecewise linearization to modify the model to be able to solve it with mixed integer linear programming solvers. Afterwards, they illustrated how the model compares against other linear stockpiling models in the literature and finally, the model was tested on a small dataset to evaluate the performance of the model and show the errors introduced by linearization.

Kumar and Chatterjee [22] proposed and applied a mathematical formulation for production scheduling with stockpiling in a coal mine. Their formulation follows the same approach and assumes a fixed predetermined reclamation grade for the stockpile and show that the observed element head grades are within the required boundaries. Moreno et al. [35] classified the production scheduling and stockpiling models in the literature and proposed a new modeling approach. Moreover, they provided extensive computational results for the models they studied and developed. We will discuss their proposed model in the next chapter in more details.

Majority of studies so far illustrate the benefits of using the stochastic approach to incorporate 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 [14; 25; 19; 15]. 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 or as sources of high or low-grade ore for controlling 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 [20; 49; 39].

The use of stockpiling in the optimization process has been extensively used in open pit mining but less considered in underground mining [3; 44; 50; 36; 35; 49]. The proposed optimization approach is to consider grade uncertainty for underground open stope extraction with capital development, ventilation development, operational development, ore pass development, backfilling, and stockpiling management[1].

This research 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. Objectives of the Study

The objective of this study is to investigate techniques to:

a) quantify and access the impact of grade uncertainty on the output parameters of underground mine optimization such as: NPV, ore tonnage, head grade, annual targeted production; and
b) propose a stochastic mixed integer linear programming (SMILP) formulation for optimal production scheduling that aims at maximizing the net present value while minimizing the deviations from targeted production, caused by grade uncertainty.

3. Methodology

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

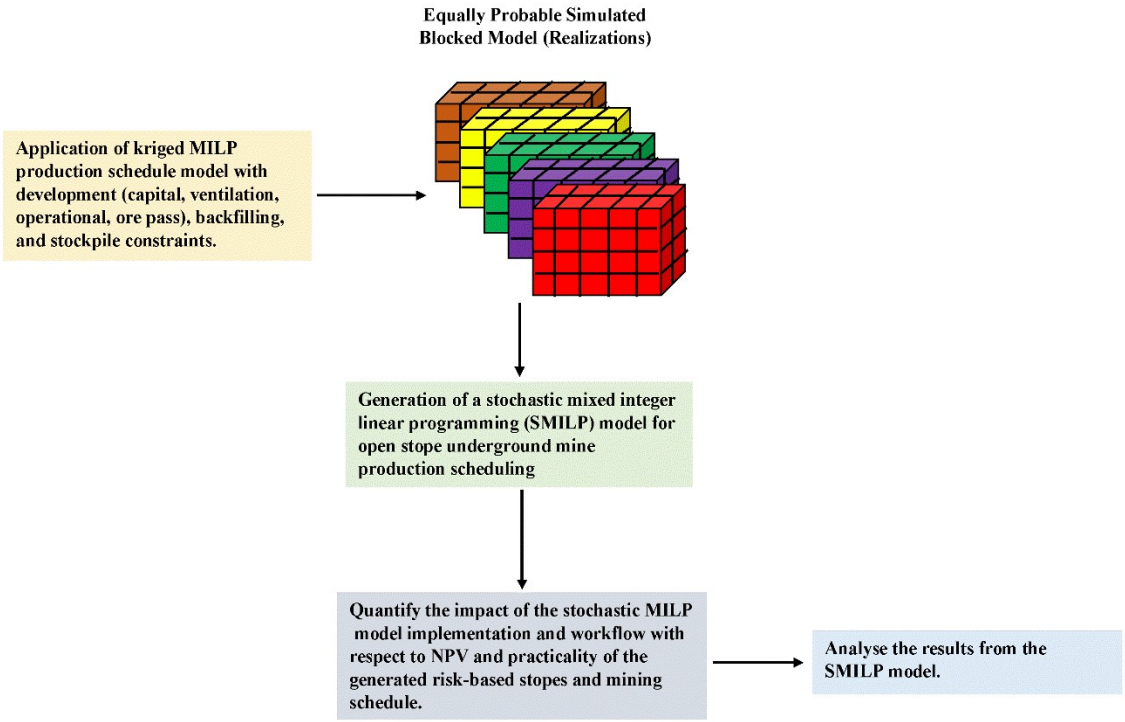


Fig. 1. Illustration of proposed approach.

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 [14; 4; 28]. 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.

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. In this step, Stanford Geostatistical Modeling Software (SGeMS) [45].
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 [16] 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.

4. 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 [15]. Presented in Fig. 2 is a 3D map of the 120 stopes with gold grades.

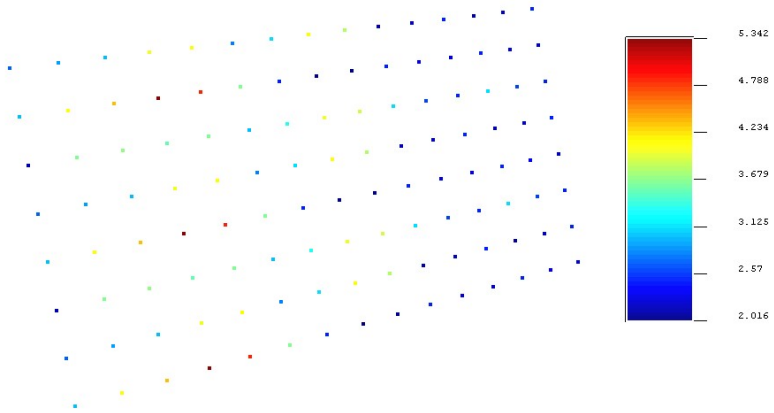


Fig. 2. Location of stopes with gold grade distribution.

4.1. 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 [17]:

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) [45].

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 [32] as shown in Fig. 3 for the gold grades.

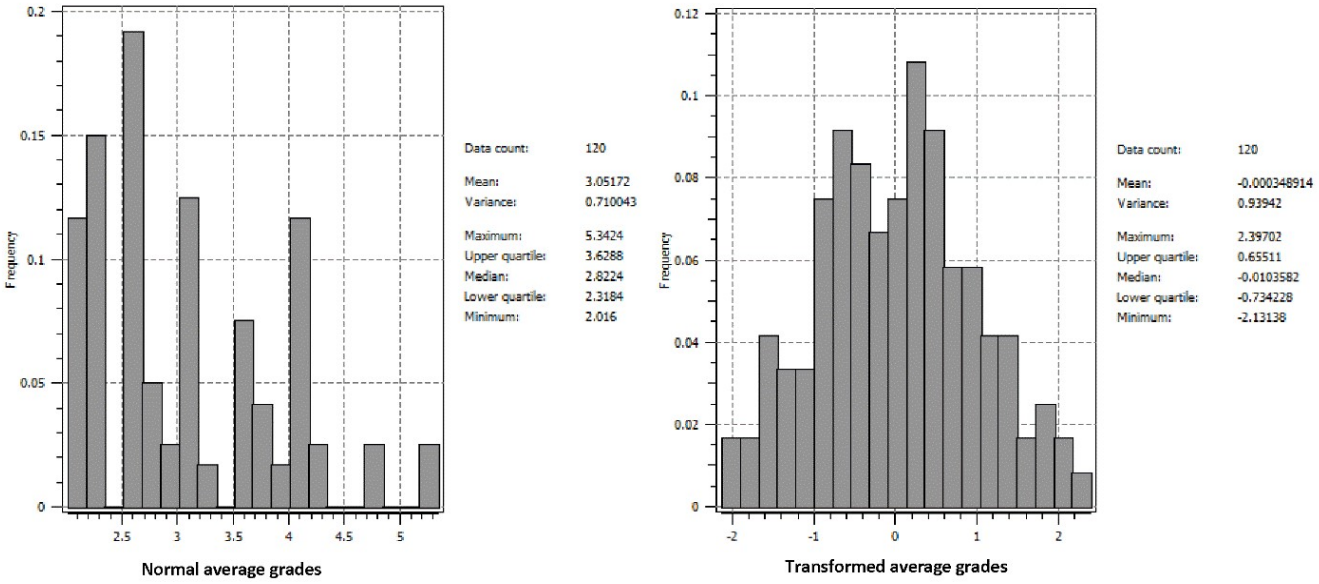


Fig. 3. Histogram and transformed normal score for gold grades.

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. Fig. 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.

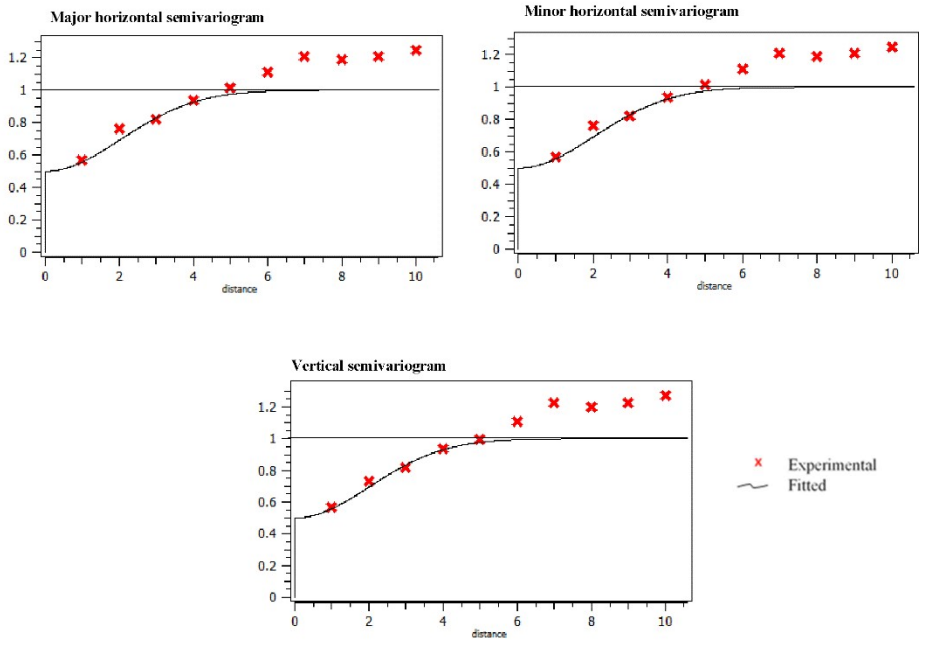


Fig. 4. Experimental directional variogram and fitted variogram models for gold grades (distance in meters).

5. Definitions and Assumptions

Open stope mining is an underground mining system applied in competent ores and mostly with no support provided for the wall or back of stopes after the ore is extracted. Stope dimensions may be the whole of the orebody (if small) or subdivided into blocks if the orebody is large. In theory, open stopes have no supports inside them. In practice, however, casual pillars of low-grade ore may be left or roof bolting (cable bolting) and timber cribs or posts may be used to support occasional patches of weak roof especially in orebodies of low dip angles. Open stope mining is comprised of horizontal development levels connected to the primary access (decline or shaft) at regular vertical intervals along the orebody (Fig. 5). Stopes may be designed as rectangular or square shapes according to dimensions with respect to the general outline of the deposit. A level access or drive representing a level is developed in the foot wall to serve as access for movement of broken materials from stopes on a level by haulage equipment directly out of the mine or into an ore pass. A crosscut which is a horizontal opening is driven perpendicular to the orebody and connects a stope to the drive.

A major drawback of open stope mining is that the span of the stope is limited by the rock strength. Thus, weaker rocks may limit stope width to about 20 m. According to Potvin and Hudyma [40], open stope mining is characterized by relatively small, single lift stopes ranging from 20,000 to 100,000 t per stope, and generally have fast stope turnaround times. For open stopes, host rock mass conditions are the controlling parameter in stope dimensioning. Dilution control and mining recovery are also a high priority.

Stoping sequence in open stope mining is predominantly driven firstly by the grade of ore (high grade), secondly by operational requirements such as access, ventilation, and backfilling, and lastly by rock mechanics considerations (stress management). Essentially, producing the best possible grade early in a mining project, along with consistent tonnage output throughout the project life, are the fundamentals of a successful underground mining operation. Options for extraction sequence in open stope mining include bottom-up and top-bottom, with bottom-up being the most common due

to its advantages as a geotechnically effective means of stope stress management. When mining in high-stress conditions, extraction usually progresses from the bottom of a mine shaft or mine decline toward its top. As extraction progresses and stress concentrates, the extraction horizon moves towards the shallower levels of the mine to areas of lower pre-mining stresses. As a result, excessively induced stress and deteriorating ground conditions are better managed by the bottom-up approach.

For most open stope mines, backfilling may be done to achieve improved recovery of the mineral deposit. Backfilling helps to provide regional stability and local support in deep mining conditions. It also serves as a floor to work on in short lifts, bottom-up extraction sequences. Backfilling options mostly employed in open stope mining are rock fill, cemented rock fill, hydraulic fill and paste fill technology [40].

The scope of this formulation considers capital development (decline), ventilation development, operational development (drive and crosscut), backfilling, ore pass development and stockpile management. These developments are often completed at one time as a permanent facility for subsequent development and operation. Fig. 5 illustrates a schematic representation of open stope mining layout.

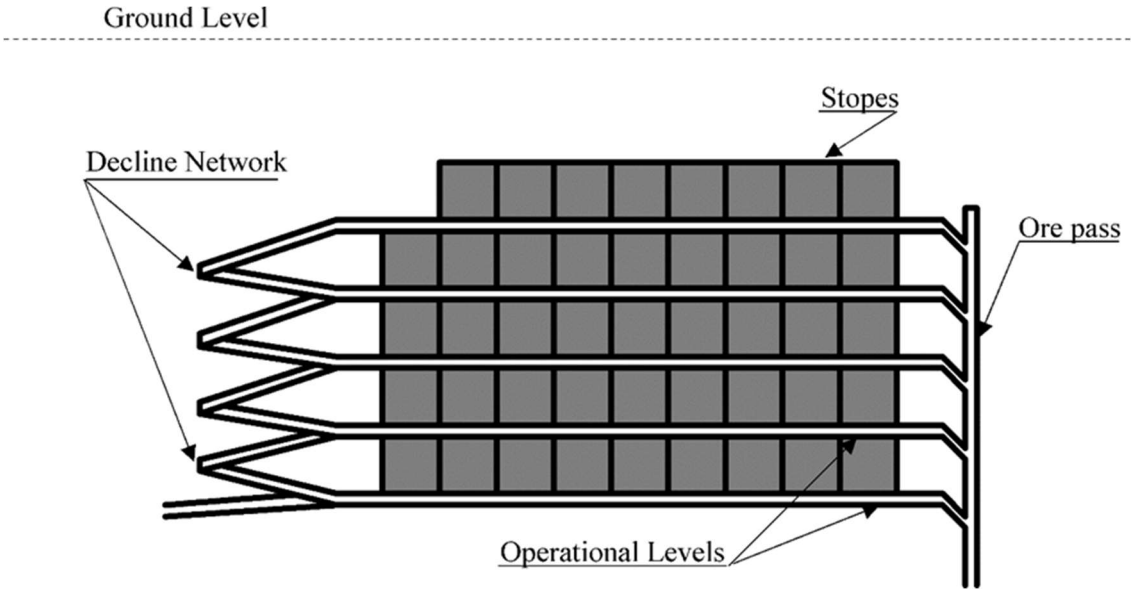


Fig. 5. Schematic representation of open stope mining layout.

5.1. 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.

5.2. Decision variables

$x^t_{k,\mathrm{m}} \in [0,1]$ continuous variable representing the portion of stope k to be extracted as ore and processed in period t directly from the mine m through the ore pass. k is linked to the stope extraction variable b and only provides a non-zero value when b is non-zero.

$j^t_{k,si} \in [0,1]$ continuous variable representing the portion of stope k to be extracted as ore and sent to the stockpile si in period t through the ore pass. si is linked to the stope extraction variable b and only provides a non-zero value when b is non-zero.

$u^t_{k,so} \in [0,1]$ continuous variable representing the portion of stockpile so to be reclaimed and processed in period t from the stockpile. Stockpile so is linked to stope k and extraction variable b and only provides a non-zero value when b is non-zero.

$y^t_k \in [0,1]$ 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.

$d^t_c \in [0,1]$ continuous variable representing the portion of capital 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.

$x^t_{k,l} \in [0,1]$ continuous variable representing a portion of stope extraction k on a level l in period t.

g^t_{so} a continuous decision variable representing the predetermined grade of ore from the stockpile to processing plant in period t.

$b^t_k \in \{0,1\}$ binary integer variable; equal to one if the extraction of stope k is to be scheduled in time t, otherwise it is zero.

$b^t_{c,l} \in \{0,1\}$ binary integer variable controlling the precedence of capital developments. $b^t_{c,l}$ is equal to one if capital development cd 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.

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

$lc^t_l \in \{0,1\}$ 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.*

5.3. Sets

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

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

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

$C_l = \{1,...,C_l\}$ set of all capital development on a level 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 a level 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 a level 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 a level 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(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, there is a set $D_a(L) \subset OD_l$, defining the number of operational developments on that level that must be done before a stope and an ore pass can be extracted; where L is the total number of operational developments on a level in the set $D_a(L)$.

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

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

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

5.4. Parameters

$R^t_{k,p}$ revenue generated by selling the final mineral commodity in stope *k* in period *t* from the ore pass.

$R^t_{k,so}$ revenue generated by selling the final mineral commodity in stope *k* in period *t* from the stockpile.

i discount rate.

o_k ore tonnage in stope *k*.

w_k waste tonnage in stope *k*.

g_k average grade of mineral in ore portion of stope *k.*

r^t processing recovery: the portion of mineral recovered in stope *k* in period *t.*

sp^t selling price in value terms obtainable per unit of mineral commodity.

sc^t selling cost in value terms per unit of mineral commodity.

mp^t_k extra cost in value terms per tonne of ore for mining and processing of stope *k* in period *t*.

rc^t mining recovery of stopes in period t.

di_k mining dilution of stopes k.

C^t_k total cost in value terms of capital development for stope *k* in period *t.*

c^t_k variable cost in value terms per length of capital development for stope *k* in period *t*.

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

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

E^t_k total cost in value terms of operational development for stope *k* in period *t*.

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

Q^t_k total cost in value terms of mining from stope *k* in period *t*.

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

F^t_k total cost in value terms of backfilling stope *k* in period *t*.

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

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

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

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

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

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

d_{cl} capital development length $_{cl}$.

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

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

d_{vl} ventilation development length $_{vl}$.

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

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

d_a operational development length $_a$.

$T_{m,lb}^t$ lower bound on available mining capacity in period *t* (tons).

$T_{m,ub}^t$ upper bound on available mining capacity in period *t* (tons).

$T_{pr,lb}^t$ lower bound on ore processing capacity in period *t* (tons).

$T_{pr,ub}^t$ upper bound on ore processing capacity in period *t* (tons).

$L_{p,lb}^t$ lower bound on ore pass development length in period *t* (tons).

$L_{p,ub}^t$ upper bound on ore pass development length in period *t* (tons).

$T_{sp,lb}^t$ lower bound on stockpile capacity in period *t* (tons).

$T_{sp,ub}^t$ upper bound on stockpile capacity in period *t* (tons).

$gr_{pr,lb}^t$ lower bound on acceptable average grade of mineral at processing plant in period *t*.

$gr_{pr,ub}^t$ upper bound on acceptable average grade of mineral at processing plant in period *t*.

$gr_{si,lb}^t$ lower bound on acceptable average grade of mineral at stockpile in period *t*.

$gr_{si,ub}^t$ upper bound on acceptable average grade of mineral at stockpile in period *t*.

$V_{f,lb}^t$ lower bound on backfilling for period *t*.

$V_{f,ub}^t$ upper bound on backfilling for period *t*.

d_{fv} backfilling volume fv.

d_p ore pass development length p.

N_{lc}^{t} the maximum number of active levels available for operational development in period *t.*

N_{le}^{t} the maximum number of active levels available for stope extraction in period *t.*

N_{xd} the maximum length of stope extraction duration for stopes.

$pntCT_{g,-}^{t}$ per-unit penalty cost in terms of the lower grade target deviation in period *t*.

$pntCT_{g,+}^{t}$ per-unit penalty cost in terms of the upper grade target deviation in period *t*.

$gdev_{s,-}^{t}$ continuous variable; the shortage from the grade lower bound in period *t* for realization *s*.

$gdev_{s,+}^{t}$ continuous variable; the excess from the grade upper bound in period *t* for realization *s*.

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

$pntCT_{o,+}^{t}$ per-unit penalty cost in terms of the upper ore tonnage target deviation in period *t*.

$odev_{s,-}^{t}$ continuous variable; the shortage to the ore tonnage lower bound in period *t* for realization *s*.

$odev_{s,+}^{t}$ continuous variable; the excess from the ore tonnage upper bound in period *t* for realization *s*.

6. 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). The 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 is a 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 shortfalls from target production levels. The objective function of the SMILP model in Eq. (2) is to maximize the expected NPV and at the same time minimize the deviations from the production targets. The first part of the objective function comprises the total discounted cashflow from direct mining to the processing plant and from stockpiling to the processing of ore material for all realizations. The second part of the function minimizes the costs associated with deviating from the ore grade operating targets for all realizations. The third part minimizes the total costs associated with deviating from the ore tonnage operating targets. Thus, the second and third parts aim to control grade uncertainty by minimizing the variability from the ore grade and ore tonnage targets. The per-unit penalty costs are denoted by $pntCT_{g}^{t}$ and $pntCT_{o}^{t}$ in Eq. (2). Deviations are discounted in terms of Geological Risk Discounting (GRD) [23]. The application of GRD 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 and leaves the higher-risk stopes for later periods. 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 become available in the form of operational exploration, new schedules will be produced for later periods. The per-unit value of penalty costs is defined based on the impact

of one unit of deviation from the related production target on the overall mining strategy and they are defined based on trial and error with consideration of the magnitude of different production targets. Therefore, the per-unit value of the penalty can be altered to prioritize the most critical operational targets according to the optimization requirements in the mining complex. When the GRD is set to zero, a balanced-risk profile is produced. The concept presented in Appianing et al. [2] 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_t factors in Eqs. (3) and (4), discounted cost of stope extraction Eq. (5), discounted cost of capital 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). There are four binary decision variables that indicate the time of capital development, b_c , ventilation development, b_v , operational development, b_a , and ore pass development, b_p to be scheduled. There are also seven continuous decision variables that indicate the portion of a stope mined y_k , the portion of the stope processed x_k , the portion of capital development completed d_c , ventilation development d_v , operational development d_a , ore pass development d_p , backfilling f_k , and stockpiling $u_{k.so}$ in each period. 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.

$$
\begin{aligned}
Max \frac{1}{S}\sum_{s=1}^{S}\sum_{t=1}^{T}\sum_{k=1}^{K}&\left[\frac{\begin{array}{l}(R_{k,p}^{t}\times x_{k,\mathrm{m}}^{t})+(R_{k,so}^{t}\times u_{k,so}^{t})-(Q_k^t\times y_k^t)-(C_k^t\times d_{cd}^t)\\ -(H_k^t\times d_{vd}^t)-(E_k^t\times d_{od}^t)-(Z_k^t\times d_{ops}^t)-(F_k^t\times f_k^t)\end{array}}{(1+i)^t}\right]\\
-\frac{1}{s}\sum_{s=1}^{S}\sum_{t=1}^{T}&\left[\frac{(pntCT_{g,+}^{t}\times gdev_{s,+}^{t})+(pntCT_{g,-}^{t}\times gdev_{s,-}^{t})}{(1+g)^t}\right]\\
-\sum_{t=1}^{T}&\left[\frac{(pntCT_{o,+}^{t}\times odev_{+}^{t})+(pntCT_{o,-}^{t}\times odev_{-}^{t})}{(1+g)^t}\right]
\end{aligned}
\tag{2}
$$

$$R_{k,so}^{t}=(g_{k,s}\times o_k\times r_k\times rc^t\times(sp^t-sc^t))-(o_k\times(1+di_k)\times mp_k^t) \tag{3}$$

$$R_{k,p}^{t}=(g_{k,s}\times o_k\times r_k\times rc^t\times(sp^t-sc^t))-(o_k\times(1+di_k)\times(mp_k^t+cstp_k^t)) \tag{4}$$

$$Q_k^t=q_k^t\times(o_k+w_k) \tag{5}$$

$$C_k^t=c_k^t\times d_c \tag{6}$$

$$H_k^t=h_k^t\times d_v \tag{7}$$

$$E_k^t=e_k^t\times d_a \tag{8}$$

$$Z_k^t=z_k^t\times d_p \tag{9}$$

$$F_k^t = f_k^t \times d_{fv} \tag{10}$$

6.1. 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 Fig. 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.

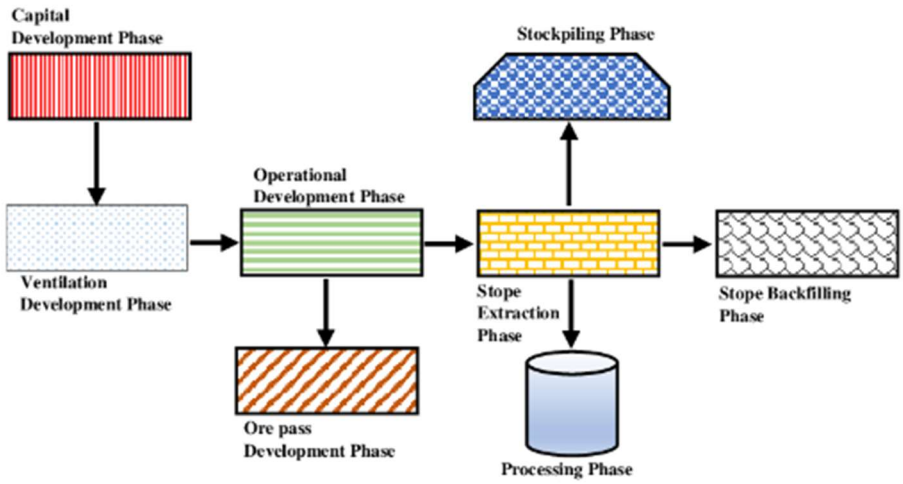


Fig. 6. Constraints dependencies.

6.1.1. Capital Development Constraints

Eq. (11) defines the capital development capacity constraint for the mine. The inequality ensures that the total length of capital development required in a period is within the stated lower and upper limits of the total available equipment capacity for developing the mine. Eqs. (12) to (15) control the precedence relationships between the sections of capital development leading to each mining level and the operational development on each level.

Eqs. (12) to (14) ensure that the set of capital development representing a section above a level must be completed before the capital development $d_{c,l}^t$ of the level commences. Eq. (15) ensures that the ventilation development $b_{v,l}^t$ on a level linking the capital development can only commence after completion of a set of required capital developments $\sum_{t=1}^{t} d_{c,l}^t$ above and on that level.

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

$$b_{c,l}^t - \sum_{t=1}^{t} d_{s,l}^t \le 0, \ \forall l \in (1,...,L), s \in D_c(L); \tag{12}$$

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

$$b_{c,l}^{t} - b_{c,l}^{t+1} \leq 0, \quad \forall l \in \{1,...,L\}, t \in \{1,...,T-1\}, c \in \{1,...,C\}; \tag{14}$$

$$b_{v,l}^{t} - \sum_{t=1}^{t} d_{c,l}^{t} \leq 0, \quad \forall l \in \{1,...,L\}, c \in D_c,(L), v \in D_v(L); \tag{15}$$

6.1.2. Ventilation Development Constraints

Ventilation is required to provide airflow into development and workings for the comfort of workers and functioning of equipment. Eqs. (16) to (20) present the set of constraints defining the ventilation requirements to enhance stope extraction. Eq. (16) defines the ventilation development capacity constraint for the mine. The inequality ensures 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. (17) to (20) control the precedence relationships between the sections of ventilation development leading to each mining level and the operational development on each level.

Eqs. (17) to (19) 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. (20) ensures that the operational development $d_{a,l}^{t}$ on a level linking the ventilation development $b_{vd,l}^{t}$ can only commence after completion of a set of required ventilation developments $\sum_{t=1}^{t} d_{v,l}^{t}$ above and on that level.

$$L_{v,lb}^{t} \leq \sum_{v=1}^{V} \left(d_{vl} \times d_{v}^{t} \right) \leq L_{v,ub}^{t}, \quad \forall t \in \{1,...,T\}; \tag{16}$$

$$b_{v,l}^{t} - \sum_{t=1}^{t} d_{s,l}^{t} \leq 0, \quad \forall l \in \{1,...,L\}, s \in D_v(L); \tag{17}$$

$$\sum_{t=1}^{t} d_{v,l}^{t} - b_{v,l}^{t} \leq 0, \quad \forall l \in \{1,...,L\}, v \in \{1,...,V\}; \tag{18}$$

$$b_{v,l}^{t} - b_{v,l}^{t+1} \leq 0, \quad \forall l \in \{1,...,L\}, t \in \{1,...,T-1\}, v \in \{1,...,V\}; \tag{19}$$

$$b_{a,l}^{t} - \sum_{t=1}^{t} d_{v,l}^{t} \leq 0, \quad \forall l \in \{1,...,L\}, a \in D_a(L), v \in D_v(L); \tag{20}$$

6.1.3. Operational Development Constraints

If a stope is scheduled to be mined in a period, a set of operational development must be ready ahead or in that period. Eqs. (21) to (25) present the set of constraints defining the operational development and lateral precedence relationships for stope extraction sequence. This includes the type and length of each operational development (level drives and crosscuts). Eq. (21) defines the operational development capacity constraints for the mine. This equation ensures that the total length of operational developments required in each period is within the defined lower and upper limits of the total available equipment capacity for developing the mine.

Eqs. (22) to (24) control the lateral precedence relation of the operational development required for each stope. Eq. (25) ensures that for each stope, there is a set of operational developments $\sum_{t=1}^{t} d_{a,l}^{t}$ that must be completed before mining the stope $b_{k,l}^{t}$.

$$L_{a,lb}^{t} \leq \sum_{a=1}^{A} \left(d_{a} \times d_{a}^{t} \right) \leq L_{a,ub}^{t}, \quad \forall t \in \{1,...,T\}; \tag{21}$$

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

$$\sum_{t=1}^{t} d_{a,l}^{t} - b_{a,l}^{t} \le 0, \quad \forall l \in \{1,...,L\}, a \in \{1,...,A\}; \tag{23}$$

$$b_{a,l}^{t} - b_{a,l}^{t+1} \le 0, \quad \forall l \in \{1,...,L\}, t \in \{1,...,T-1\}, a \in \{1,...,A\}; \tag{24}$$

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

6.1.4. Ore Pass Development Constraints

Eq. (26) defines the ore pass development capacity constraint for the mine. The inequality ensures 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. (27) to (30) control the precedence relationships between the sections of ore pass development leading to each mining level and the operational development on the level.

Eqs. (27) to (29) ensure that the set of ore pass developments representing a section above a level must be completed before the ore pass $d_{p,l}^{t}$ of the level commences. Eq. (30) 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 developments $\sum_{t=1}^{t} d_{a,l}^{t}$ above and on that level.

$$L_{p,lb}^{t} \le \sum_{p=1}^{P} \left(d_p \times d_p^{t} \right) \le L_{p,ub}^{t}, \quad \forall t \in \{1,...,T\}; \tag{26}$$

$$b_{p,l}^{t} - \sum_{t=1}^{t} d_{s,l}^{t} \le 0, \quad \forall l \in \{1,...,L\}, \ s \in D_p(L); \tag{27}$$

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

$$b_{p,l}^{t} - b_{p,l}^{t+1} \le 0, \quad \forall l \in (1,...,L), t \in \{1,...,T-1\}, \ p \in \{1,...,P\}; \tag{29}$$

$$b_{p,l}^{t} - \sum_{t=1}^{t} d_{a,l}^{t} \le 0, \quad \forall p \in \{1,...,P\}, a \in D_a(L), l \in (1,...,L); \tag{30}$$

6.1.5. Mining and Processing Capacity Constraints

Eqs. (31) and (32) define the mining capacity constraint. Mining is controlled by the continuous decision variable y_k^t. This inequality ensures that the total tonnage of rock material extracted in each period is within the acceptable lower and upper limits of the total available equipment capacity for the mining operation. Eqs. (33) and (34) are the processing capacity constraints that control the quantity of mill feed for the mine in each period and in each realization. We introduce continuous variables $odev_{s,+}^{t}$ and $odev_{s,-}^{t}$ which serve as buffers to allow deviations. They are however penalized in the objective function. Penalizing such deviations ensure that the proportion of ore processed at the plant is within the required targets as much as is feasible. The constraint also ensures that the processing capacity does not exceed a pre-defined limit. Ore extraction is controlled by the continuous decision variables $x_{k,\mathrm{m}}^{t}$ and $u_{k,so}^{t}$ respectfully.

$$T_{m,lb}^{t} \le \sum_{k=1}^{K}\left[(o_k + w_k)\times y_k^t\right] \le T_{m,ub}^{t}, \quad \forall t \in \{1,...,T\}; \tag{31}$$

$$T_{m,lb}^{t} \le \sum_{k=1}^{K}\left[(o_k + w_k)\times y_k^t\right] \ge T_{m,ub}^{t}, \quad \forall t \in \{1,...,T\}; \tag{32}$$

$$T_{pr,lb}^{t} \le \sum_{k=1}^{K}\left[((o_k \times x_{k,\mathrm{m}}^{t}) + \sum_{so=1}^{SO} u_{k,so}^{t}) - odev_s^t\right] \le T_{pr,ub}^{t}, \forall t \in \{1,...,T\}; \tag{33}$$

$$T_{pr,lb}^{t} \le \sum_{k=1}^{K}\left[((o_k \times x_{k,\mathrm{m}}^{t}) + \sum_{so=1}^{SO} u_{k,so}^{t}) + odev_s^t\right] \ge T_{pr,ub}^{t}, \forall t \in \{1,...,T\}; \tag{34}$$

6.1.6. Grade Blending Constraints

The grade blending constraints are presented in Eqs. (35) to (38). The ore grade schedule per period ensures that the material extracted satisfies the ore quality specification of the processing plant, stockpile and ore pass bin. Based on the cut-off grades or head grade of the plant, limiting grade requirements for appropriate ore blending are defined within lower and upper grade targets for the mining operation. Like the processing quantity constraints, the excess and shortage of the desired grade range in each period across all geological realizations are penalized in the objective function.

$$\sum_{k=1}^{K}\left[(g_k - gr_{pr,ub}^{t})\times(o_k \times x_{k,m}^{t}) + \sum_{so=1}^{SO}(g_{k,so}^{t} - gr_{pr,ub}^{t})\times(u_{k,so}^{t}\times o_k) - gdev_{s,+}^{t}\right] \le 0; \forall t \in \{1,...,T\}, \forall p \in \{1,...,SO\} \tag{35}$$

$$\sum_{k=1}^{K}\left[(gr_{pr,lb}^{t} - g_k)\times(o_k \times x_{k,u}^{t}) + \sum_{so=1}^{SO}(gr_{pr,lb}^{t} - g_{so}^{t})\times(u_{k,so}^{t}\times o_k) + gdev_{s,-}^{t}\right] \ge 0; \forall t \in \{1,...,T\}, \forall p \in \{1,...,SO\} \tag{36}$$

$$\sum_{k=1}^{K}((g_k - gr_{si,ub}^{t})\times(o_k \times j_{k,si}^{t}) - gdev_{s,+}^{t}) \le 0; \quad \forall t \in \{1,...,T\}, \forall si \in \{1,...,SI\} \tag{37}$$

$$\sum_{k=1}^{K}((gr_{si,lb}^{t} - g_k)\times(o_k \times j_{k,si}^{t}) + gdev_{s,-}^{t}) \ge 0; \quad \forall t \in \{1,...,T\}, \forall si \in \{1,...,SI\} \tag{38}$$

6.1.7. Stope Extraction Precedence Constraints

Eqs. (39) to (41) control the lateral precedence relationships of stope extraction on each level of the mining operations. The mining 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 centre of the mine towards to the periphery of the mine.

$$b_k^t - \sum_{t=1}^{t} y_s^t \le 0, \quad \forall s \in G_k(S), k \in \{1,...,K\}; \tag{39}$$

$$\sum_{t=1}^{t} y_k^t - b_k^t \le 0, \quad \forall k \in \{1,...,K\}; \tag{40}$$

$$b_k^t - b_k^{t+1} \le 0, \quad \forall t \in \{1,...T-1\}, k \in \{1,...,K\}; \tag{41}$$

6.1.8. Backfilling Management Constraints

The backfilling constraints include backfilling capacity and sequencing constraints and stope status constraints. Eq. (42) presents the backfilling capacity constraint. 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. (43) 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. (44) ensures that stope ore extraction precedes backfilling. Eq. (45) 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 further limit the exposure time of the void area after mining to reduce potential excessive geotechnical stresses prior to backfilling. The type of backfill material (uncemented rock fill, cemented paste fill (curing time), or cemented rock fill) is not considered during the optimization process for backfilling.

$$V_{f,lb}^{t} \le \sum_{k=1}^{K}\left(d_{fv} \times f_{k}^{t}\right) \le V_{f,ub}^{t}, \quad \forall t \in \{1,...,T\}; \tag{42}$$

$$b_{k}^{t} + f_{k}^{t} \le 1, \quad \forall t \in \{1,...,T\}, k \in \{1,...,K\}; \tag{43}$$

$$f_{k}^{t} - \sum_{t=1}^{t}(x_{k,\mathrm{m}}^{t} + j_{k,si}^{t}) \le 0, \quad \forall t \in \{1,...,T\}, k \in \{1,...,K\}; \tag{44}$$

$$b_{k}^{t} \le b_{k}^{t+1} + f_{k}^{t+1}, \quad \forall t \in \{1,...,T-1\}, k \in \{1,...,K\}; \tag{45}$$

6.1.9. 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 Fig. 7. When a stope is being extracted or backfilled, the adjacent stopes cannot be mined. As illustrated in Fig. 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). Also, when a stope is being backfilled, the adjacent stopes cannot be exploited. Eqs. (46) and (47) ensure that all forms of adjacent stope extraction or backfilling activities are avoided to prevent excessively large unsupported voids.

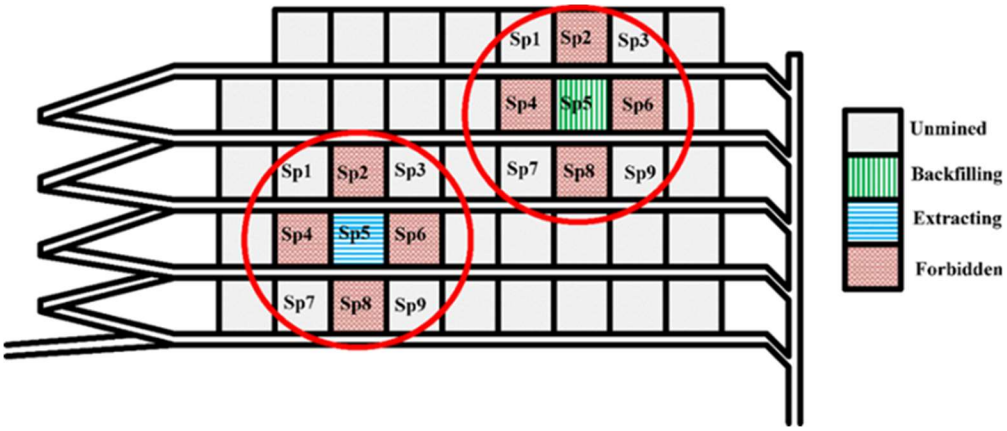


Fig. 7. Schematic illustration of non-adjacent stope extraction and backfilling.

$$b_{k}^{t} + b_{j}^{t} \le 1, \quad \forall t \in \{1,...,T\}, k \in \{1,...,K\}, j \in A_{k}(J); \tag{46}$$

$$f_{k}^{t} + b_{j}^{t} \le 1, \quad \forall t \in \{1,...,T\}, k \in \{1,...,K\}, j \in A_{k}(J); \tag{47}$$

6.1.10. 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. (48) to (51) control the maximum number of simultaneous active levels in each period in the schedule. In Eqs. (48) and (49), 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. (50) and (51), 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.

$$\sum_{t=1}^{t}\left(\frac{1}{D}\sum_{d=1}^{D}d_{a,l}^{t}\text{-}lc_l^t\right)\le 0,\quad \forall t\in\{1,...,T\},\ l\in\{1,...,L\},\ \text{a}\in L_l(D); \tag{48}$$

$$\sum_{t=1}^{t}\left(\frac{1}{M}\sum_{m=1}^{M}x_{k,\text{m}}^{t}\text{-}le_l^t\right)\le 0,\quad \forall t\in\{1,...,T\},\ l\in\{1,...,L\},\ k\in L_l(M); \tag{49}$$

$$\sum_{l=1}^{L}lc_l^t\le N_{lc}^t,\quad \forall t\ \in\{1,...,T\}; \tag{50}$$

$$\sum_{l=1}^{L}le_l^t\le N_{le}^t,\quad \forall t\ \in\{1,...,T\}; \tag{51}$$

6.1.11. Stope Extraction Duration Constraints

The length of stope extraction depends on notably, stope size, rate of production, and mining plan. Eq. (52) 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.

$$\sum_{t=1}^{T}y_k^t\le N_{xd},\quad \forall t\ \in\{1,...,T\}; \tag{52}$$

6.1.12. Stockpile Management Constraints

Eqs. (53) and (54) are the stockpile capacity constraints that control the quantity of ore feed to the stockpile. The constraint also ensures that the stockpile capacity does not exceed a pre-defined limit. The continuous decision variable $j_{k,si}^t$ controls ore to the stockpile. Eq. (55) ensures that the quantity of ore sent to the stockpile exceeds the quantity sent out of the stockpile to the plant, thus, at the end of the mine-life, there could be some amount of ore left in the stockpile and Eq. (56) ensure that reclamation from the stockpile stops if the predetermined average grade exceeds the actual grade of the material sent to the stockpile the ore sent to the stockpile must be reclaimed by the end of the mine-life.

$$T_{si,lb}^t\le\sum_{k=1}^{K}\left[(o_k\times j_{k,si}^t)\right]\le T_{si,ub}^t,\ \forall t\in\{1,...,T\}; \tag{53}$$

$$T_{si,lb}^t\le\sum_{k=1}^{K}\left[(o_k\times j_{k,si}^t)\right]\ge T_{si,ub}^t,\ \forall t\in\{1,...,T\}; \tag{54}$$

$$\sum_{i=1}^{t}\sum_{k=1}^{K}(u_{k,so}^{i}\times o_k)\le \sum_{i=1}^{t-1}\sum_{k=1}^{K}(o_k\times j_{k,si}^{i}),\ \forall t\in\{1,...,T\};\tag{55}$$

$$\sum_{i=1}^{t}\sum_{k=1}^{K}(u_{k,so}^{i}\times o_k\times g_{k,so}^{t})\le \sum_{i=1}^{t-1}\sum_{k=1}^{K}(o_k\times g_k\times j_{k,si}^{i}),\ \forall t\in\{1,...,T\};\tag{56}$$

6.1.13. Variables Control Constraints

Eq. (57) defines the relationship between mining, ore extraction, and stockpiling variables controlling the stope mining, ore stockpiling, and waste decisions. Thus, the continuous variables $x_{k,\mathrm{m}}^{t}$ 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. Eqs. (58) and (59) ensure that the total fractions of stopes and backfilling volumes over the scheduling periods sum up to one. Eqs. (60) to (61) 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. (62) to (65) ensure that all developments (capital, 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 capital, ventilation, operational, and ore pass development to ensure they are within desired ranges. Eq. (66) ensures that all continuous decision variables are non-negative. Eq. (67) defines all binary variables as non-negative and integers.

$$x_{k,\mathrm{m}}^{t}+u_{k,so}^{t}\le y_k^t,\ \forall t\in\{1,...,T\},k\in\{1,...,K\};\tag{57}$$

$$\sum_{t=1}^{T}f_k^t\le 1,\ \forall k\in\{1,...,K\};\tag{58}$$

$$\sum_{t=1}^{T}x_{k,\mathrm{m}}^{t}\le 1,\ \forall k\in\{1,...,K\};\tag{59}$$

$$\sum_{t=1}^{T}j_{k,si}^{t}\le 1,\ \forall k\in\{1,...,K\};\tag{60}$$

$$\sum_{t=1}^{T}u_{k,so}^{t}\le 1,\ \forall k\in\{1,...,K\};\tag{61}$$

$$\sum_{t=1}^{T}d_c^t\le 1,\ \forall c\in\{1,...,C\};\tag{62}$$

$$\sum_{t=1}^{T}d_v^t\le 1,\ \forall v\in\{1,...,V\};\tag{63}$$

$$\sum_{t=1}^{T}d_a^t\le 1,\ \forall a\in\{1,...,A\};\tag{64}$$

$$\sum_{t=1}^{T}d_p^t\le 1,\ \forall p\in\{1,...,P\};\tag{65}$$

$$x_{k,\mathrm{m}}^{t},\ j_{k,si}^{t},\ u_{k,so}^{t},\ y_k^t,\ f_k^t,\ d_c^t,\ d_v^t,\ d_a^t,\ d_p\ge 0\tag{66}$$

$$b_k^t,\ b_{c,l}^t,\ b_{v,l}^t,\ b_{a,l}^t,\ b_{p,l}^t\ge 0 \text{ and integers}\tag{67}$$

7. Case Studies

Two case studies are presented. For Case study 1, the MILP model is implemented without the stockpiling management constraints and for Case study 2, the MILP model is implemented with a grade controlled stockpiling management constraints.

In both case studies, the proposed MILP formulation model was applied to 120 stopes designed for a gold deposit. To assess the model's effectiveness, we incorporated active levels and extraction duration constraints as specified. Table 2 provides details about the gold deposit's characteristics and the designed stopes. Additionally, Fig. 8 displays a cross-section of the block model, illustrating the distribution of gold grades within the deposit. For a visual representation of the 120 designed stopes, please refer to Fig. 9**,** showing the sectional layout created using Promine software [41]. IBM CPLEX Optimization Studio V12.6.3 [16] was integrated within a MATLAB 2023a [31] environment to define the modelled framework and solve the optimization problem at a gap tolerance of 5%. 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.

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 [29; 33; 13].

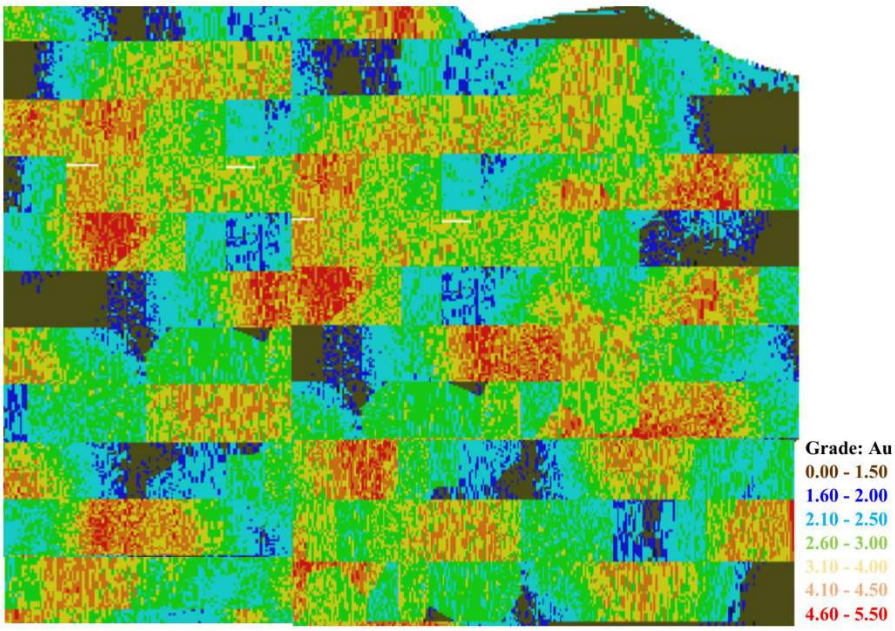


Fig. 8. Cross-section of the block model depicting the distribution of gold grades (Not drawn to scale).

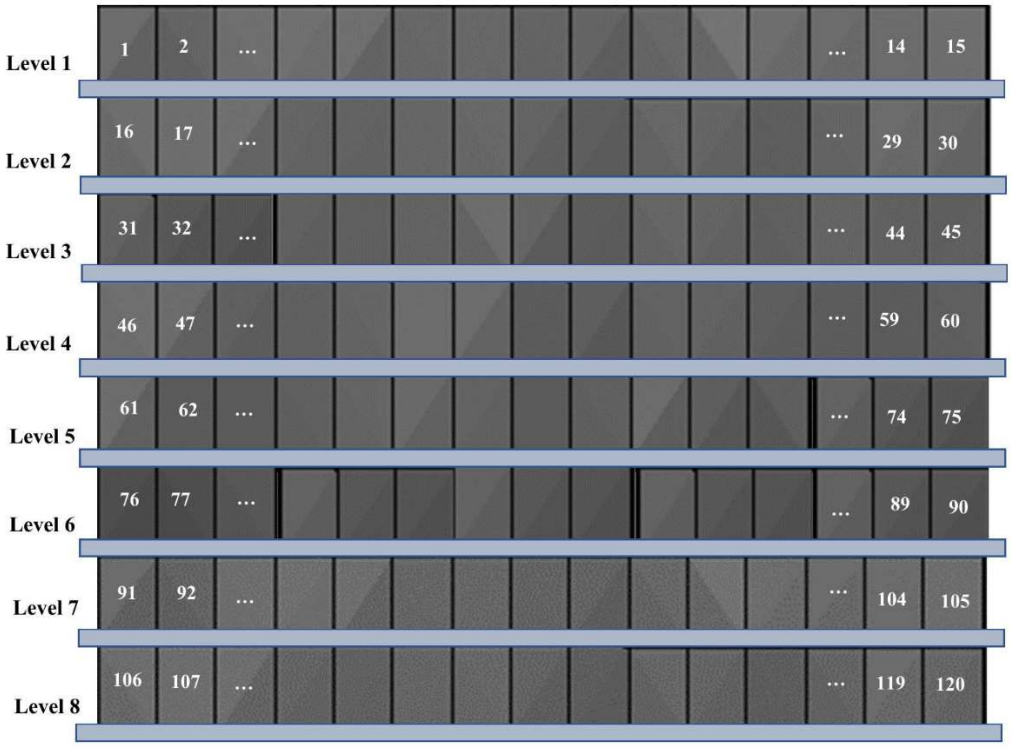


Fig. 9. A sectional layout of the mineralized stopes.

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 (Periods)	2
Maximum ore pass development (m/period)	143
Maximum active levels*	7

Mining dilution factor of 10% was applied to stopes at the periphery of the orebody, and mining dilution factor of 5% was applied to the remaining stopes. All the lower boundaries equal zero in this case study. Due to the implementation of backfilling of the stopes, which enhances ground control and increases flexibility in operating multiple active mining levels, the optimizer was allowed more flexibility in operating multiple active mining levels.

7.1. Results and Discussion - Case Study 1

Upon implementing the MILP model formulation without stockpiling, the open-stope underground gold project benefited from optimized schedules for capital, ventilation, operating, and ore pass development, as well as mining, processing, and backfilling production schedules for a 25-year mine-life. The case study involved 22,600 decision variables, consisting of 13,600 binary integer variables and 9,000 continuous variables. Furthermore, 57,412 constraints were generated to achieve the desired optimization. The solution time was 4.2 hours.

Fig. 10 illustrates the schedules for capital, ventilation, and ore pass development. Capital and ventilation development activities took place during the initial 5 years of the mine-life to facilitate the commencement of operational development. In addition to the optimized schedules for capital investment, ventilation, operational development, mining, processing, and backfilling, the MILP model also factored in ore pass development for the open-stope underground gold project. Ore pass development took place during two specific periods: Between Years 2 to 4: During this time frame, ore pass development activities were carried out to establish efficient and safe channels for transporting mined ore from the stopes to the processing plant, waste dump and later stockpile. Between Years 17 and 18: A second phase of ore pass development occurred in this later period, aiming to further optimize the transport system for mined ore to support the mining operation during this phase of the mine's life. As depicted in Fig. 11 throughout the mine's life, operational development occurred at varying rates based on production requirements.

The MILP model resulted in an impressive NPV (Net Present Value) of 636.98 million dollars. During the project's lifespan, a total of 2.49 Mt of material were mined and 2.20 Mt were processed.

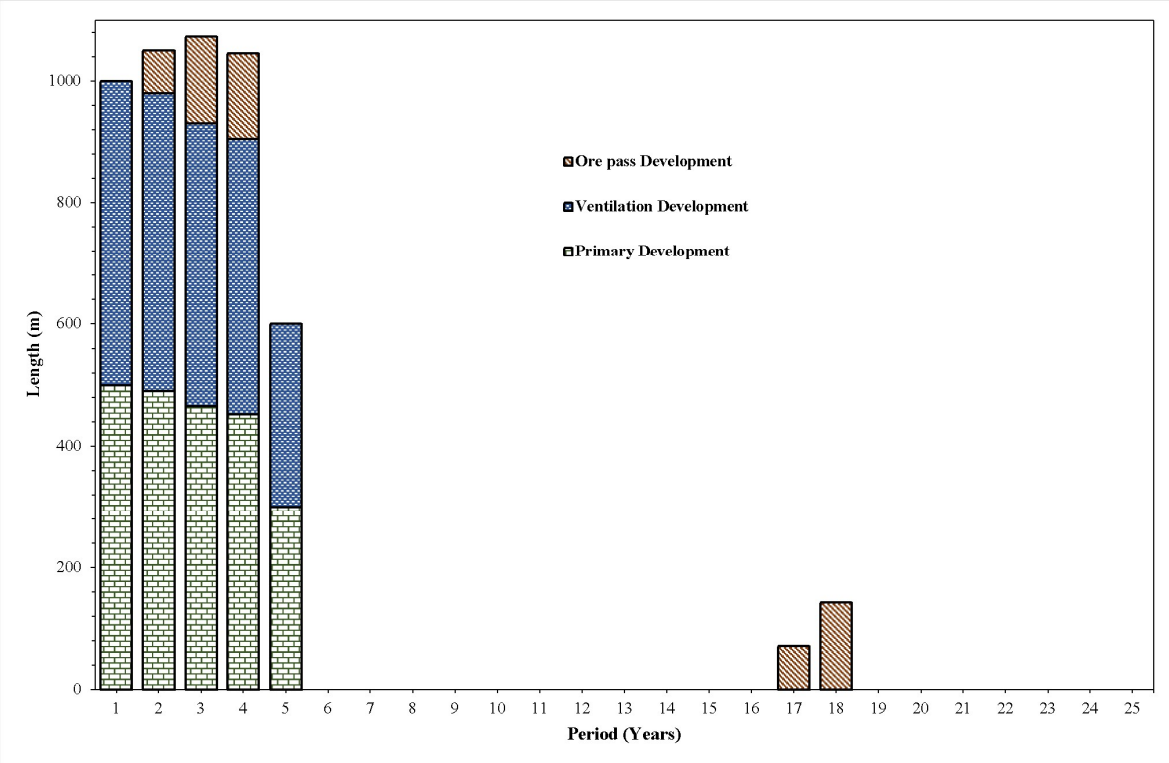


Fig. 10. Capital, ventilation, and ore pass development schedule.

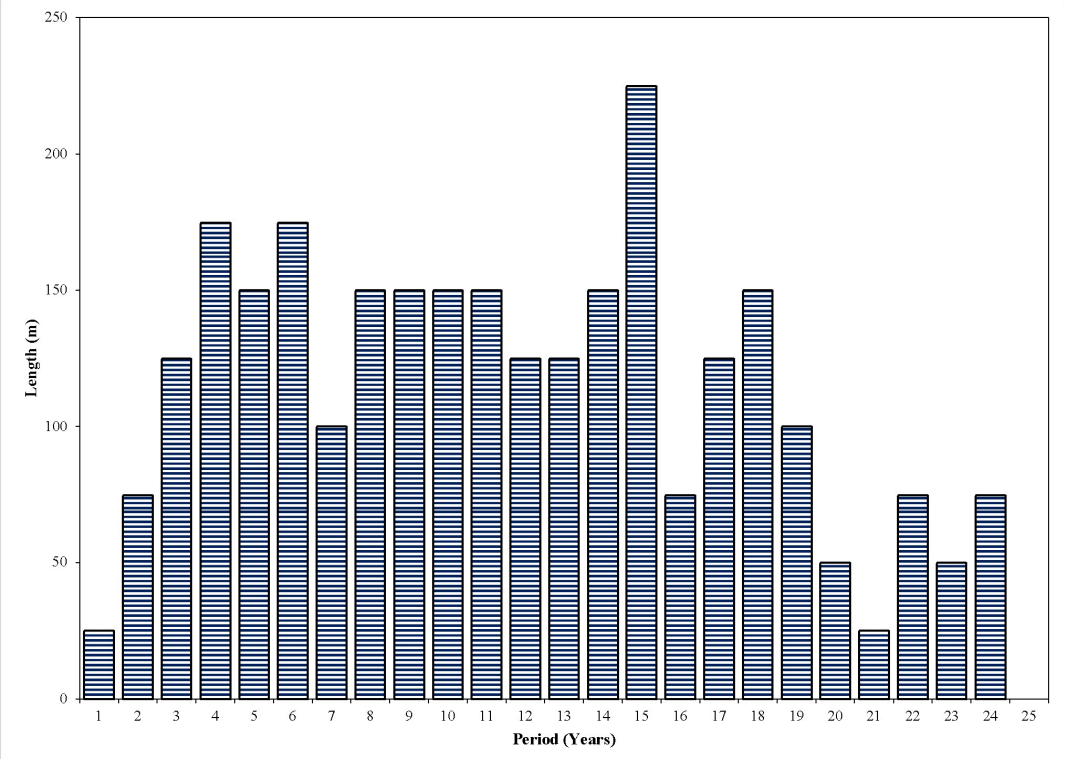


Fig. 11. Operational development schedule.

Fig. 12 showcases the schedule, of both the mined material, which includes waste dilution material. The mining operations commenced in Year 1 ramping up following the completion of capital, ventilation, and some initial operational development. From Year 4 to Year 14, the mining capacity was 140 Kt maximizing output during this period and is gradually decreased to 120 Kt from Year 15 to Year 19 and to 80 Kt from Year 20 to Year 25 as part of the mine's planned ramp-down strategy to complete its 25-year life cycle.

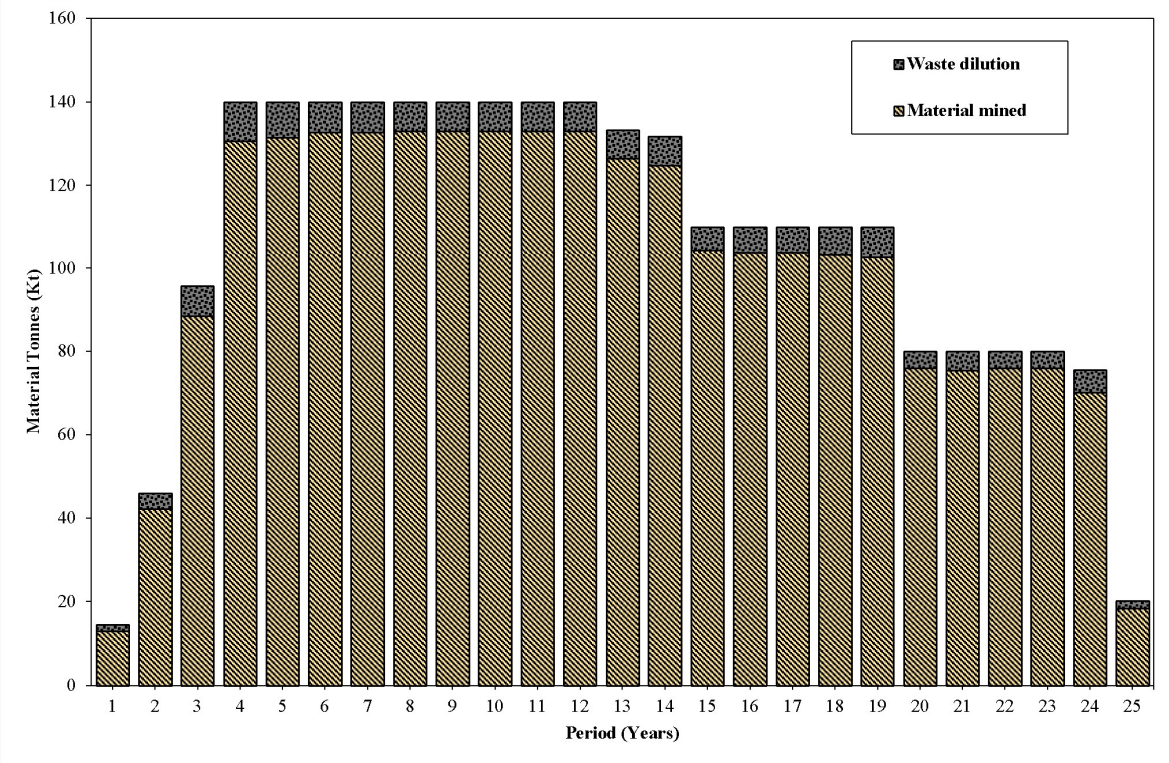


Fig. 12. Mined material with estimated waste dilution.

An essential aspect displayed in the schedule is the consideration of variable waste dilution during the optimization process. Stopes situated at the periphery of the orebody contribute more waste dilution compared to those located within the core of the orebody. By incorporating this variable waste dilution factor into the optimization, the model ensures a more accurate representation of the real-world mining scenario, leading to improved resource management and better decision-making throughout the mine's operational life.

Displayed in Fig. 13 is the material processed and the average grade distribution curve. Based on the average grade profile, the MILP model prioritizes targeting high-grade areas during the early years of mining to maximize the Net Present Value (NPV) of the project. However, during the initial three years, due to the development phase, only a limited number of stopes are available for extraction. As a result, the mining system is constrained to lower grades that are immediately accessible on the upper levels of the deposit. As the development progresses and more stopes become available for extraction, the processing plant's head grade experiences an improvement from Year 1 to Year 7 before starting to decline gradually. Consequently, medium to high-grade ores are primarily extracted during the early years of mining, from Year 1 to Year 10. Subsequently, from Year 11 to Year 25, the mining operation shifts towards extracting medium-grade ores as the higher-grade areas become depleted. This approach allows for strategic resource management and efficient extraction of the higher-grade material when it can contribute the most to the project's overall financial success. As the mine matures and the higher-grade zones are depleted, the focus shifts towards mining medium-grade ores to sustain the operation over the remaining mine-life.

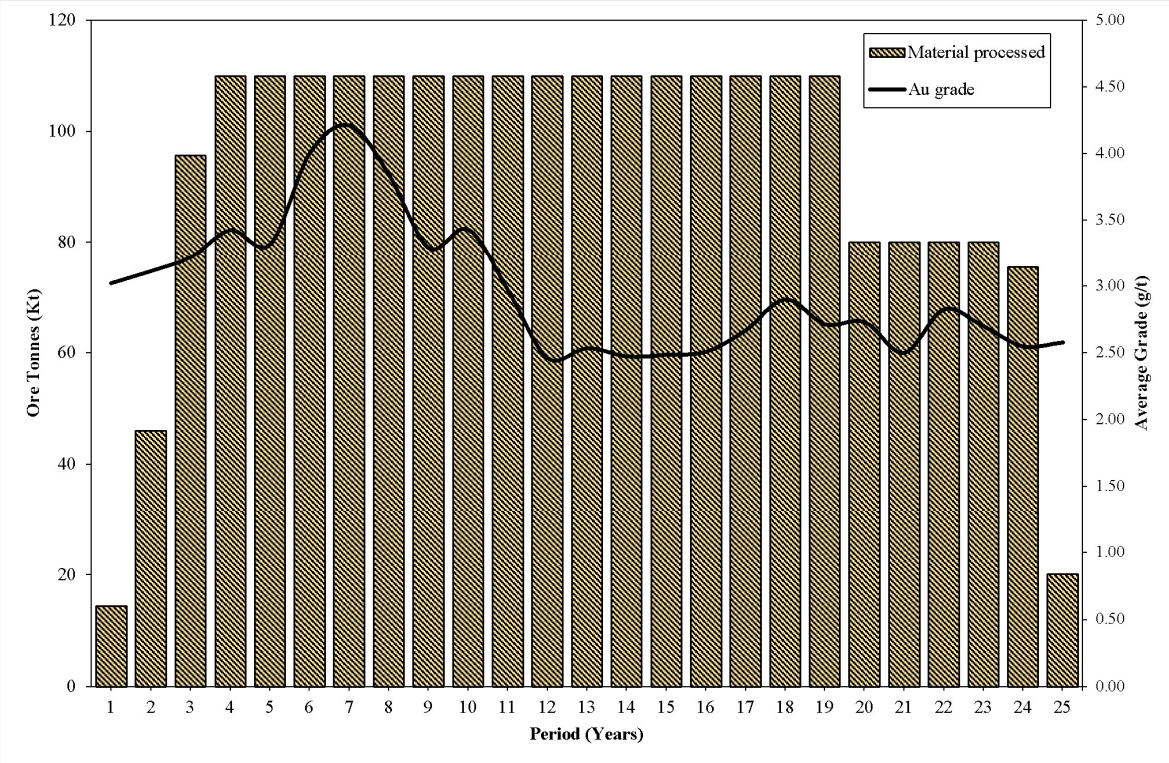


Fig. 13. Material processed with average grade curve.

The plant's operation started in Year 1 processing all available material from mining at a fixed capacity of 110 Kt. After ramping up from Year 1 to Year 3, full plant capacity was achieved from Year 4 to Year 19 and gradually ramps down at 80 Kt from Year 20 to the end of mine-life.

The stope production phases are presented in a sequential manner in Fig. 14. The schedule demonstrates the order in which each phase is completed, ensuring a systematic mining process: Operational Development: This phase involves the construction of drives and crosscuts within the mine, creating access to the different areas of the orebody. Operational development is prioritized and completed before moving on to stope extraction. Stope Extraction: Once the operational development is finished, the stope extraction phase begins. This is the main phase of mining, where ore is excavated from the stopes. The order of stope extraction follows the planned sequence, ensuring optimal resource utilization. Backfilling: After stope extraction, the backfilling phase takes place. The mined stopes are filled with suitable material to provide ground support and stability. This backfilling process enhances ground control and safety in the underground mining operation.

By following this sequence of production phases, the mining operation can maintain an organized and efficient workflow. Operational development is completed first to facilitate access to the orebody, ensuring a smooth transition to stope extraction. Once the extraction is completed, backfilling is implemented to enhance ground control and create a safer working environment. This systematic approach contributes to the overall success and productivity of the open stope underground gold project over its 25-year mine-life.

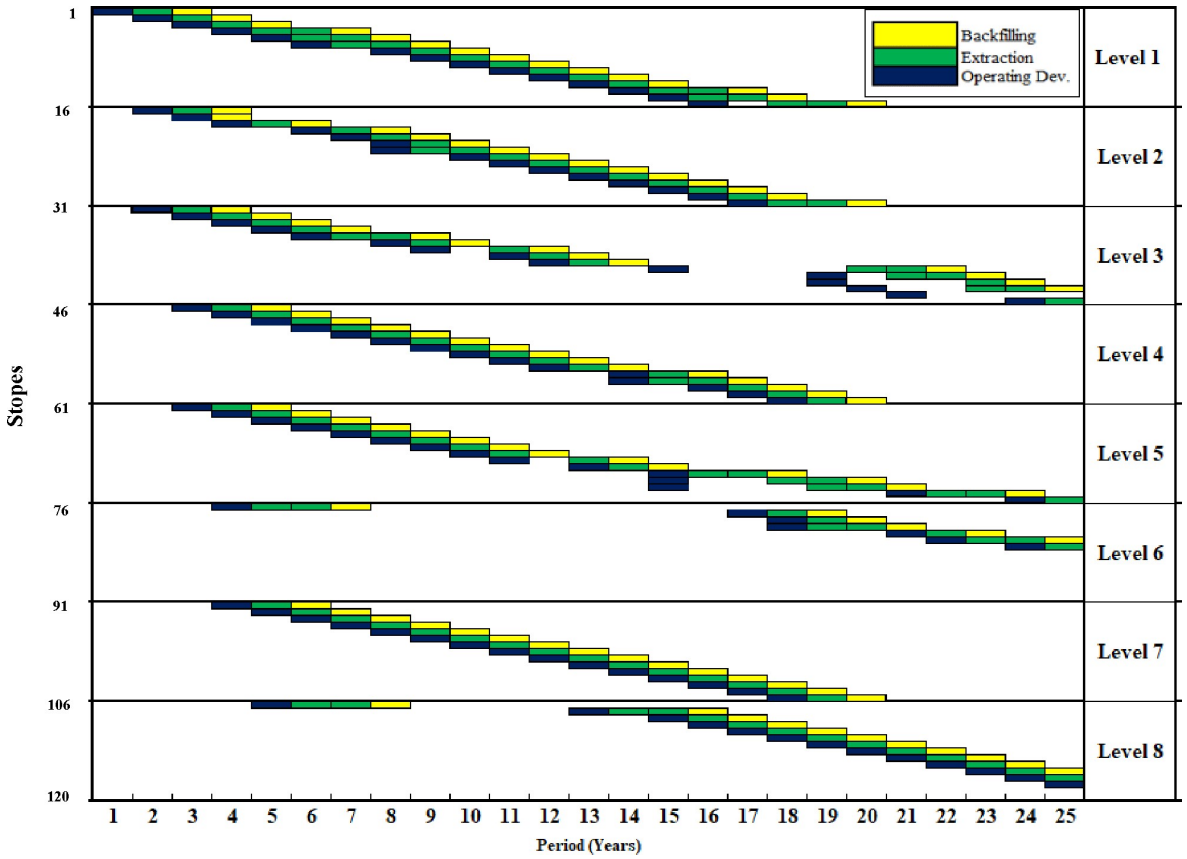


Fig. 14. Annual operational development, stope extraction and backfilling schedule level.

In the mining operation, there were some specific instances where the planned sequence of operational development and extraction was altered due to the availability of higher-grade stopes on other levels. These variations resulted in breaks in extraction, which affected certain stopes.

On Level 6, after the extraction and backfilling of Stope 76 in Period 7, there was no immediate stope operational development or extraction until Period 17 when Stope 77 development started. This deviation was caused by the presence of higher-grade stopes on Level 7, which were prioritized for extraction. Additionally, on Level 8, there was a break in extraction between Periods 9 and 12. Stopes 84 to 90 on level 6 and stope 120 on Level 8, which had average grades between 1.1 g/t to 1.38 g/t, were not extracted before the end of the mine-life.

Furthermore, at the end of the mine-life, some stopes were not backfilled due to the absence of other available stopes for extraction on those levels. Specifically: Stopes 45 on Level 3, 75 on Level 5, 82 on Level 6, and Stopes 118 and 119 on Level 8 respectively. Also, on Level 8, operational development, and extraction for Stope 119 occurred in Periods 25. These variations and decisions were made based on the optimization process and the availability of different ore grades in the deposit, aiming to maximize the project's NPV while maintaining efficient resource utilization and safety considerations.

7.2. Results and Discussion – Case Study 2

The implementation of the MILP model formulation with grade controlled stockpiling management constraint and its associated cost proved to be highly advantageous for the project maintaining all original constraints and associated parameters. The optimization process resulted in well-optimized schedules for various aspects of the mining operation, contributing to its successful operation over a 25-year mine-life. The MILP model involved a total of 28,600 decision variables among which, 13,600 were binary integer variables, used for making discrete decisions, and 15,000 were continuous

variables, used for continuous optimization. To ensure the optimization adhered to all the project's requirements and limitations, a total of 57,702 constraints were generated and incorporated into the model. The optimization process was carried out effectively, achieving the desired results within a reasonable time frame of 3.2 hours. The optimized schedules for capital investment, ventilation, operational development, ore pass development, mining, stockpiling, processing, and backfilling allowed for the efficient utilization of resources and maximizing a resulting NPV of 718.00 million dollars which is approximately 10% higher than case study 1. Presented in Table 4 are the stockpile parameters used for the implementation.

Table 4. Stockpile parameters.

Stockpile	Value
Maximum grade value of Au (g/t)	1.40
Minimum grade value of Au (g/t)	0.10
Average grade value of Au (g/t)	0.75
Rehandling cost ($/t)	0.5

Fig. 15 the material mined schedule is presented with the implementation of grade control stockpile management constraints. These constraints were introduced to regulate the stockpile capacities over the mine-life. The maximum mining capacity was set at 140 Kt from Year 1 to Year 14, 120 Kt from Year 15 to Year 19, and 80 Kt from Year 20 until the end of the mine-life. Throughout the mining operation, the stockpile management constraints were effectively maintained, allowing for a controlled accumulation of ore. As a result, the total material mined from the open stope underground gold project amounted to 2,522,912.50 t. This optimized material mined schedule, combined with the grade control stockpile management, contributed to efficient resource utilization, smooth production, and improved project economics over the 25-year mine-life.

Presented in Fig. 16 is the schedule of material sent to and from the stockpile. The implementation of the grade control strategy is evident in this schedule. Low-grade material was sent to the stockpile during specific periods: from Year 4 to Year 11 and Years 14 and 15. This allowed for the selective mining of higher-grade material from the mine while stockpiling the lower-grade material for future use. From Year 20 until the end of the mine-life, grade-blended stockpiled material is sent from the stockpile to the processing plant as needed. This demonstrates the effective utilization of the stockpile to provide a continuous supply of material to the plant, ensuring efficient processing and resource management in the later stages of the mining operation. A total of 191,987.50 tons of material were stockpiled, contributing to the overall strategic planning and grade management of the project.

In Fig. 17, a comprehensive schedule is displayed, encompassing both the material processed directly from the mine and that from the stockpile. This integrated schedule demonstrates how the material is efficiently managed and processed throughout the 25-year mine-life, optimizing the production and economic performance of the open stope underground gold project. The implementation of the grade control strategy, stockpiling, and selective blending of material ensures a consistent supply of high-grade ore to the processing plant, maximizing the project's overall financial returns.

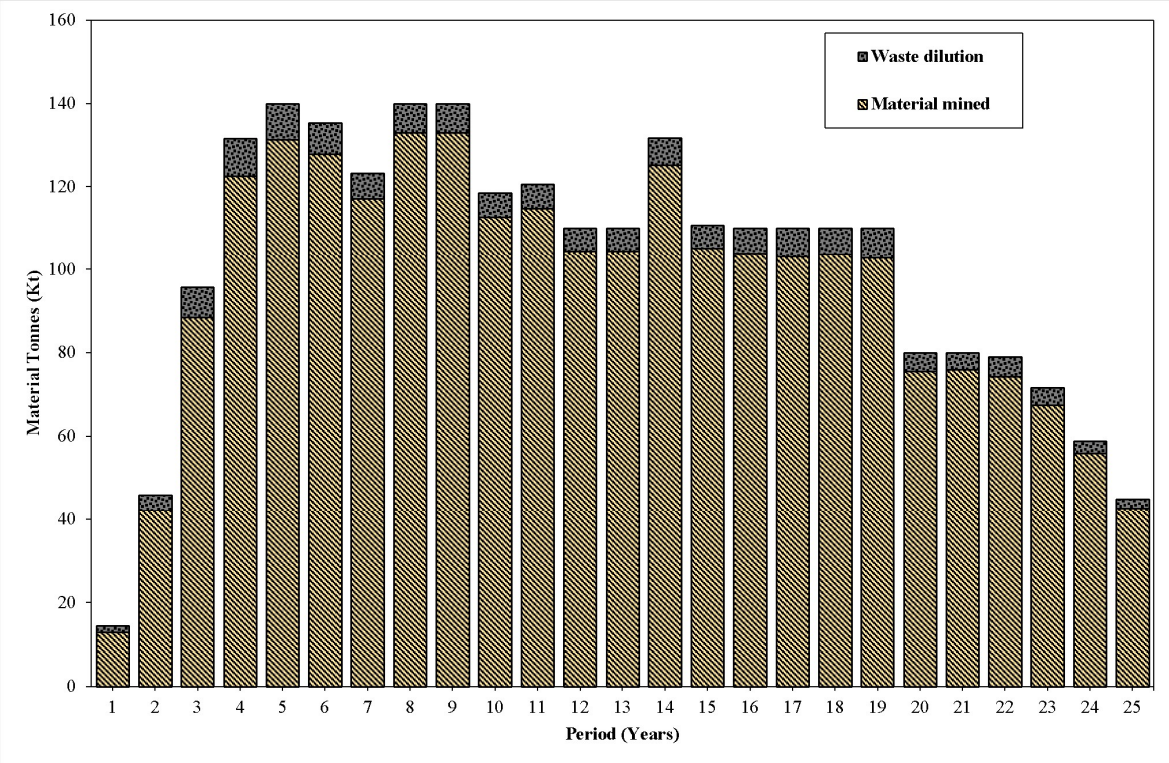


Fig. 15. Material mined considering grade control stockpile management.

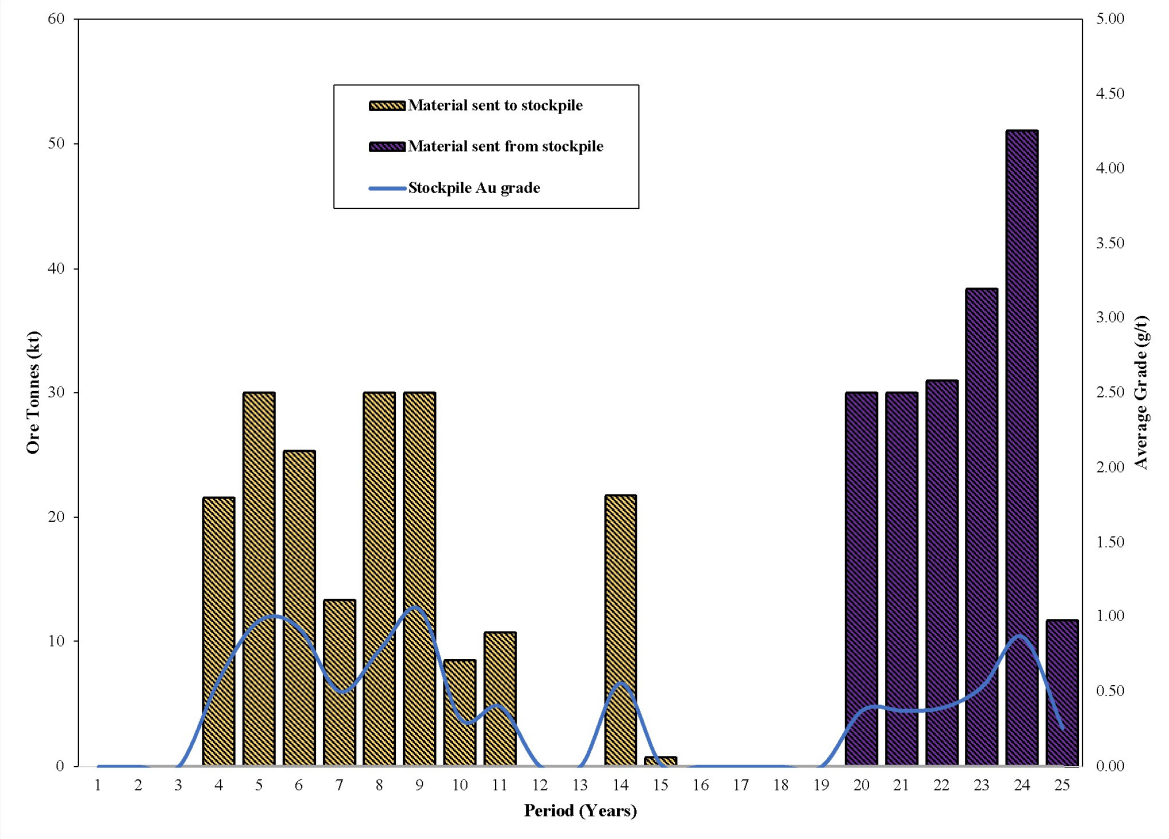


Fig. 16. Stockpiled material schedule and grade curve.

In Fig. 17, the comprehensive schedule for material processing is presented, which includes both material processed directly from the mine and material sourced from the stockpile. The implementation of the optimizer's strategy is evident in this schedule, resulting in various operational phases: After gradual ramping up from Year 1 to Year 3, the processing plant achieved full capacity from Year 4 to Year 19. During this period, the mining operation supplied sufficient high-grade material directly from the mine to meet the plant's processing capacity. From Year 20 to the end of the mine-life (Year 25), the processing plant's full capacity was not achieved due to various factors, such as declining ore grades and depletion of higher-grade areas in the mine. To ensure consistent plant operations and maximize output, the optimizer efficiently utilized the available grade blended material from the stockpile to meet the plant's processing capacity. The material processing statistics from the entire mine-life are as follows: 2,330,925.00 t of material were processed directly from the mine. 191,987.50 t of material were sourced from the stockpile and processed in the plant.

Overall, a total of 2,522,912.50 t of material were mined and processed, reflecting an optimized approach that effectively utilized available resources and improved the project's economic performance. The blended grade curve, comprising both direct processed grades and stockpile grades, ensured a consistent supply of material to the plant, contributing to the project's success over the 25-year mine-life.

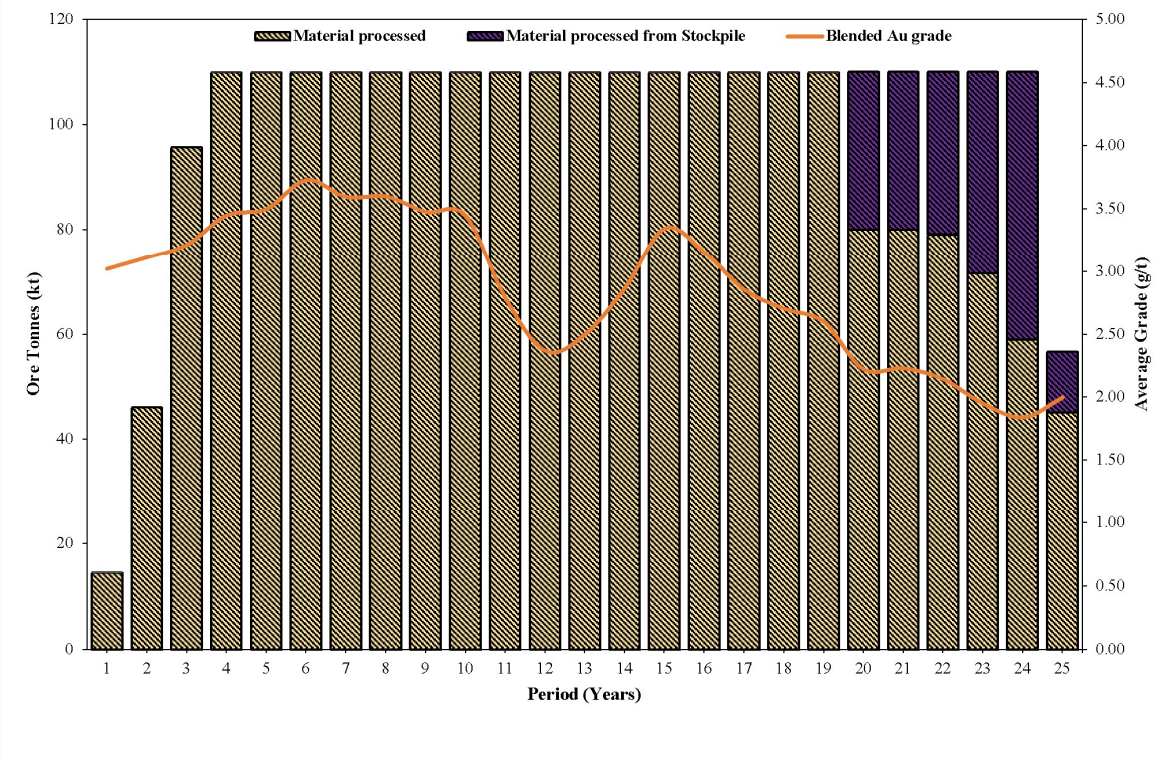


Fig. 17. Direct processed material, material from stockpile and grade blended curve schedule.

In Fig. 18, the stockpile inventory profile is presented, showcasing the accumulation and depletion of material over the mine-life. The profile demonstrates the following trends: From Year 4 to Year 11 and again from Year 14 to Year 15, the stockpile inventory gradually increased. During these periods, lower-grade material was selectively sent to the stockpile while higher-grade material was processed directly from the mine. This strategic stockpiling ensured a steady supply of material to the processing plant during periods of lower-grade mining, thereby maintaining a consistent production rate. From Year 20 to the end of the mine-life (Year 25), the stockpile inventory shows a gradual decline. As the mining operation entered its later stages and higher-grade areas in the mine became depleted, the stockpile was utilized to supplement the plant's processing needs. This utilization led

to the gradual depletion of material from the stockpile. Overall, the stockpile inventory profile demonstrates how the optimizer effectively managed material storage, strategically using the stockpile to maintain steady plant operations and optimize the overall material processing. By carefully controlling the stockpile and using it to complement the direct mining process, the project could adapt to varying ore grades, ensuring continuous production, and maximizing the project's economic performance throughout its 25-year mine-life.

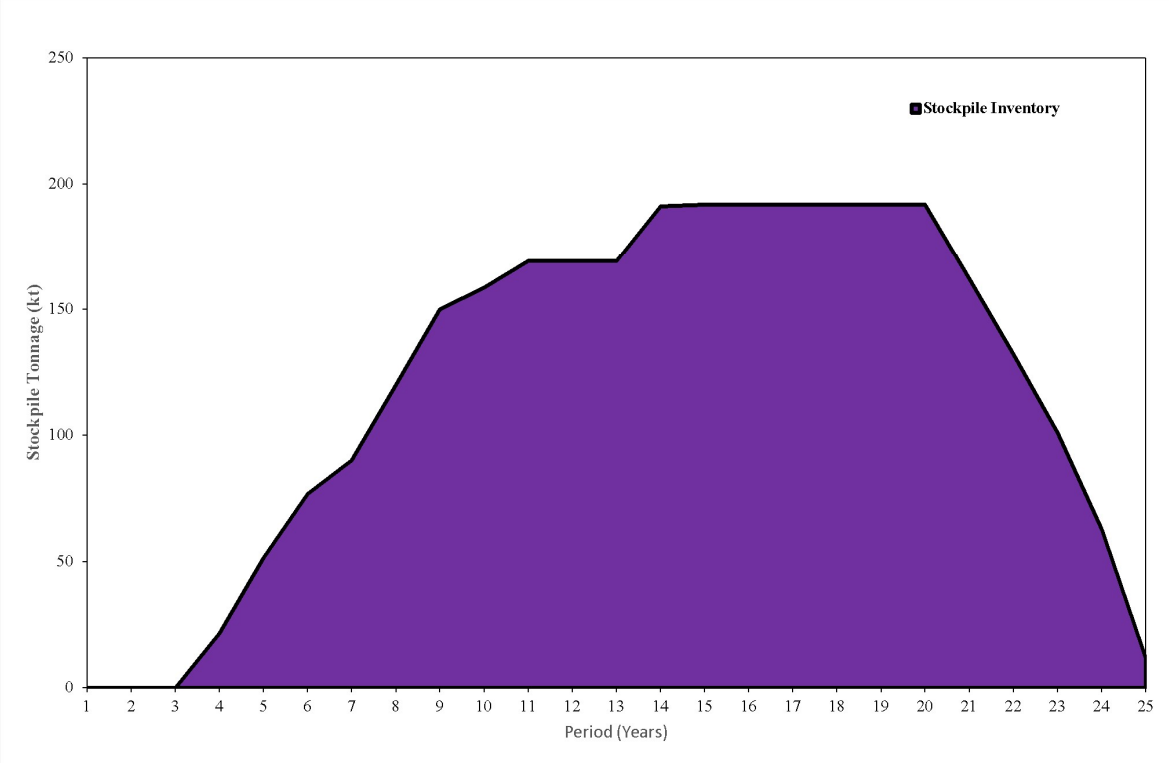


Fig. 18. Stockpile inventory profile.

8. Conclusion and Future work

In this paper, a MILP optimization framework which includes a grade control stockpiling management constraint for open stope mining production scheduling has been presented. The original model without stockpile was first implemented and results discussed and the model with stockpile was subsequently presented, and results discussed as well. The model's objective function maximizes the NPV of the mining operation while generating a practical stope extraction sequence. In addition to the mining and processing productivity constraints, capital development (decline), ventilation development, operational development, backfilling, active levels control, and maximum stope extraction duration constraints have been modelled and implemented. Thus, the identified limitations of existing underground production scheduling models in relation to generating global life-of-mine plans that integrate development like decline, ventilation, operational development, and ore pass resolved with this MILP framework.

The incorporation of grade control stockpile management has proven to be a significant improvement to the model, resulting in a substantial increase in the Net Present Value (NPV) of the open-stope underground gold project. By efficiently managing stockpiles and strategically blending grades, the model was able to optimize material utilization and ensure a continuous supply of high-grade ore to the processing plant when needed. This enhanced approach contributed to the overall profitability of the project. The approximate 10% increase in NPV is a testament to the effectiveness of the grade control stockpile management strategy. The model's ability to adapt to varying ore grades, store low

grade material in the stockpile during high-grade periods and utilize the stockpile during low grade periods allowed for a more stable and profitable operation throughout the mine's life. By strengthening the model with grade control stockpile management, the mining operation achieved better financial outcomes and improved resource utilization. This optimization provided a competitive advantage, allowing the project to realize its full potential and enhance its economic viability over the 25-year mine-life.

The ongoing implementation of the Stochastic Mixed Integer Linear Programming (SMILP) framework is an exciting phase of the research. The stochastic stage focuses on documenting the case study and analyzing the optimization results obtained through the model. The documentation process will involve carefully detailing the methodology, data inputs, constraints, and objectives used in the SMILP framework for the case study. The researchers will explain the various components of the model, such as the decision variables, objective functions, and constraints, as well as any specific modifications made to address the unique characteristics of the open-stope underground gold project.

This analysis will involve evaluating the performance of the SMILP framework in achieving its goals, such as maximizing the Net Present Value (NPV), optimizing production schedules, and efficiently managing grade control and stockpiling. The impact of different parameters and constraints on the results will be assessed and any other areas for further improvement will be identified. The analysis of the optimization results will play a crucial role in validating the effectiveness and practicality of the SMILP framework for real-world mining projects. It will provide valuable insights into the model's capabilities and limitations, allowing us to draw meaningful conclusions and recommendations for its implementation in other mining scenarios. It is envisaged that findings and insights from the case study and analysis will likely contribute to the advancement of selective mining optimization techniques and their application in the mining industry. The documentation and analysis will also pave the way for potential future research, refinement of the model, and its broader adoption in the field of mining and mineral resource management.

9. References

[1] Afum, B. O. and Ben-Awuah, E. (2021). A review of models and algorithms for surface-underground mining options and transitions optimization: Some lessons learnt and the way forward. MDPI, 1 (1), 112-134.

[2] Appianing, E. J. A., Ben-Awuah, E., and Pourrahimian, Y. (2023). Life-of-mine optimization for integrated open stope development and production scheduling using a mixed-integer linear programming framework. Mining Technology, 132 (2), 106-120.

[3] Bley, A., Boland, N., Froyland, G., and Zuckerberg, Z. (2012). Solving mixed integer nonlinear programming problems for mine production planning with stockpiling. Computers and Operations Research, 31.

[4] Carpentier, S., Gamache, M., and Dimitrakopoulos, R. (2016). Underground long-term mine production scheduling with integrated geological risk management. Mining Technology, 125 (2), 93-102.

[5] Dimitrakopoulos, R. (2011). Stochastic optimization for strategic mine planning: a decade of developments. Journal of Mining Science, 47 (2), 138-150.

[6] Dimitrakopoulos, R., Farrelly, C., and Godoy, M. (2002). Moving forward from traditional optimization: grade uncertainty and risk effects in open-pit design. Mining Technology, 111 (1), 82-88.

[7] Dimitrakopoulos, R. and Grieco, N. (2009). Stope design and geological uncertainty: quantification of risk in conventional designs and a probabilistic alternative. Journal of Mining Science, 45 (2), 152-163.

[8] Dimitrakopoulos, R., Martinez, L., and Ramazan, S. (2007). A maximum upside/minimum downside approach to the traditional optimization of open pit mine design. Journal of Mining Science, 43 (1), 73-82.

[9] Dimitrakopoulos, R. and Ramazan, S. (2004). Uncertainty based production scheduling in open pit mining. Society for Mining, Metallurgy, and Exploration Transactions, 316 (2004), 106-112.

[10] Dimitrakopoulos, R. and Ramazan, S. (2008). Stochastic integer programming for optimising long term production schedules of open pit mines: methods, application and value of stochastic solutions. Mining Technology, 117 (4), 155-160.

[11] Gholamnejad, J. and Kasmaee, S. (2012). Optimum blending of iron ore from Choghart stockpile by using goal programming. Journal of Central South University, 19 (4), 1081-1085.

[12] Godoy, M. and Dimitrakopoulos, R. (2011). A risk quantification framework for strategic mine planning: method and application. Journal of Mining Science, 47 (2), 235-246.

[13] Gregg, B., Jenna, H., Tucker, J., Darren, K., Garth, K., Chris, M., Mclennan, V., and Preciado, H. (2019). NI 43-101 Technical Report on Cozamin Mine Zacatecas, Mexico, pp. 1-215.

[14] Grieco, N. and Dimitrakopoulos, R. (2007). Managing grade risk in stope design optimisation: probabilistic mathematical programming model and application in sublevel stoping. Mining Technology, 116 (2), 49-57.

[15] Huang, S., Li, G., Ben-Awuah, E., Afum, B. O., and Hu, N. (2020). A stochastic mixed integer programming framework for underground mining production scheduling optimization considering grade uncertainty. IEEE, 8 (2020), 24495-24505.

[16] ILOG, I. (2019). CPLEX reference manual and software. Ver. 12.10.0, Pullman, WA, USA.

[17] Issaaks, E. H. and Srivastava, R. M. (1989). An introduction to applied geostatistics. New York, Oxford University Press, pp. 1-587.

[18] Khodayari, F. and Pourrahimian, Y. (2019). Long-term production scheduling optimization and 3D material mixing analysis for block caving mines. Mining Technology, 128 (2), 65-76.

[19] Khodayari, F., Pourrahimian, Y., and Liu, W. V. (2019). Production scheduling with horizontal mixing simulation in block cave mining. Journal of Mining Science, 55 789-803.

[20] Koushavand, B., Askari-Nasab, H., and Deutsch, C. V. (2014). A linear programming model for long-term mine planning in the presence of grad uncerrtainty and a stockpile. International Journal of Mining Science and Technology, 24 (2014), 451-459.

[21] Kuchling, K. (2016). Ore stockpiling. K. J. Kuchling Consulting Ltd. Mineral Industry Consulting Services, Retrieved July 4, 2022 from:

[22] Kumar, A. and Chatterjee, S. (2017). Open-pit coal mine production sequencing incorpoating grade blending and stockpiling options: An Application from an Indain mine. Engineering Optimization, 49 (5), 762-776.

[23] Leite, A. and Dimitrakopoulos, R. (2007). Stochastic optimisation model for open pit mine planning: application and risk analysis at copper deposit. Mining Technology, 116 (3), 109-118.

[24] Leite, A. and Dimitrakopoulos, R. (2014). Stochastic optimization of mine production scheduling with uncertain ore/metal/waste supply. International Journal of Mining Science and Technology, 24 (6), 755-762.

[25] MacNeil, J. A. and Dimitrakopoulos, R. G. (2017). A stochastic optimization formulation for the transition from open pit to underground mining. Optimization and Engineering, 18 (3), 793-813.

[26] MacNeil, J. A. L. (2015). Determining optimal open pit to underground mine transition depth using stochastic mine planning techniques. MEng Thesis, McGill University, Montreal, Pages 79.

[27] Magagula, N. S. (2016). Stochastic characterisation of a mining production system. MSc Thesis, University of the Witwatersrand,, Johannesburg, Pages 164.

[28] Malaki, S. (2016). Block-cave extraction level and production scheduling optimization under grade uncertainty. MSc Thesis, University of Alberta, Edmonton, Pages 157.

[29] Malhotra, D., Mandziak, T., and Marek, J. (2016). NI 43-101 Technical Prefeasibility Report on Dediktepe Project Balikeir Province, Turkey, pp. 1-244.

[30] Martinez, L. (2009). Why accounting for uncertainty and risk can improve final decision making in strategic open pit mine evaluation. in Proceedings of Project Evaluation Conference, Australian Institute of Mining and Metallurgy, pp. 1-12.

[31] Mathworks, I. (2023). MATLAB Software. Ver. 9.14.0.2206163 (R2023a), Washington St, Chicago, US.

[32] Mbadozie, O. and Ben-Awuah, E. (2020). Incorporating Grade Uncertainty in Oil Sands Mine Planning and Waste Optimization using Stochastic Mathematical Programming. in Proceedings of 6th UMaT Biennial International Mining Conference, University of Mines and Technology, Tarkwa, Ghana, pp. 72-90.

[33] McCarthy, B., Sawyer, V., Rowe, D., Simmons, G., Gray, J. N., Lightwood, G., Defilippi, C., Browne, R., Bidart, M., and Winkelmann, N. (2018). NI 43-101 Technical Preliminary Economic Assessment and Independent Report for the Goldstrike Project. Washington County, Utah, USA, pp. 1-252.

[34] Montiel, L., Dimitrakopoulos, R., and Kawahata, K. (2016). Globally optimising open-pit and underground mining operations under geological uncertainty. Mining Technology, 125 (1), 2-14.

[35] Moreno, E., Rezakhah, M., Newman, A., and Ferreira, F. (2017). Linear models for stockpiling in open-pit mine production schdeuling problems. European Journal of Operational Research, 260 (1), 212-221.

[36] Mousavi, A., Kozan, E., and Lui, S. (2016). Open-pit block sequencing optimization: A mathematical model and solution technique. Engineering Optimization, 48 (11), 1932-1950.

[37] Noriega, R., Pourrahimian, Y., and Ben-Awuah, E. (2022). Optimisation of life-of-mine production scheduling for block-caving mines under mineral resource and material mixing uncertainty. International Journal of Mining, Reclamation and Environment, 36 (2), 104-124.

[38] Paravarzar, S., Askari-Nasab, H., pourrahimian, Y., and Emery, X. (2021). Operational mine planning in block cave mining: a simulation-optimisation approach. International Journal of Mining, Reclamation and Environment, 35 (3), 199-218.

[39] Paravarzar, S., Askari-Nasab, H., Pourrahimian, Y., and Emery, X. (2021). Simultaneous multi-sector block cave mine production scheduling considering operational uncertainties. Mining Technology, 130 (1), 36-51.

[40] Potvin, Y. and Hudyma, M. (2000). Small and Large Open Stope Mining in Canada. Australian Centre for Geomechanics, (2000), 1-19.

[41] Promine, I. (2018). Promine software. Ver. 2018, Montreal, Quebec, Canada.

[42] Ramazan, S. and Dimitrakopoulos, R. (2004). Traditional and new MIP models for production scheduling with in-situ grade variability. International Journal of Surface Mining, 18 (2), 85-98.

[43] Ramazan, S. and Dimitrakopoulos, R. (2012). Production scheduling with uncertain supply: a new solution to the open pit mining problem. Optimization and Engineering, 14 (2), 361-380.

[44] Ramazan, S. and Dimitrakopoulos, R. (2013). Production scheduling with uncertainty supply: a new solution to the optimization problem. Optimization and Engineeri g, 14 (2), 361-380.

[45] Remy, N., Boucher, A., and Wu, J. (2009). Applied geostatistics with SGeMS: A users' guide. Cambridge University Press, Cambridge, Pages 63.

[46] Sabour, S. A. and Dimitrakopoulos, R. (2011). Incorporating geological and market uncertainties and operational flexibility into open pit mine design. Journal of Mining Science, 47 (2), 191-201.

[47] Silva, M. d. F., Dimitrakopoulos, R., and Lamghari, A. (2015). Solving a large SIP model for production scheduling at a gold mine with multiple processing streams and uncertain geology. Mining Technology, 124 (1), 24-33.

[48] Smith, M. L. and Wicks, S. J. (2014). Meduim-Term Production Scheduling of the Lumwana Mining Complex. Interfaces, 44 (2), 176-194.

[49] Tabesh, M. and Askari-Nasab, H. (2017). Linearized stockpile modeling for long-term open-pit production planning. Mining Optimization Laboratory 8(8), 1-20.

[50] Tabesh, M., Askari-Nasab, H., and Peroni, R. (2015). A comprehensive approach to strategic open pit mine planning with stockpile consideration. in Proceedings of APCOM, pp. 326-332.

Intelligent Agent-Based Simulation and Deep Reinforcement Learning for Smart Mining Operations

Solomon Acheampong, Pedro Pablo Vasquez-Coronado and Eugene Ben-Awuah
Mining Optimization Laboratory (MOL)
Laurentian University, Sudbury, Canada

ABSTRACT

Real-time intelligent decision-making in a mining environment with huge amounts of mine operations data is the basis for smart mining. By leveraging a deep reinforcement learning algorithm using the Deep Q Networks (DQN), the objective of this research is to enhance shovel-truck productivity by accurately detecting and overcoming operational obstacles within the mining environment. The research aims to develop an intelligent system that effectively supervises the operations of a short-term open pit mine through the combination of simulation and intelligent agents. This includes modelling the mining operation and employing agent-based simulation to control equipment fleet and implementing a reinforcement learning agent for intelligent decision-making. The proposed methodology establishes a virtual experimental environment by incorporating a decision model supported by discrete event simulation. The intelligent supervisory agent is trained using deep reinforcement learning techniques to determine mining zones based on key performance indicators such as ore grade and tonnage. The model's effectiveness and performance are evaluated through the examination of experimental scenarios; utilizing experimental designs to verify and validate the proposed approach.

1. Introduction

Smart mining is a concept that involves the use of advanced technologies to optimize mining operations. One of the key components of smart mining is real-time intelligent decision-making, which requires the processing of huge amounts of mine operations data. To do this, researchers are looking into using deep reinforcement learning algorithms based on Deep Q Networks (DQN) to improve shovel-truck productivity by accurately detecting and getting around operational obstacles in a mining environment [44].

Simulation modelling is a powerful tool that has been widely used in various industries to replicate real-world scenarios and test different strategies and decision-making processes [26]. In the context of mining operations, simulation models can provide valuable insights into the performance of different mining strategies and help identify areas for improvement. On the other hand, deep reinforcement learning is a branch of artificial intelligence that combines deep learning and reinforcement learning techniques to enable intelligent agents to make optimal decisions in complex environments [25].

One of the key challenges in the mining industry is the need for real-time decision-making. Mining operations are complex and dynamic, and decisions need to be made quickly to avoid delays and maximize productivity. The use of intelligent systems that can make real-time decisions based on data analysis is therefore critical for the success of mining operations. The development of intelligent

ISBN: 978-1-55195-503-2

and autonomous mining systems is an area of active research, with many companies and research institutions investing in this field. The use of AI and simulation modelling is expected to play a key role in the development of these systems, enabling mining companies to optimize their operations and improve safety and efficiency.

In this article, we will explore how this approach can be used to optimize mining operations and improve efficiency and safety in the mining industry. The methodology involves the development of a simulation model that replicates mining operations and the application of deep reinforcement learning techniques to train an intelligent agent. The results of the experiments conducted using the simulation model demonstrate the effectiveness of the intelligent system in achieving the desired production targets and optimizing the allocation of resources.

By making a deep reinforcement learning-based model of an intelligent system, this research contributes to the field of simulation optimization of intelligent and autonomous mining systems. The findings of this research have implications for the mining industry, as they provide insights into the potential benefits of using intelligent systems for decision-making in mining operations.

2. Literature Review

The literature review covers three main areas: operational planning, simulation modelling, and artificial intelligence (AI), including machine learning (ML) and deep learning (DL).

2.1. Operational planning

Operational planning in short-term open pit mining refers to the process of developing and implementing a plan for the day-to-day operations of continuous mining. It involves several activities, including setting production targets, allocating resources, establishing schedules, and managing operations. The goal of operational planning is to ensure that the mining operates efficiently and effectively to achieve its strategic objectives.

The operational planning process typically begins with the development of a mining plan, which outlines the mining objectives, resource requirements, and production targets. This plan is then used to develop a detailed operational plan, which outlines the specific steps that will be taken to achieve these goals. This might include identifying the equipment needed, establishing schedules and workflows, and allocating resources to different parts of the mining operation.

This also involves monitoring and controlling the mining operation to ensure that it is meeting its target and operating effectively. These include the use of real-time data and performance metrics, as well as regular assessments of the mining operation to identify areas for improvement.

2.2. Simulation Modelling

Many industries use simulation on a regular basis. Its main objective is to mathematically or virtually express operations or concepts in real or hypothetical situations. The 1940s saw the beginning of simulation [5]. As a digital tool for resolving challenging real-world problems, simulation has developed over time to model neural cells in the brain. Simulation can be done in a variety of ways, including continuous, discrete, stochastic, and deterministic.

Simulation is the representation of real-world situations mathematically or visually in a virtual setting. It enables the realistic representation of arbitrary decisions made in real-world circumstances [38]. In recent decades, data analysis and calculation speed have increased, making simulation more accurate, practical, and realistic.

Hashemi and Sattarvand [17] used Discrete event simulation (DES) to evaluate the Sungun copper mine haulage system. The authors were able to construct intricate systems and truck-to-loader assignments using this method to track performance. When comparing the flexible truck assignment for loaders to the fixed assignment system, the authors found a 7.8% improvement.

Manriquez et al. [27] conducted a case study on a truck and shovel excavator mining system in snowfall conditions using discrete event simulation (DES). They found that a specific operating policy could increase productivity by 32% when considering previous snowfall events. DES's ability to simulate intricate mining systems and snow removal operations highlights its importance in enhancing efficiency.

A simulation model aims to simulate the behavior or operation of a modelled system to determine optimal settings and levels of operation for optimal performance. Performance is a key performance indicator (KPI), and parameters are equivalent to decision variables [33]. These elements are multi-attribute behaviors in supply chain decision-making. Intelligent agents communicate with the simulation to improve results.

Modern simulation modelling was examined by Jovanoski et al. [22] and Grigoryev [16] using discrete event, agent-based, and system dynamics techniques. Different levels of abstraction and particular applications are used with each method. Fig. 1 illustrates how each technique serves a particular range of abstraction levels and their associated applications. High-level strategic modelling is done with the help of system dynamics (SD). While agent-based simulation (AB) can range from highly abstract models where agents even represent businesses to highly detailed models where agents represent physical objects, discrete event (DE) modelling only allows for low and medium-level abstractions.

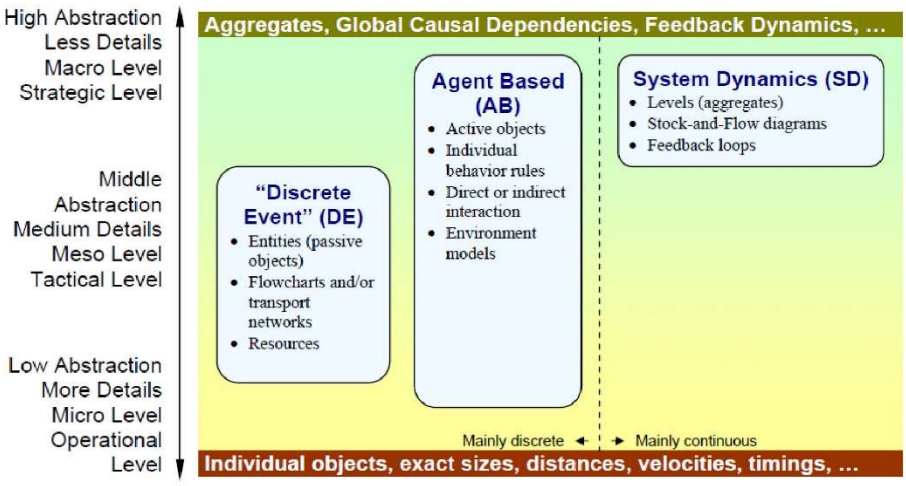


Fig. 1. Method in simulation modelling [22].

2.3. Artificial Intelligence

The debate on machine intelligence dates back to the 1940s, with Sir Alan Turing's paper [39] measuring machines' ability to mimic human intelligence. Arthur Samuel [32] introduces the theory of machines learning from raw data, categorized into two approaches: search, pattern recognition, learning, planning, and induction. DL is a subset of ML that uses neural networks and is inspired by McCulloch and Pitts' theory [28]. DL's feature extraction technique frees developers from manually crafting feature engineering algorithms.

Deep reinforcement learning (DRL) is a branch of reinforcement learning (RL) that incorporates the use of deep neural networks that mirror the functionality of the human brain. When compared to supervised and unsupervised machine learning techniques, RL enhances itself through rewards and penalties [35]. Deep Q network (DQN) is a DRL algorithm usually implemented on a Markov decision process stage to train agents to take decisive and good actions to maximize a reward function. The policy trains and improves itself through experience by performing a series of actions and receiving rewards (negative or positive) from the environment.

The Markov Decision Process (MDP) is a mathematical framework for simulating a decision-control scenario in a discrete-time stochastic environment [6]. With the actor acting as the agent, it consists of states and actions. The agent chooses an action at random among the possible actions from a particular state (or states) for each step in the process, which can exist in any random state. The environment motivates the agent by giving it a reward or feedback, Ra (s, s') in a looped process until an optimal policy is obtained. Fig. 2 presents the Markov decision process workflow.

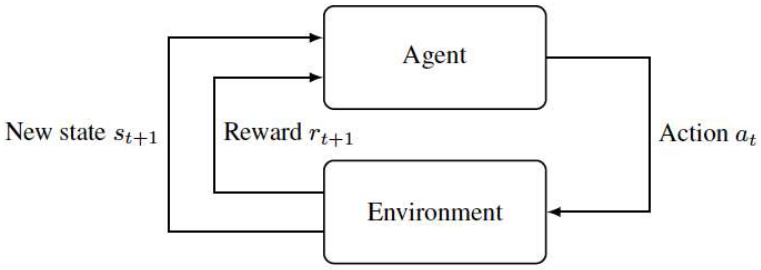


Fig. 2. Markov decision process workflow of agent using DQN [15].

Every policy employing the MDP framework must adhere to the four MDP elements. State (s), Action (a), Probability of action (Pa), also known as the Transition Probability Distribution Function, and Reward Function (Ra) are the terms used to characterize them.

The state of an instance determines its mode or configuration. Any random variable from a state space that a policy can be at any given time (t) is the state (s). Depending on the kind of system being modelled, the state space might either be continuous or discrete. All the orders and actions that may be carried out by a policy during a specified number of epochs or episodes are referred to as the Action (a).

2.4. Transition Probability Distribution Function

This is the probability that results in a shift in states (S). A state space, a transitional probability matrix that describes every possible transition, and an initial state (S1) from the state space make up the process. The matrix of transitions is shown in Fig. 3 below.

$$P = \begin{bmatrix} P_{1,1} & P_{1,2} & \dots & P_{1,j} & \dots & P_{1,S} \\ P_{2,1} & P_{2,2} & \dots & P_{2,j} & \dots & P_{2,S} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ P_{i,1} & P_{i,2} & \dots & P_{i,j} & \dots & P_{i,S} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ P_{S,1} & P_{S,2} & \dots & P_{S,j} & \dots & P_{S,S} \end{bmatrix}.$$

Fig. 3. Transitional probability matrix / The Markov Matrix [12].

The equation for the transition probability distribution function is shown in Eq. **Error! Reference source not found.** .

$$P_{ss'}^{a} = P[S_t + 1 = S' | S_t = S_1, a_t = a] \quad (1)$$

$P_{ss'}^{a}$ = Probability of action a, issued in state s, ending up in state s^1 with reward r

2.5. Reward Function Theory

After an agent takes a step and switches from one state s_1, to another state s_2, the environment responds with a reward (R_t), which is information. Maximizing total rewards is the agent's aim.

$$R_t = r_t + 1 + \gamma r_t + 2 + \gamma^2 r_t + 3 \dots \gamma^n r_t + n \quad (2)$$

From Eq. **Error! Reference source not found.**, γ is the discount factor between 0 and 1. Discount factors are the additives that enable the agent to comprehend the significance of future rewards. When the discount factor is set between 0 and 1, the agent starts to look for current and potential rewards accountability. The following illustrates the equation of the transition reward function.

$$R_{ss^1}^{a} = \mathrm{E}[r_t + 1 \mid S_t = S, a_t = a, S_t + 1 = S^1] \quad (3)$$

2.6. Bellman optimality

The Bellman optimality or equation, is used to calculate the expected value of a given policy π. From Eq. **Error! Reference source not found.**, a discount factor is introduced for the agent to account for immediate and future rewards. According to the Bellman equation [43], a long-term reward R_{t+n} for a given action is equal to the sum of the reward of the current action R_t and the expected reward from future actions R_{t+1}.

$$V(s) = \max_{\pi}(R(s,a) + \gamma V(s')) \quad (4)$$

From Eq. (4), V(s) is the value of the state. i.e., the numeric representation of a state, which guides the agent to find its path.

2.7. Policy Function

A Policy π is a function in charge of causing the agent to take an action (a) in a state (s). The sum of all the possible actions equals 1, i.e.

$$\Sigma_a \pi(s,a) = 1 \quad (5)$$

2.8. State Value Function (V^{π})

The expected total rewards to be received starting with a state is presented in Fig. 4.

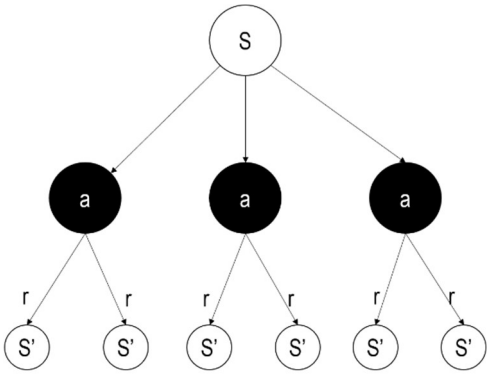


Fig. 4. Diagram illustrating state value function [12].

The state value function's mathematical model is presented in Eq. (6).

$$V^{\pi}(s) = \sum_{\alpha} \pi(s,a) \sum_{s'} P_{ss'}^{\alpha} R_{ss'}^{a} + \lambda \sum_{\alpha} \pi(s,a) \sum_{s'} P_{ss'}^{a} V^{\pi}(s') \quad (6)$$

From Eq. (6), $\pi(s,a)$ is the policy given state and action, $\sum_{s'} P_{ss'}^{\alpha} R_{ss'}^{a}$ is the sum product of the probability of action *a* issued in state s ending up in a new state s', returning an expected reward R.

2.9. Action Valueunction (Q^{π})

The action value is the worth of a decision made in a situation where the expected total reward is returned. It is depicted in Fig. 5.

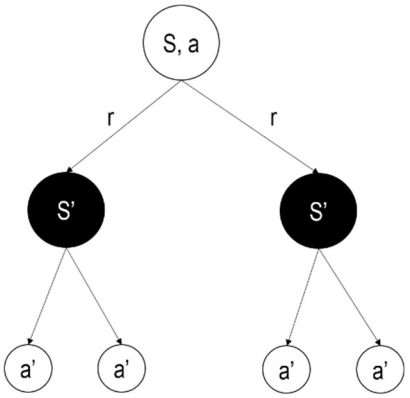


Fig. 5. Diagram illustrating action value function [12].

Mathematical model behind action value function is illustrated in Eq. (7).

$$Q^{\pi}(s,a) = \sum_{s'} P^{a}_{ss'} R^{a}_{ss'} + \gamma \sum_{s'} P^{a}_{ss'} V^{\pi}(s') \tag{7}$$

From Eq. (7), $Q^{\pi}(s,a)$ is the policy given state and action, $\sum_{s'} P^{\alpha}_{ss'} R^{a}_{ss'}$ is the sum product of the probability of action *a* issued in state s ending up in a new state s', returning an expected reward R given a state value of $V^{\pi}(s')$.

2.10. Optimal Policy

An optimal policy strategy is an action that maximizes some objective or reward in a system or process. The optimal policy maps states to actions, indicating the action that should be taken in each state to maximize the expected return. The optimal policy estimates the expected return of taking an action in a state. The optimal policy can be deduced as shown in Eq. (8).

$$V\pi(s) = \max_{\pi} V_{\pi}(s) \tag{8}$$

2.11. Greedy Policy

This function allows the agent to prioritize the most optimal steps. The relationship between state value and action value can be represented by Eq. (9).

$$V(s_t) = \max_{\pi} Q(s_t, a) \tag{9}$$

From Eq. (9), the Bellman equation can be expressed as shown in Eq. (10).

$$Q(s_t a_t) = r(s_t, a_t) + \gamma \frac{\max}{a_{t+1}} Q(s_{t+1}, a_{t+1}) \tag{10}$$

2.12. Deep Q Network

Deep learning is a type of machine learning approach that comprises two or more layers, weights and biases, and artificial neurons known as perceptron. Weights and biases play a very vital role in deep learning. The weight determines how much influence the input vector has on the output [43].

On the other hand, the biases, which are typically independent and constant with a value of 1, are added to the following layer. It serves as an assurance that even when an input vector contains zero values, there will still be an activation in the neurons [43]. Eq. (11) represent the mathematical equation of a neuron.

$$Y = \sum (weight * input) + bias \tag{11}$$

2.13. Stochastic Gradient Descent

When training a deep neural net on a dataset, the gradient descent functions as an optimization process to minimize the loss, normally called the loss function. The loss function serves as a check as to how the model performs given the parameters of weights and biases. The gradient descent helps in finding the precise parameter to use in order to achieve a good model [43].

2.14. Back-Propagation

Back propagation simply means calculating the gradient of a loss function. During the training process of a neural network, each weight within the network is calculated automatically with a deferential algorithm, and the calculated gradients are then used to update the weights [8].

2.15. Learning Rate

During the training process of a neural network, the learning rate determines the step size for which the error gradients are calculated [42]. The learning rate ranges from 0 to 1. The higher the rate, the more the network will overshoot the minimum. The lower the range, the longer the training process.

2.16. Deep Q Learning Network

DQN is a particular kind of reinforcement learning technique that is typically used on a MDP stage to teach agents to make strategic decisions to maximize a predetermined reward function. The policy engages in a series of actions and receives rewards from the environment, either negatively or positively, as it learns from experience. [9]. The decision-process workflow is shown in Fig. 6.

The Deep Q Network is primarily made up of the following techniques: Experience Replay is an approach used in the network to stabilize network updates. A group of transitions known as the replay buffer are added to the buffer at each data collection. Experience replay's entire purpose is to calculate loss and its gradient from a small batch of transitions taken from the replay buffer [13].

Target Network: The target network serves as an error measurement. The target network ensures that the agent replays each action it takes in an environment as if it were starting over each time, taking into account every action the agent undertakes there [10].

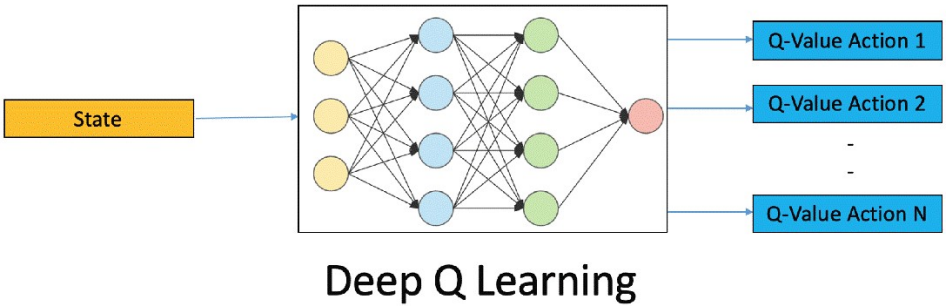


Fig. 6. Graphical examples of Deep Q learning [10].

Error! Reference source not found.illustrates the pseudocode of a DQN. Q (s, a) is for storing Q values for every time an action a_t is taken, usually by the policy or agent in a state *s*. The focus of the agent is to improve the Q value function. It learns from the Q value, which is an expected total return

from a given state-action pair. Anytime the agent makes a move, a reward is returned. Thus, R (s, a, s') becomes the new target the agent pursues from Q (s, a). γ-max is a discount factor. Discount factors cause reward functions to lose more of their value as the agent keeps on acting on the environment over time. This causes the agent to seek more rewards.

Table 1. Sample DQN algorithm.

***Hyperparameters**: replay buffer capacity N, reward discount factor γ, delayed steps C for target action-value function update, _greedy factor _*
***Input**: empty replay buffer D, initial parameters θ of action-value function Q*
Initialize target action-value function ˆQ with parameter ˆ θ ← θ
for** episode = 0, 1, 2, ... **do
Initialize environment and get observation O0
Initialize sequence S0 = (O0) and preprocess sequence φ0 = φ(S0)
for** t = 0, 1, 2, . . . **do
With probability _ select a random action At, otherwise select At = $argmax_a$ Q(φ(St), a; θ)
Execute action At and observe Ot+1 and reward Rt(s, a, s')
If the episode has ended, set Dt = 1. Otherwise, set Dt = 0
Set St+1 = (St,At,Ot+1) and preprocess φt+1 = φ(St+1)
Store transition (φt,At,Rt,Dt, φt+1) in D
Sample random minibatch of transitions (φi,Ai,Ri,Di, φi) from D
If Di = 0, set Yi = Ri + γ maxa_ˆQ(φi, a;θ). Otherwise, set Yi = Ri
Perform a gradient descent step on (Yi − Q(φi,Ai ; θ))2 with respect to θ
Synchronize the target ˆQ every C steps
If the episode has ended, break the loop
end for
end for

3. Problem statement

Data generated in the mining industry has recently increased exponentially, making it very difficult to gain knowledge in real time about the mining operation. As tons of data are processed with high-speed computers and smart software, big data mining has become more efficient and requires less work. The complexity of decision-making in mining has increased over the years due to the nature of the mineral deposits and the need to increase productivity of the operation. Mining data from day-to-day operations from monitoring devices and sensors includes the location of a truck or shovel, processing rate, and quantity of material mined.

Experimenting with these mining production systems in real life is risky, costly, and can lead to wrong decisions. Due to the complexity of these operations, the use of decision-support modelling tools is necessary and useful for understanding interactions and improving system performance. One well-known system modelling technique is simulation, which mimics the operation of the real world on a computer. By mimicking the operation of a real system, the simulation generates a predictable historical data about the system, and its observation allows inferences to be made concerning the system's operation or performance characteristics, including unexpected outages that could affect the entire system. Fig. 7 illustrates the statement of the problem comprised of mining activities and operations. Data gathered on mining operations such as production, fleet management, and dispatching can be difficult to analyze in real time as large volumes of data are generated over time.

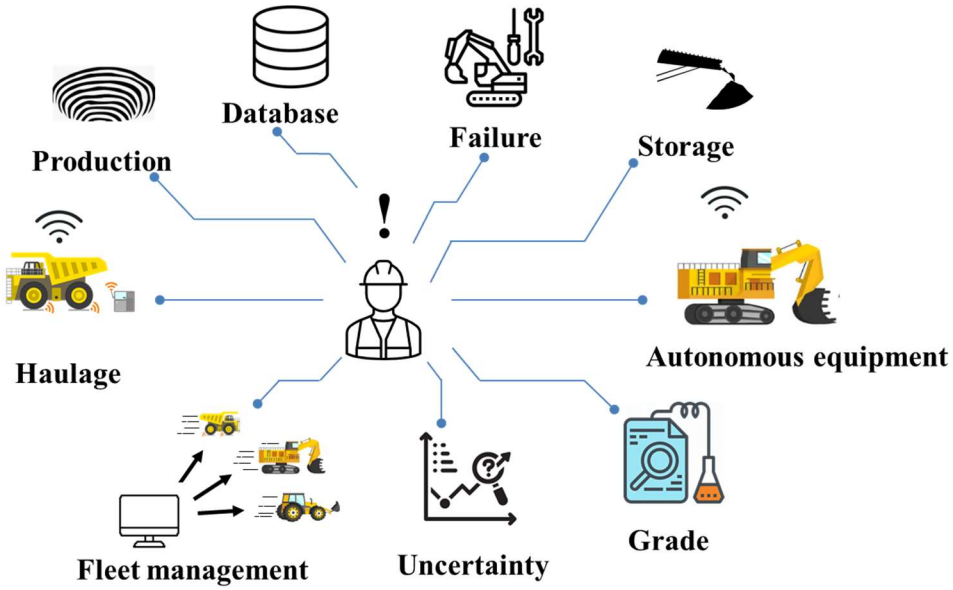


Fig. 8. Schematic representation of the problem statement

4. Methodology

The methodology outlined involves the utilization of discrete event simulation and an agent-based model, coupled with an intelligent supervisory agent, to establish a virtual environment for mining operational experiments. The research starts with long-term open pit production schedule data obtained from Whittle software optimization [36]. The schedule data contains three pushbacks, of which Pushback 1 is chosen as the focus of this research in a short-term mine planning context. The short-term production schedule data serves as an input to a simulation model that mimics the operation of the open pit mine, as shown in Fig. 9.

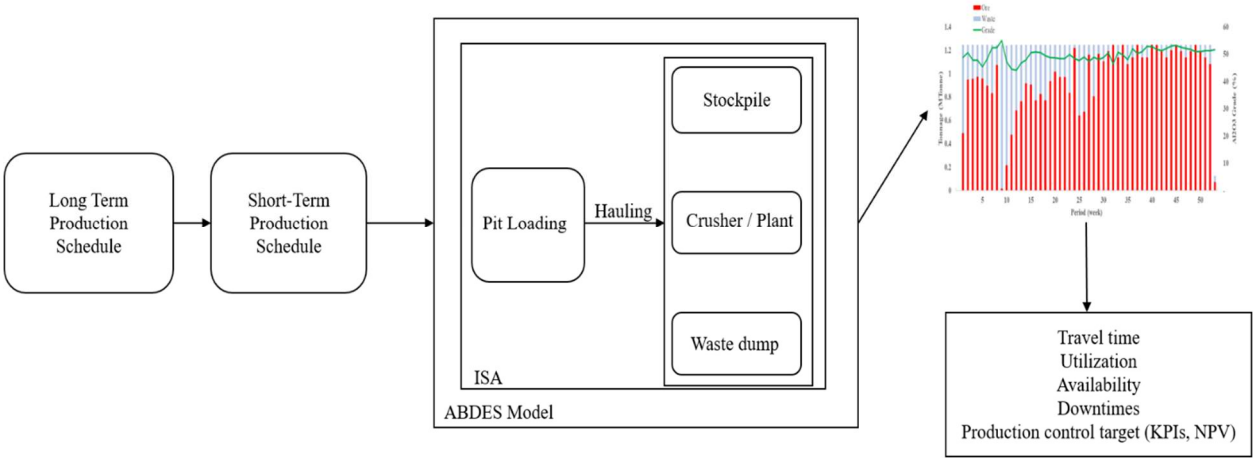


Fig. 10 Research methodology

The ISA is developed with reinforcement learning based on the DQN algorithm [11] and implemented with the object-oriented programming platform Java [12]. The DQN algorithm is suitable for both discrete state space and discrete action space. During implementation, the ISA is trained by monitoring the operational parameters, including ore tonnage and grade, truck cycle time, and shovel and plant availability. After training, the ISA is deployed to manage the mining operation by monitoring and allocating shovel digging areas as well as truck assignments to minimize production variations based on ore grade and ore tons. The ISA performs these operations by

observing the input states and parameters and choosing the best actions suitable for managing the continuous mining operation.

4.1. Proposed Algorithm

A pre-processing algorithm was created to divide the production schedule data into rows of mining blocks that represented a truck load of material before the simulation started. The algorithm generates mining zones, which function as locations for the allocation of loading equipment. The purpose of the mining zones created was to make it possible to monitor the ISA's performance. Fig. 11 illustrates the process flow integration of the ISA and the ABDES.

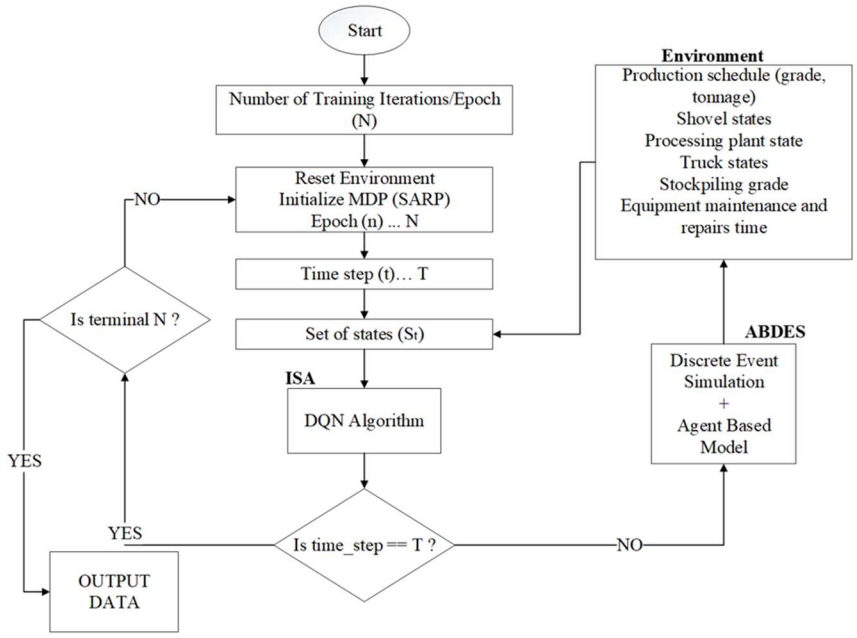


Fig. 11 Algorithm for Agent-Based Discrete Event Simulation and ISA integration

4.2. Agent-Based Discrete Event Simulation (ABDES)

This section covers the simulation sequence of the original design of the mining process. Fig. 12 illustrates the truck-shovel method of extracting earth materials from the pit.

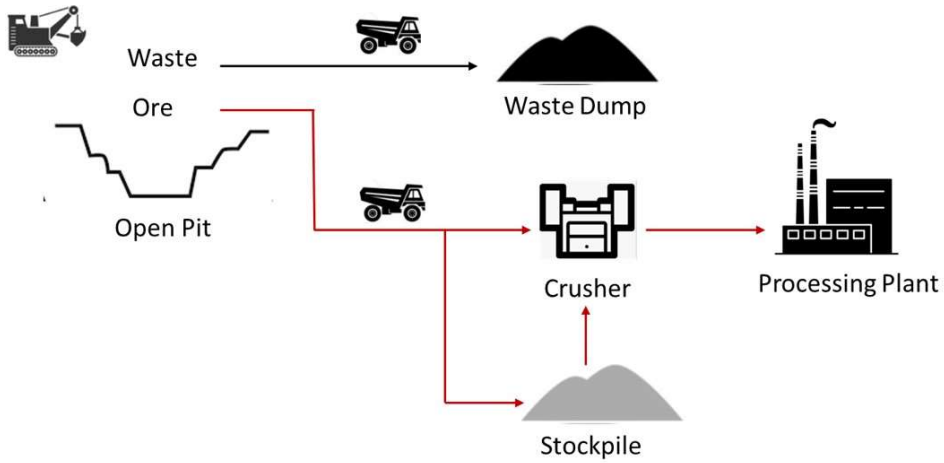


Fig. 12. Mining simulation model.

The method of simulation chosen for this research includes a DES, which simulates the flow of material from one point to the next. The ABM, on the other hand, models the behavior and activities of mine equipment and operations. Both are combined to form the ABDES, which is the interaction between the DES and ABM to provide a realistic mining operation environment.

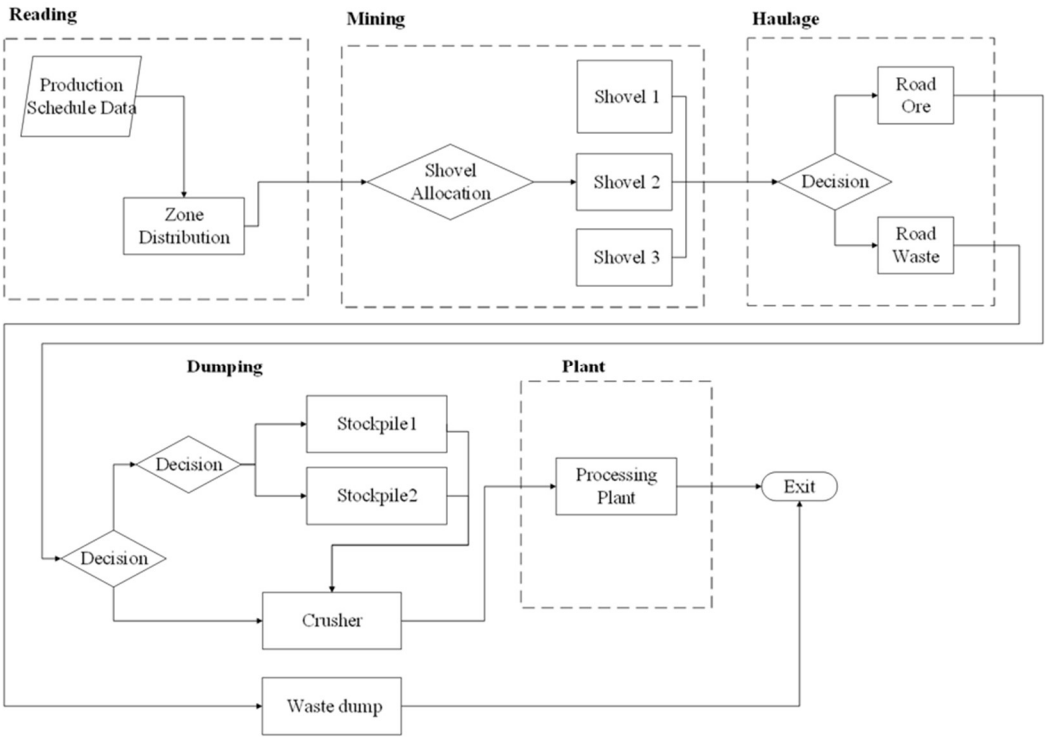


Fig. 13. Logical sequence for simulation model experiment.

4.3. Reading

Array matrix is used to store mining blocks from the production schedule data. This strategy speeds up computation and makes data accessible for the ISA to execute a tree search algorithm to find the best zones for mining. The DQN algorithm prioritizes high-grade blocks over low-grade blocks, separating high-grade, low-grade, and waste materials for mining to achieve targeted KPIs. The production model contains the following information in Table 1:

Table 1. Block model parameters.

Field	Description
BlockID	Block identification
Coordinate-X	Location in X
Coordinate-Y	Location in Y
Coordinate-Z	Location in Z
Rocktype:	0 Waste, 1 Ore
Tonnage	Amount of material
MetalContent	Contained metal
Recovery	Percentage of ore recovery
Al_2O_3 Grade	Aluminide grade
Al_2O_3 (tonnage)	Aluminide Tonnage

SiO_2 Grade	Silica grade
SiO_2 (tonnage)	Silica tonnage
Pushback	Mining phase
Period	Mining Period

4.4. Mining

The Mining node takes over the block entities from the Reading node. The Mining node deploys three shovels, and it is a requirement for the three shovels to work simultaneously. With the integration of the ISA, it ensures each shovel works in a different zone and continuously monitors the shovel activities. An agent-based model (ABM) represents shovel behavior, allowing monitoring of individual activities like loading, failure, maintenance, repairs, idle state, and active state. Trucks are modelled using ABM, with each truck acting as a self-decision sub-agent, enabling ISA monitoring of activities like idle, active, hauling, loading, unloading, failures, repairs, and maintenance.

4.5. Haulage

The Haulage node takes over truck entities from the Mining node, using 3D haul road profiles from Gems to design a haulage simulation.

4.6. Dumping

The Dumping node takes over the truck entities from the Haulage node. This node functions in the same way as in Scenario 1. However, one additional stockpile is added to segregate the quality of the stockpiled material using a predefined cut-off grade. Incoming ore materials are transported directly to the crusher if there is no queue. If there is a queue at the crusher, high-grade materials are transported to Stockpile 1, while low-grade materials are transported to Stockpile 2.

4.7. Plant

The Plant node takes over the material entities from the Dumping node. The plant is modelled using ABM to incorporate availability, utilization, maintenance, repair, failure, and downtime. Ore is sent continuously from the mine or stockpiles, and if not at full production capacity, material is received from the stockpile. Ore is reclaimed from either high- or low-grade stockpiles to minimize deviation.

4.8. Replication

The obtained values for the variables and parameters at the end of the simulation will differ significantly if the model is run more than once [14]. The objectives and necessary simulation accuracy should be used to justify the number of simulations for each individual test [19]. Within the probability distribution of all possible combinations, each replicated simulation represents a workable solution. According to Holford et al. [19], the number of simulation replicates should depend on the study's accuracy and goals.

A minimum range of 2 and a maximum of 10 replicates were established with which to run the simulation, and a 95% confidence interval was used to validate the number of replicates. Due to the different types of data and variations in the model, different numbers of replicates were used in each case.

Intelligent Supervisory Agent (ISA)

The proposed framework assumes that there are N total zones, each of which defines a set of shovels and trucks. It has been proposed that the shovels operate simultaneously, switching between various locations in accordance with real-world requirements. Shovels are given access to available trucks according to a schedule as soon as they are required. The model shows the various mining zones that the agent must select before beginning to mine. While the other zones are in the inferior level, the first zones are in the superior level. Zone distributions are viewed in Fig. 14.

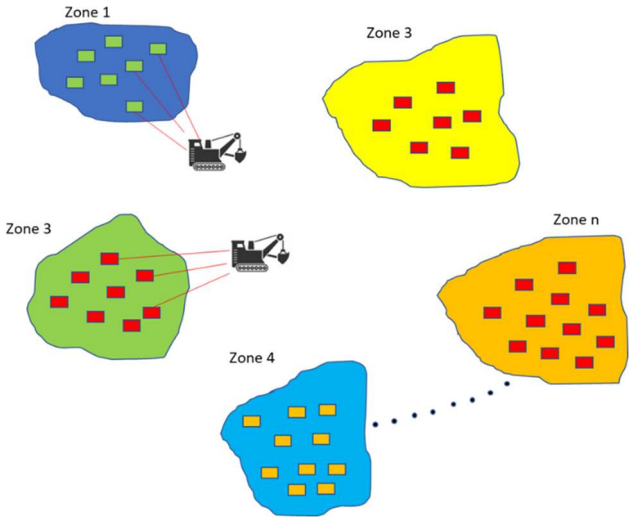


Fig. 14. Graphical representation of the zone's distribution.

4.9. Training implementation architecture

The grades and tonnages (rectangular boxes) contained in each of the zones are assumed to be known. However, these metrics are not exposed to the intelligent agent. The intelligent agent must uncover these values by training and learning from the environment. It first extracts the top-level zones and continues with the lower zones.

- Environment

The environment represents the problem to be solved. It can be described using a simulation. It is everything that comes after the agent's decision. The environment is modelled as states S, and each state s in S requires the agent to take specific actions. Failure to take the required action results in the agent receiving a negative reward or a penalty.

- State Space

The state space is a set of variables and all the possible values they can take. The State is an instance of the State Space. The State is the set of values a variable takes. At any period *t*, the state space is an observation of instances obtained from the environment. The observed states at each time step *t* are the dispatch system states, processing plant states, and production schedule states (tonnage and grade).

- Action

The environment makes available a set of actions from which the agent chooses an action. The agent influences the environment with these actions, and the environment may change states as a response to the agent's action. In this study, at each time step *t,* the agent is provided with four (4) actions with each action containing set of algorithms that control the state of the simulation. To ensure the simulation converges and the mine operation yields a high NPV, the agent is required to find which actions will support the target objective, such as:

0: Take no Action

1: Choose zones with good minimum deviation

2: Allocate available shovels for selected zones

3: Allocate available trucks for the active shovels

The agent uses two criteria to select zones: ore grade and ore tonnage. A target is set, and random restricted actions are made, starting from top-level zones. If the agent makes the wrong decision, penalty feedback is rewarded. Each block in the selected zone contains an available ore grade, which is subtracted from the target grade and tonnage per week. This minimum deviation reward is cumulative for blocks in each zone, ensuring the highest possible rewards for individual zones.

- Reward function

This function represents feedback on how well the last action contributed to achieving the target objective of the environment. The reward function $r_t(s',a)$ helps the ISA to learn the best possible actions to take to achieve its goals. The objective of the ISA is to maximize its rewards over time. Therefore, we introduce a discount factor (γ), which controls how the ISA will account for future rewards. The simulation is designed in such a way that, when the agent chooses the correct block sequencing, accurate dispatching, improved processing plant productivity, and reduced equipment maintenance and repairs, the ISA will receive a high score from the reward function at terminal stage T. The score is calculated based on the discounted cashflow accumulated over time, in weeks.

Fig. 15 represents the neural network structural design of the ISA. It comprises an input node, a hidden layer, and an output node. The input nodes are state observation snapshots from the environment. The hidden layer is where major computations occur. It takes an input from the previous node and performs a weighted sum (wx + b). The weighted sum is then transformed using a "relu" activation function, which introduces non-linearity to the model, allowing it to learn complex relationships in the data.

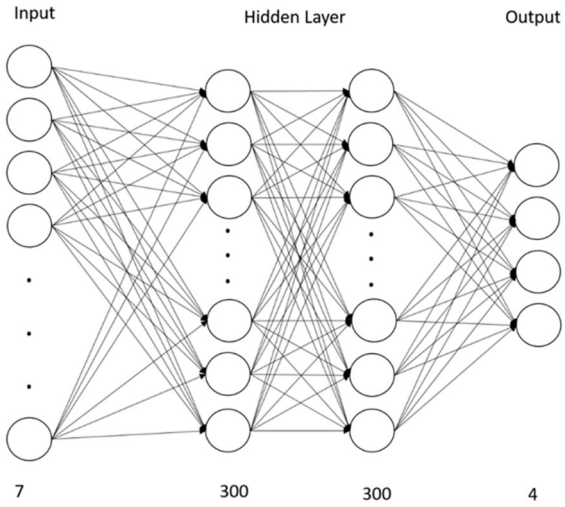


Fig. 16. Graphical representation of the training phase.

4.10. Conceptual Mining Operation Layout

The optimal pit design structure and mine layout were designed using GEOVIA GEMS [37], and the optimization was performed in Whittle [36]. The pit shell design has a total tonnage of 3,000 Mt, of which 1,566 Mt is ore with grades of 51% Al_2O_3 and 5% SiO_2.

Table presents the material that GEOVIA Whittle [36] used to generate, the designed pit boundary, and pushbacks.

Table 3. Summary of material tonnages [20]

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

The pit was divided into three phases, allowing for more individual control of the construction phases to increase cash flow and obtain higher grade zones. The pushback design was the same for all three zones, and each had a separate access ramp to make sequential exploitation easier. Fig. 17 illustrates the pushback design of the pit. Each pushback can be fully mined before moving on to the next thanks to phased mining. The area might be used as a waste dump while mining moves on to the next phase after the first phase is finished.

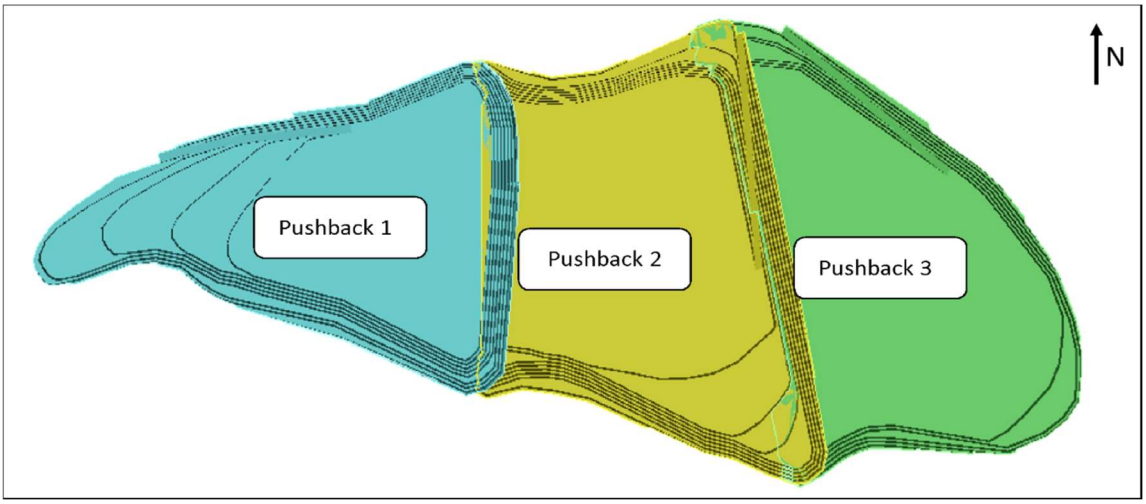


Fig. 17. Pushback designs [20]

Economic parameters considered for GEOVIA Whittle [36] to generate the final pit and pushbacks are shown in Table .

Table 4. Economic parameters [29].

Description	Value (units)
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 mine design has been designed for truck mining. The truck haulage system in the area of study has two loading points and a crushing site. The layout includes switchbacks, a road, reclaimer, a process plant, tailings, and waste dump. These settings will be used throughout the basic simulation designs. The conceptual layout is shown in Fig. 18.

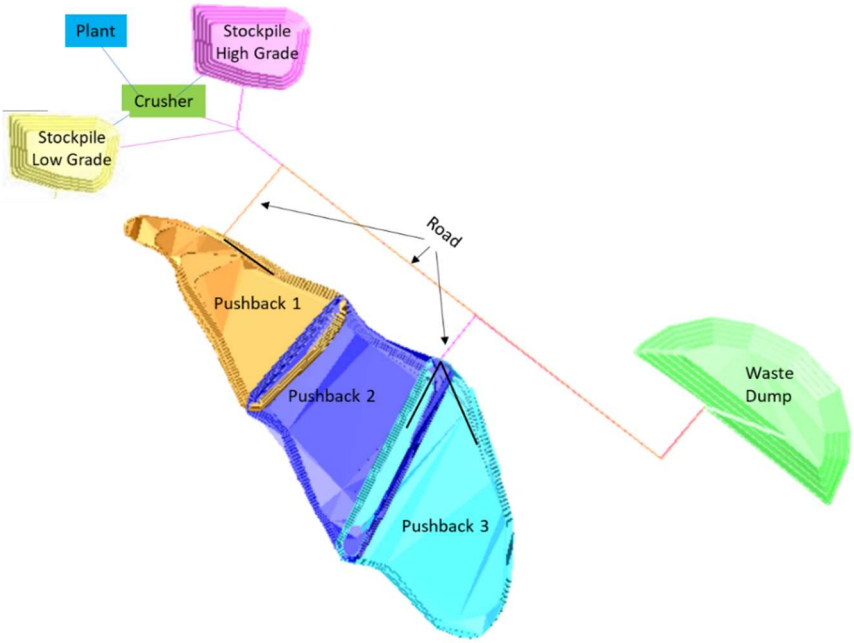


Fig. 18. The conceptual design of the operating system [20].

A strategic plan was generated using GEOVIA Whittle [36], displaying the mining, processing, and grade capacities. The mining capacity and processing capacity schedules are presented in Fig. 19 and Fig. 20 respectively.

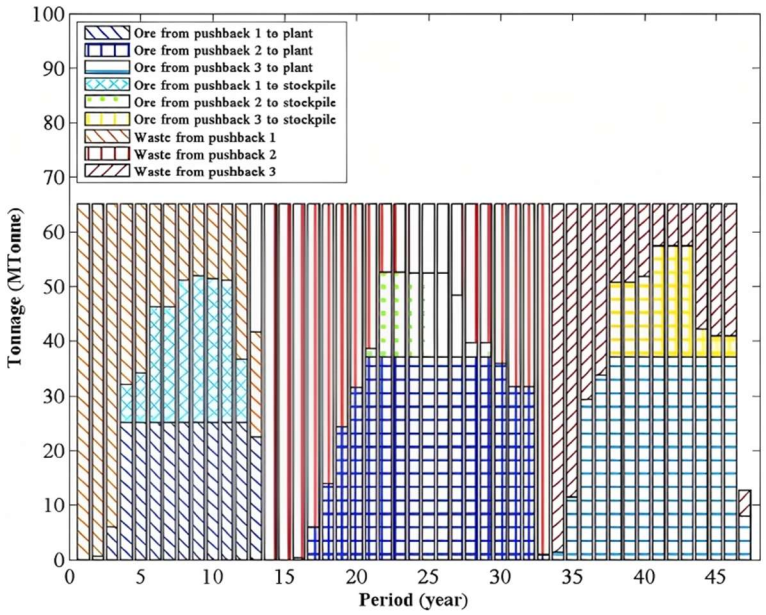


Fig. 19. Mining activity in each pushback [20].

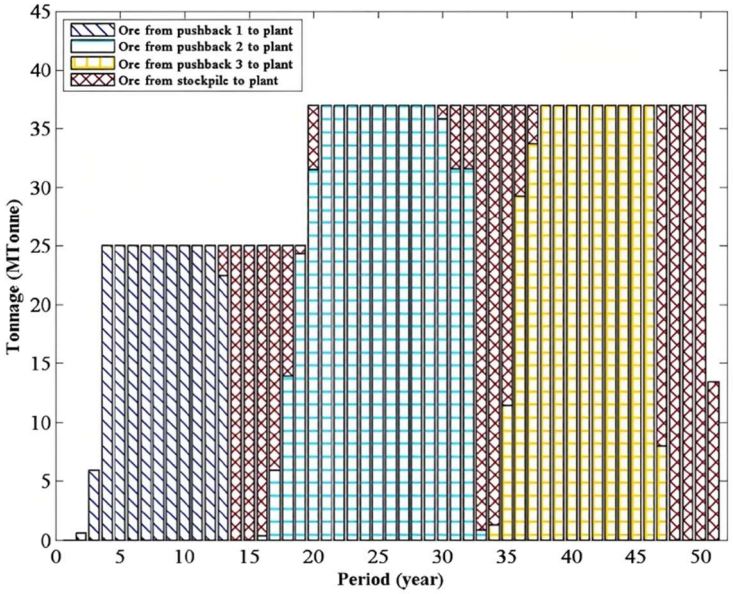


Fig. 20. Processing plant material tonnage schedule [20].

These are the parameters that GEOVIA Whittle [36] used to optimize my model.

- Life of mine is 47 years. The mining rate is 65 Mtpa.
- The processing rate from years 1 to 19 is 25 Mtpa, and 37 Mtpa from year 20 onwards.
- Processing finished in year 51.
- A stockpile is necessary to meet processing requirements.

5. Experimental Design

The design of experiments is a process with the objective of carrying out a series of tests in which deliberate changes are implemented to find out if the model behaves as expected. The testing model is like a prototype of a product, which must be tested in different ways [23]. The importance of knowing the results for each test gives us insight into the model's performance [24]. After the model is completed, verification and validation are important. Verification is the process of making sure that the model behaves as desired, and validation is the process of proving the model performs as the real system does [23].

The verification of the model was performed with a single entity following the mining block flow in the model, performing as expected. Validation was performed by changing the mining and processing ratios in the model. These ratios were decreased and increased to measure their impact on the mine life. The main effects and possible interactions between the input factors and the results were measured, concluding that the outcomes were as expected.

5.1. Cases to evaluate

There are four consecutive experiments that showcase a result in each phase. These sequential parts lay the groundwork for what comes next. The repetition creates a coherent and thorough investigation without leaving any gaps or flaws. Fig. 21 presents a schematic overview of the case study.

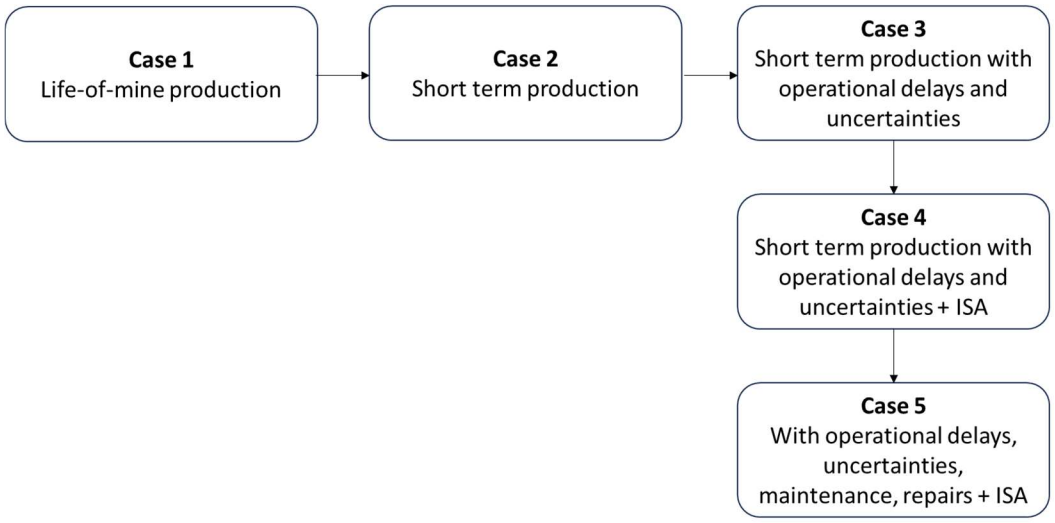


Fig. 21. Schematic overview of case study.

Only Pushback 1 data was considered in every case. The simulation was set to hours, and the following parameters were used in the application scenarios:

5.2. Case 1 – Life-of-Mine Production

The base case refers to this scenario. The intention is to replicate mining and processing operations using Anylogic software [2]. All scenarios presuppose that the mine is open every day of the year, 24 hours a day. This example replicates the realistic system, which is the GEOVIA Whittle's strategic production schedule[36].

The following configuration was set-up in the simulation model:

- Recreate mining and processing activities.
- The mining ratio is 7,420 t/h.
- The ratio for the processing plant was 2,850 t/h.

5.3. Case 2 – Short-Term Production

A short-term production schedule with weekly tonnage and grade requirements was simulated to focus on Pushback 1 Period 8. The following characteristics apply to this instance:

- There were 27 mining zones in Period 8, with 5 upper mining zones on Bench 1482 and 22 lower mining zones on Bench 1457.
- Three shovels, each with a bucket capacity of 34 m^3, were used for this experiment.
- 18 trucks, each capable of hauling 200 tons of waste and ore, were used.
- Two stockpiles (stockpiles of high and low grade)
- In this instance, no operational delays were considered.

Case 3 – Short-Term Production Schedule Simulation with Operational Delays and Uncertainties

The operating delays are added as deterministic parameters in this scenario. The following characteristics apply to this situation:

- Similar mining rate, haulage, and equipment fleet to Case 2.

- Spotting time has a normal distribution with a mean of 46 seconds and a standard deviation of 2.3 seconds.
- Mining rate per shovel is a triangular distribution with minimum, peak and maximum values of 2000 t/h 2474 t/h, 3000 t/h, respectively. This gives a total peak mining rate of 7420 t/h for 3 operating shovels.
- Processing plant feed rate is a normal distribution with a mean and standard deviation of 2853 t/h, 285 t/h, respectively.
- The haulage model uses a 3D design of the haulage profile imported from Geovia Gems. A normal distribution with a mean and standard deviation of 37, 3 respectively, is used for the truck speed.

Case 4 – Short-Term Production Schedule Simulation with Operational Delays, Uncertainties, and ISA Integration

Case 4 discusses the experimental behavior of the ISA from Case 3 when uncertainties are introduced in the mining system. The objective of this case is to test the performance of the ISA when launched in an environment with stochastic parameters. The operational parameters were similar to the mining and processing rates and operational uncertainties from Case 2.

Case 5 – Short-term Production Schedule Simulation with Operational Delays, Uncertainties, Maintenance, Repairs, and ISA Integration

Case 5 is a combination of Case 4 with the addition of equipment failure maintenance and repairs and ISA integration. In this experiment, we included all operational parameters to test the performance of the ISA. Mining and processing rates were similar to Case 2. Table illustrates the operational and uncertainty parameters for the simulation. The normal parameter takes the input value as the mean and the square root of the mean value as its standard deviation.

Table 5. Parameters for equipment maintenance schedule, failure, and repair.

	Failure	Maintenance	Repair
Shovels	Uniform distribution (1- 180hrs failure event)	250 hrs. maintenance schedule	Normal distribution (2hrs repair time)
Plant	Uniform distribution (1 - 5 weeks)	3 months maintenance schedule time Normal distribution (10hrs – 12hrs maintenance time).	Normal distribution (100 minutes repair time)
Trucks	Uniform distribution (1 -38hrs failure event)	168 maintenance schedule events 2 hrs. maintenance time	Normal distribution (1 - 2hrs repair time)

6. Results

6.1. Case 1 – Life-of-mine production

This case was created to replicate the long-term production schedule for Pushback 1 from Whittle Optimization.

6.2. Case 2 – Short term production

The evaluation for this scenario was done on a short-term basis for Pushback 1 and Period 8. According to the mining plan, 65 Mt needed to be mined. Fig. 22 shows the mining production schedule. The simulation finished in Week 53. The mining production is steady throughout all periods; however, the ore drops in Weeks 9 and 10. Fig. 23 shows a schedule for weekly mining production based on shovel activity. Fig. 24 illustrates the plan view of mining according to zones and shovel allocation. Mining commences in Zone 1 and ends in Zone 27 in a sequential form. Fig. 25 shows the weekly schedule for plant feeding from stockpiles and pit mining. The plant processed

51 Mt of ore in total. Fig. 26 is the stockpile inventory, which demonstrates how materials accumulate over time in the high- and low-grade stockpiles. In general, material is reclaimed to the plant after both stockpiles reach a maximum of 26 Mt in Week 52.

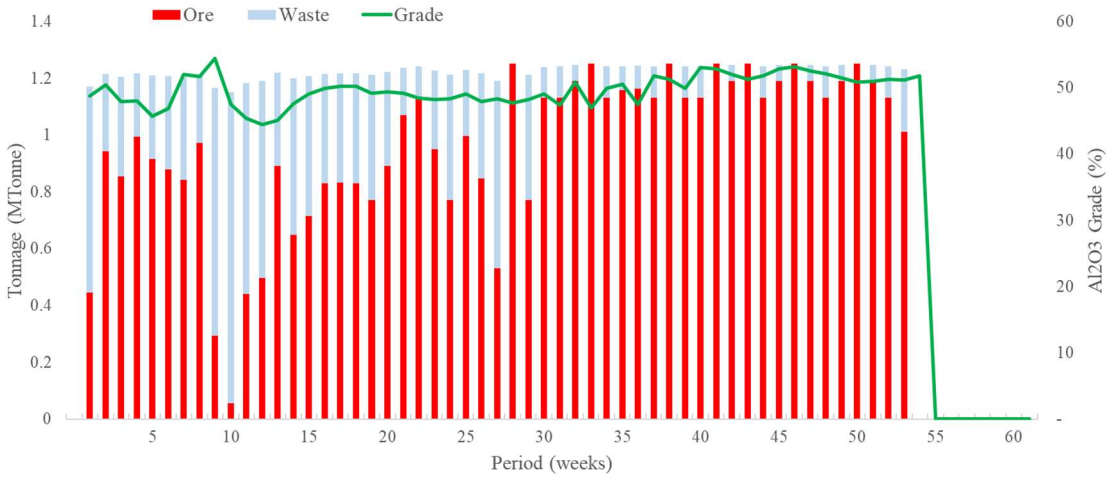


Fig. 22. Weekly mining production schedule showing material types.

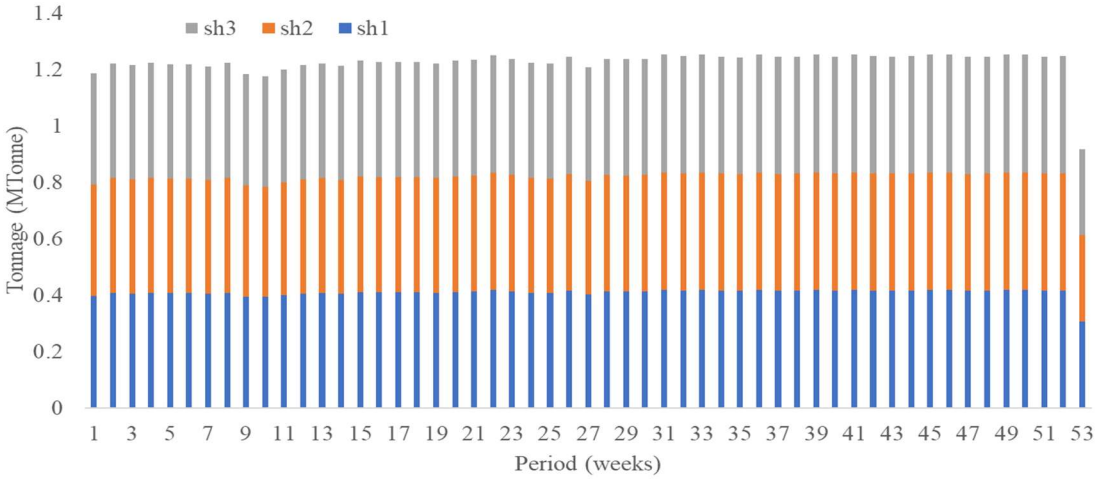


Fig. 23. Weekly mining distribution schedule showing zones.

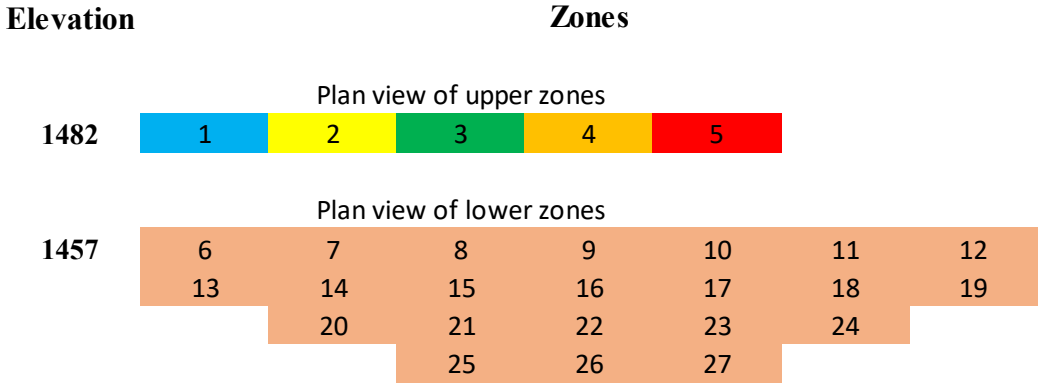


Fig. 24. Plan view of mining zones for shovel allocation.

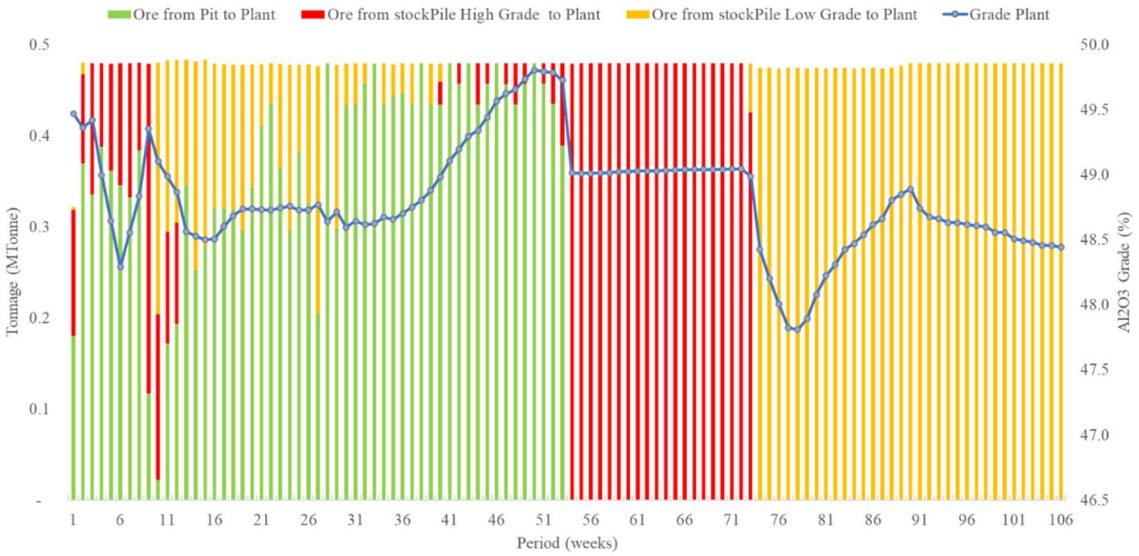


Fig. 25. Weekly plant feed schedule showing material sources.

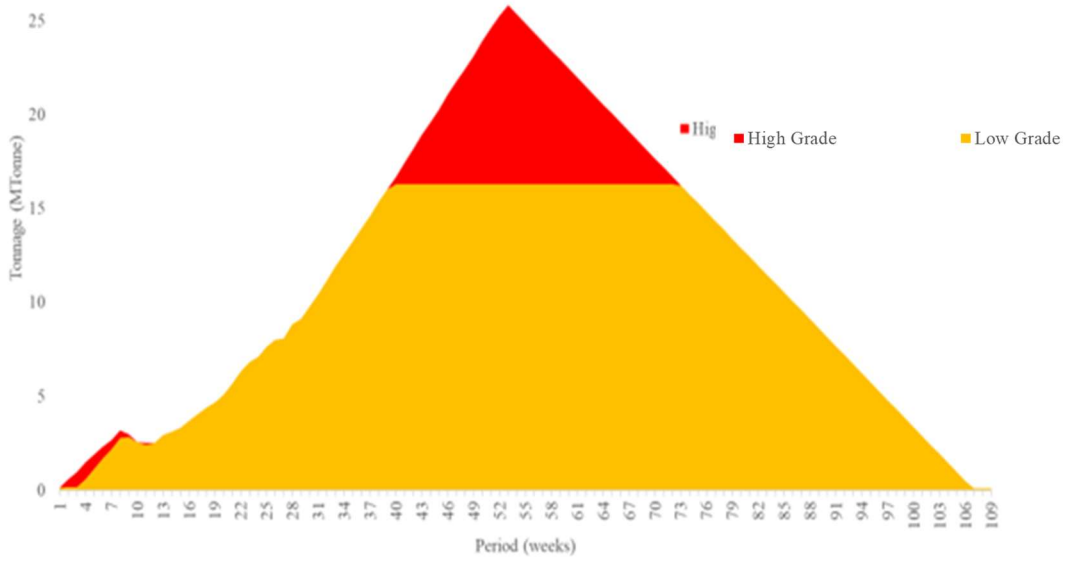


Fig. 26. Stock inventory showing high- and low-grade material.

6.3. Case 3 – Short-term Production Schedule Simulation with Operational Delays and Uncertainties

Fig. 27 illustrates the weekly mining production schedule by material types, and Fig. 28 shows the weekly mining production schedule by shovel activity. Fig. 29 illustrates the weekly mining production schedule by mining zones following a predetermined extraction sequence like Case 2. The pit mining operation for ore and waste lasted for 54 weeks. In Week 10, only waste rocks were extracted from the pit, which was supplemented by material from the stockpiles. Fig. 30 illustrates the weekly plant feed schedule from pit mining and stockpile reclamation lasting for 106 weeks with a steady weekly processing rate of 480,000 tons. Fig. 31 shows how the stockpile inventory is accumulated in the high-grade and low-grade stockpiles, reaching a peak of 26 Mt in Week 52, followed by reclamation to the plant after pit mining ends.

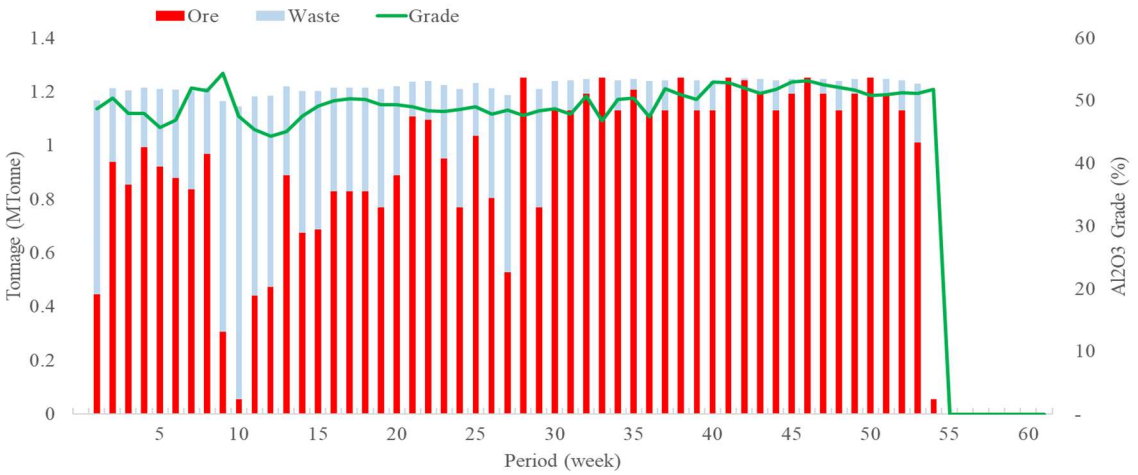


Fig. 27. Weekly mining production schedule showing material types.

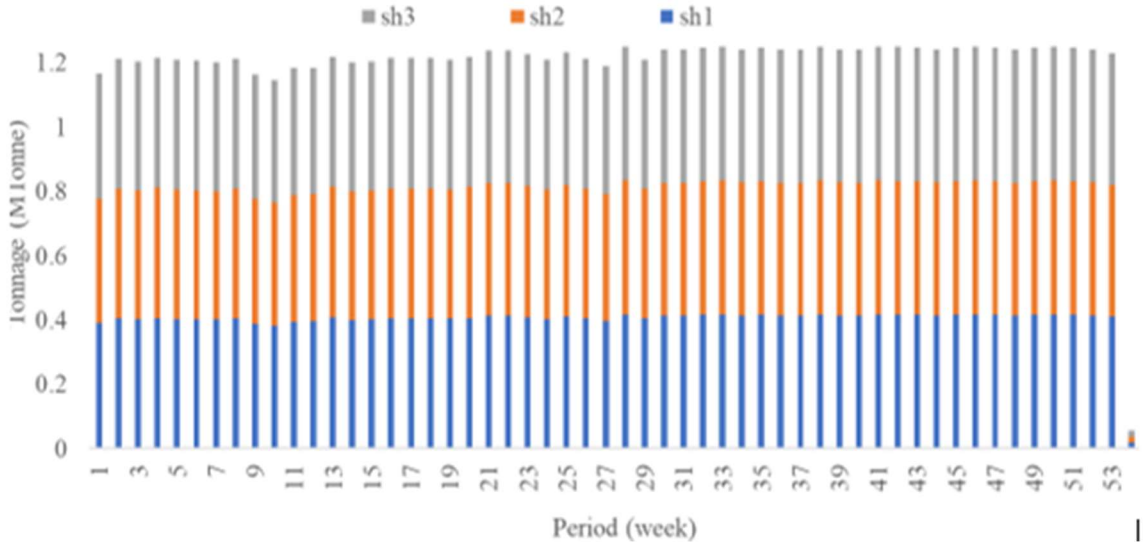


Fig. 28. Weekly mining production schedule showing shovel tonnes.

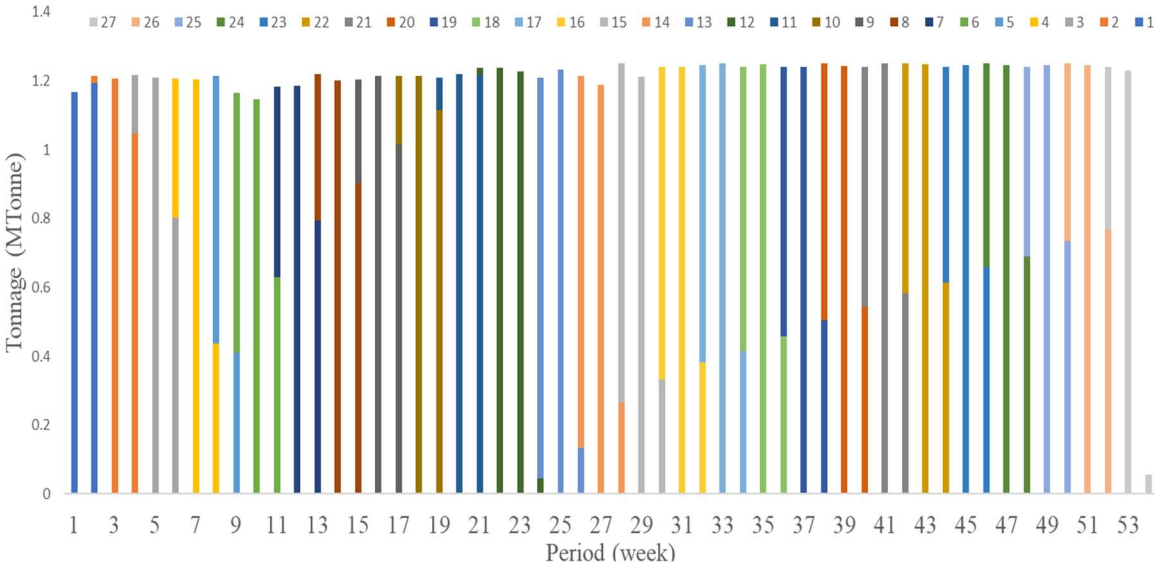


Fig. 29. Weekly mining production schedule showing mining zones.

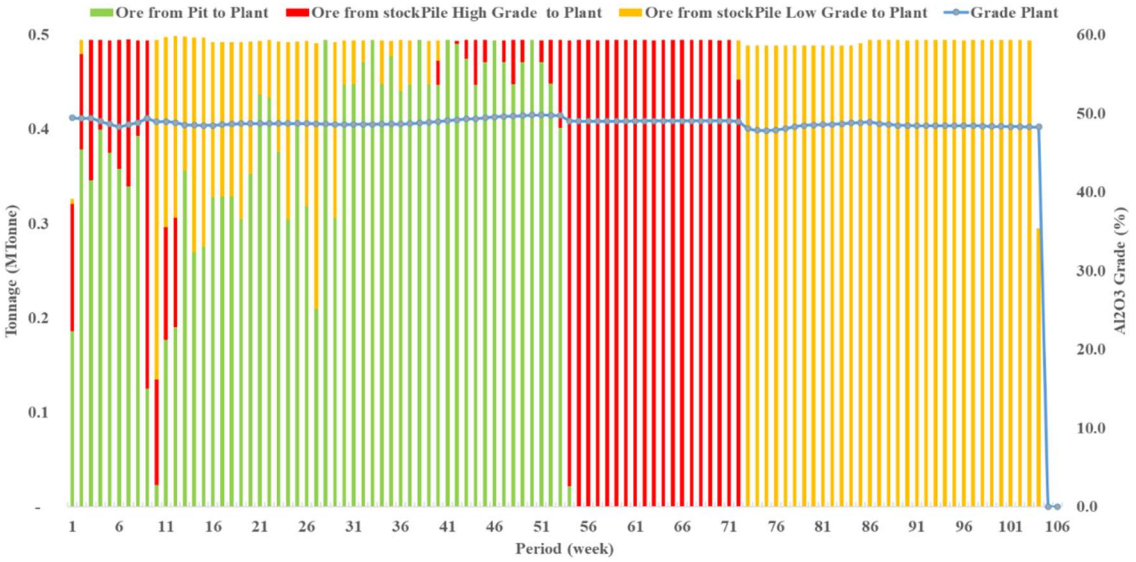


Fig. 30. Weekly plant feed schedule showing material sources.

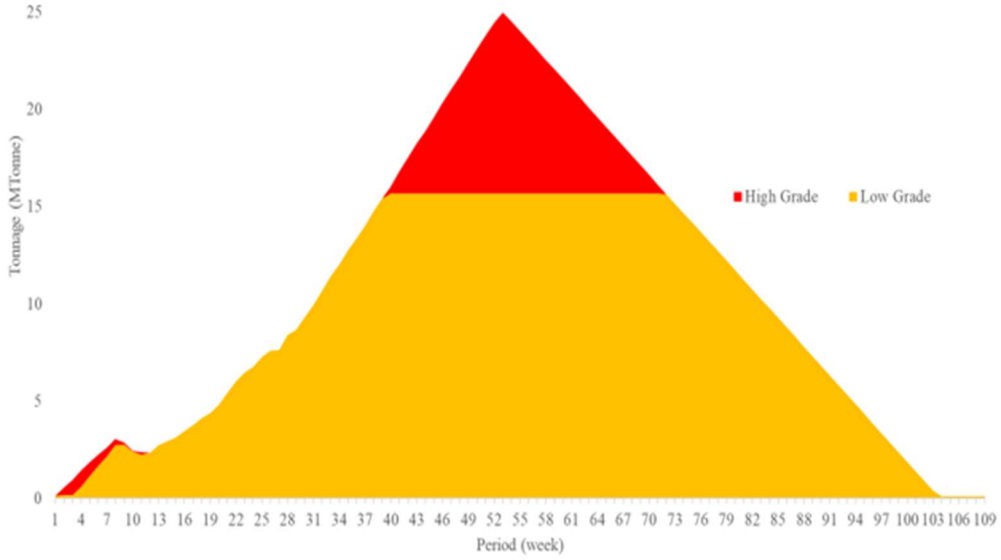


Fig. 31. Weekly stockpile inventory showing high and low grade material.

6.4. Case 4 – Short-term Production Schedule Simulation with Operational Delays, Uncertainties, and ISA Integration

The weekly mining production schedule for material types is shown in Fig. 32. Pit mining took 55 weeks, with only two shovels working from Week 52 to Week 55. This was due to the ISA's restriction on one shovel per zone at any time. The haulage distance from the pit to the waste dump is longer, resulting in reduced shovel productivity. Fig. 33 is the weekly mining production schedule showing mining zones. It shows when each mining zone is extracted based on the priorities and choice of actions of the ISA. The weekly plant feed schedule in Fig. 34 shows material from the pit and stockpiles. Fig. 35 shows the stockpile inventory and how material accumulates in both the high- and low-grade stockpiles reaching a peak of 26 Mt in Week 52 before reclamation to the plant. The ISA controls the reclamation of materials by blending high- and low-grade materials for a stable plant feed grade.

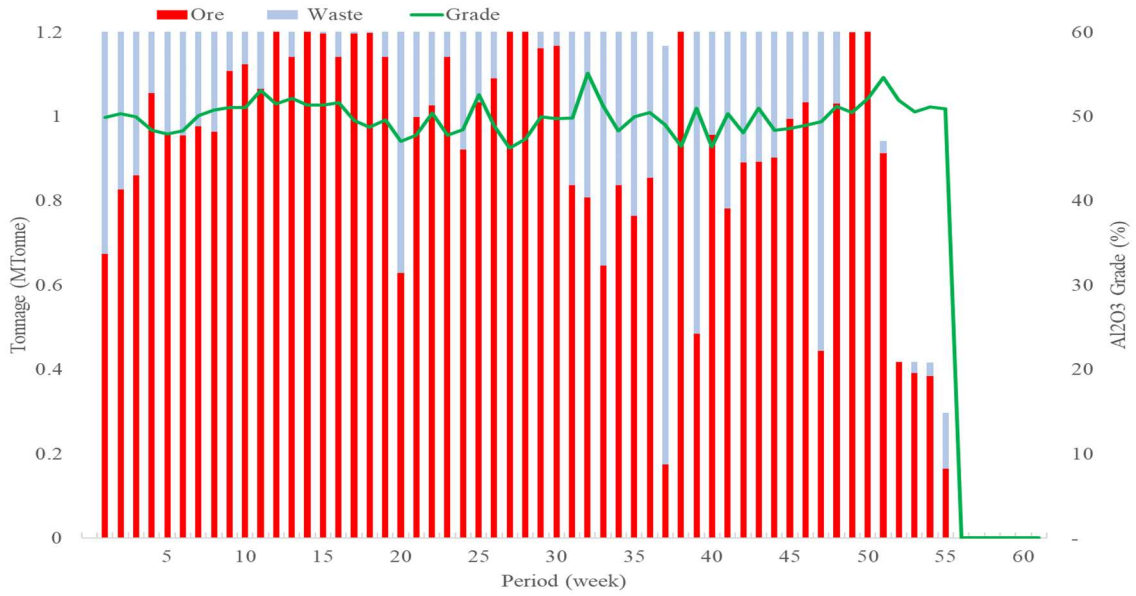


Fig. 32. Weekly mining production schedule showing material types.

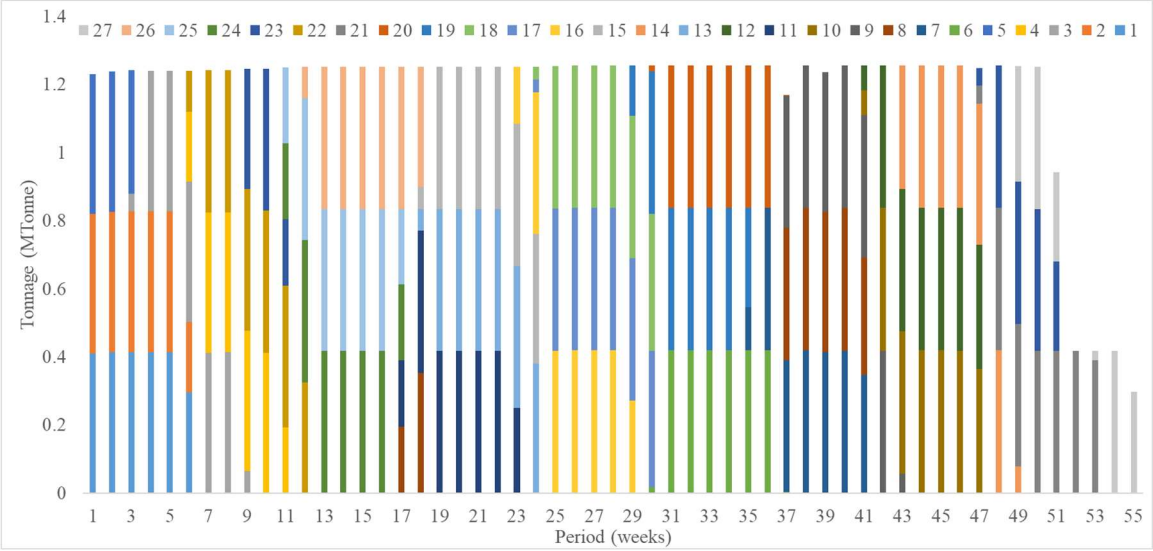


Fig. 33. Weekly mining production schedule showing mining zones.

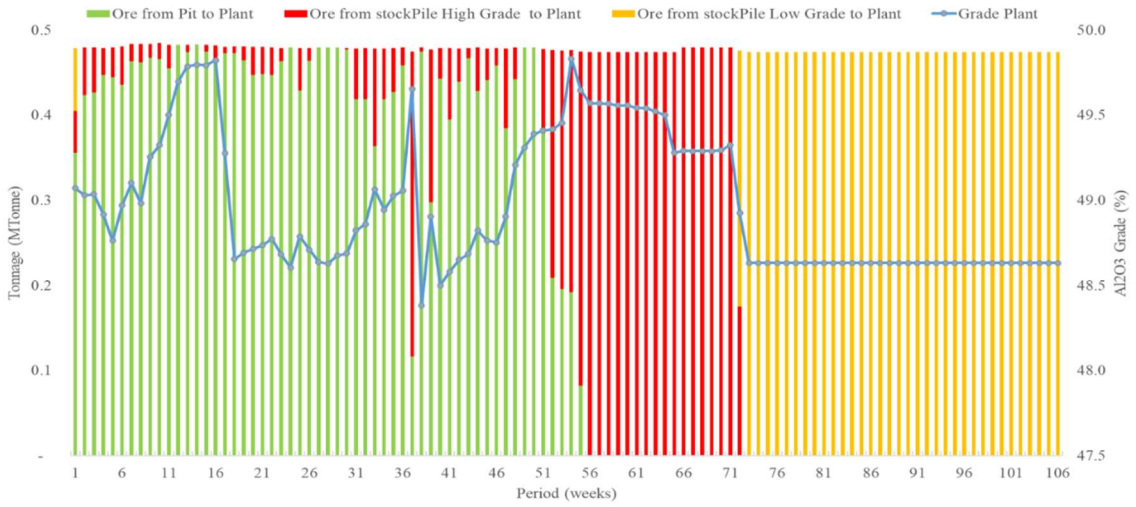


Fig. 34. Weekly plant feed schedule showing material sources.

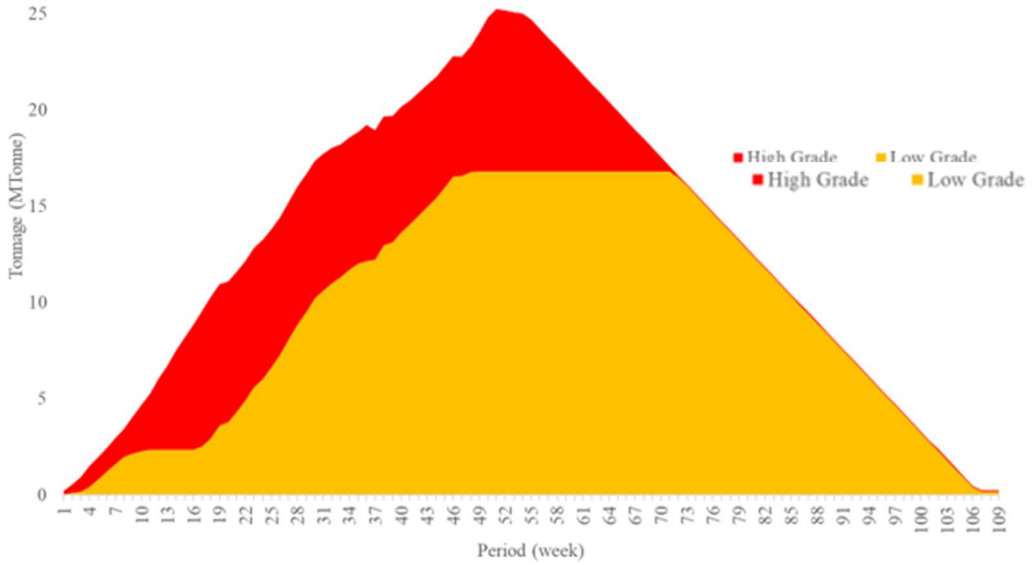


Fig. 35. Weekly stockpile inventory showing high- and low-grade material.

6.5. Case 5 – Short-term Production Schedule Simulation with Operational Delays, Uncertainties, Maintenance, Repairs, and ISA Integration

Fig. 36 is the weekly mining production schedule showing ore and waste material mined over the period. Pit mining lasted for 56 weeks, and only one shovel worked from Week 52 to Week 56. The ISA is restricted to allowing only one shovel to work in a zone at any point in time. Fig. 37 is the weekly mining production schedule showing mining zones. It shows when each mining zone is extracted based on the priorities and choice of actions in the ISA. Fig. 38 illustrates the weekly plant feed schedule, showing material from pit mining and stockpiles. The consistent shortfalls over the period were due to the failure and maintenance of the plant. Fig. 39 shows the stockpile inventory. The stockpile accepts material when the crusher is busy. It stores high- and low-grade materials, which are then reclaimed by the plant when pit mining ends.

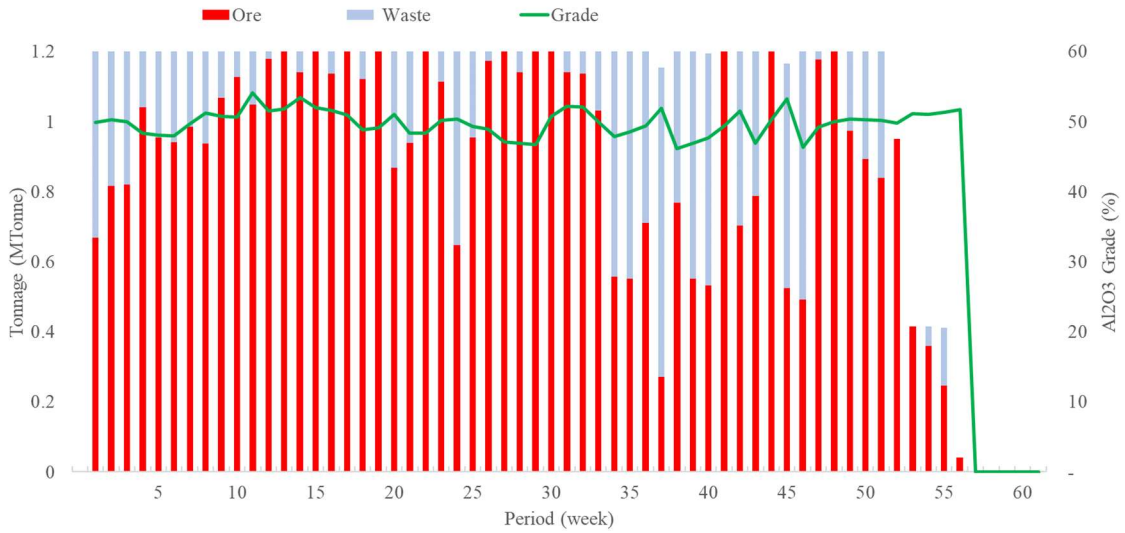


Fig. 36. Weekly mining production schedule showing material types.

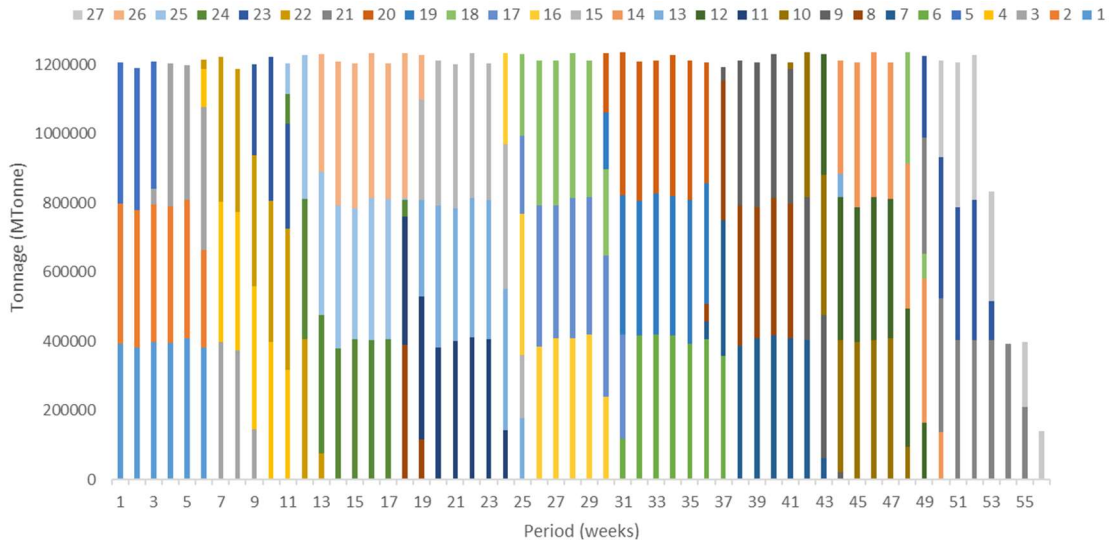


Fig. 37. Weekly mining production schedule showing mining zones.

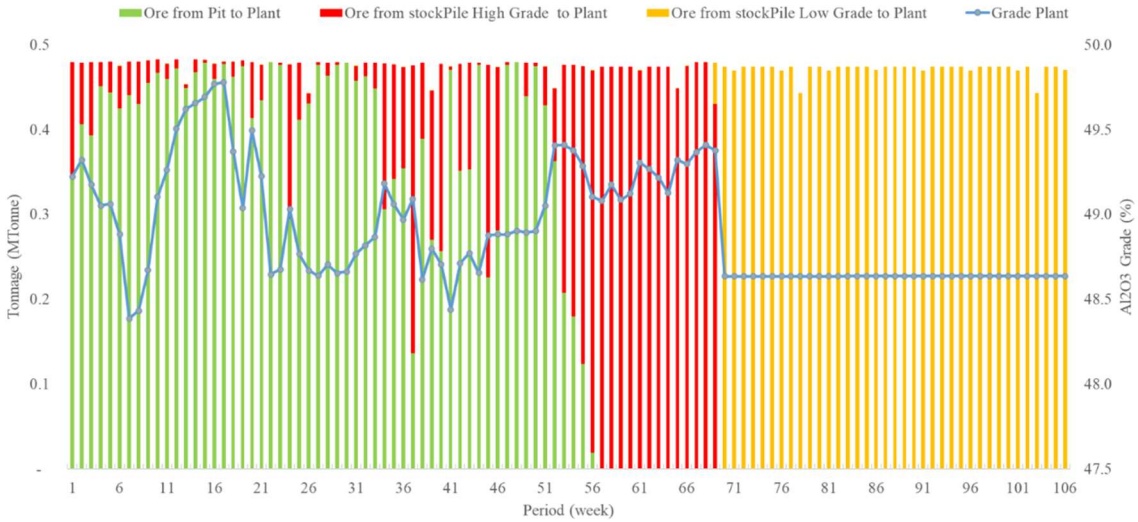


Fig. 38. Weekly plant feed schedule showing material sources.

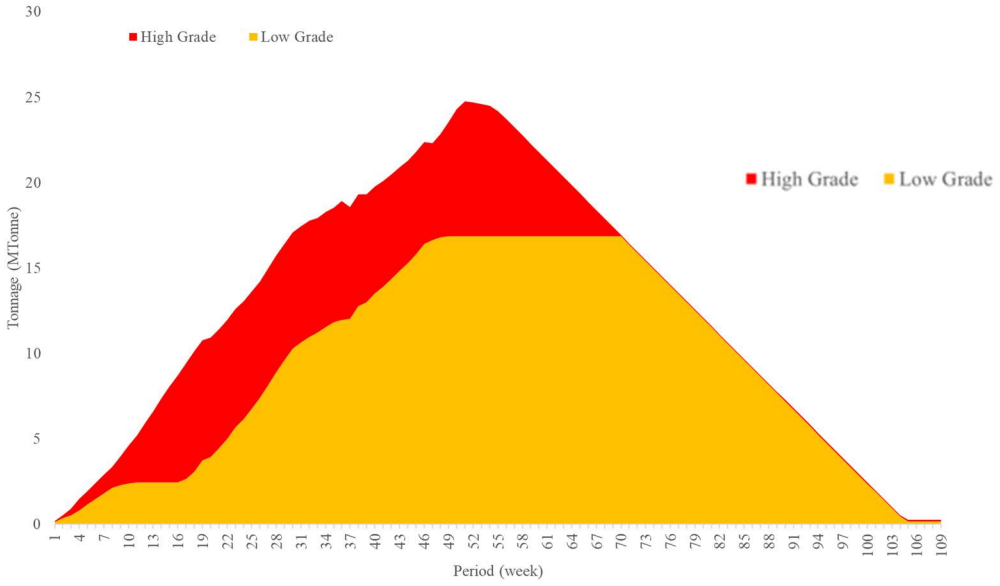


Fig. 39. Weekly stockpile inventory showing high- and low-grade material.

7. Comparison experimental results and discussion

Fig. 40 represents the weekly mining production, and Fig. 41 shows the grade of ore tonnage mined according to the experimental cases. The ISA did well to improve mining production in the early weeks. Fig. 42 illustrates the weekly ore tonnage processed. There are observed shortfalls in plant processing for Case 5. These shortfalls are attributed to plant failure and a poor maintenance schedule. Fig. 42 shows the ore tonnage processed which achieved a steady 480,000t/week for Case 3. The shortfalls in Case 5 are attributed to the equipment failure and maintenance for plant. In Fig. 43, an increase in grade occurred in the early weeks for Cases 4 and 5 due to the ISA performing grade blending from the stockpile. Fig. 44 shows the metal content of the ore processed is higher than in Case 4 despite the lower ore tonnage. Comparing Case 5 to the other cases after period 50, Case 5 has lower stockpile levels, as shown in Fig. 45.

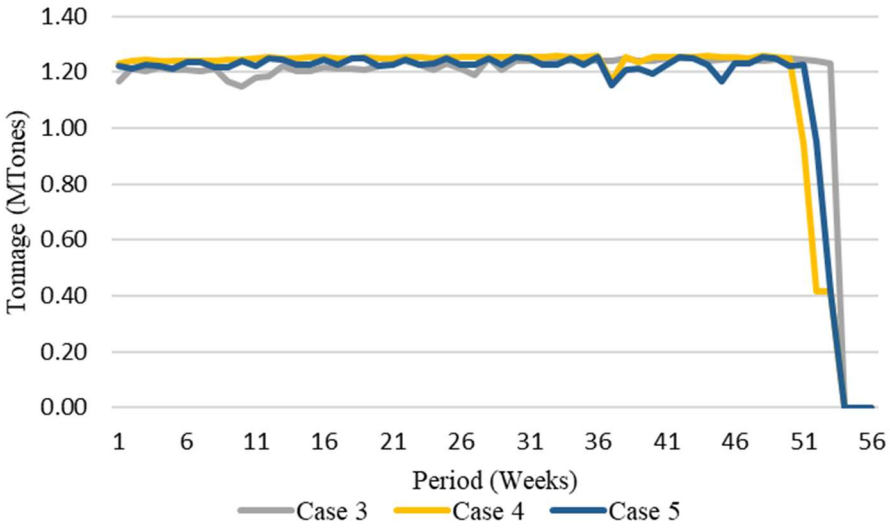


Fig. 40. Comparisons of experimental cases for mining production.

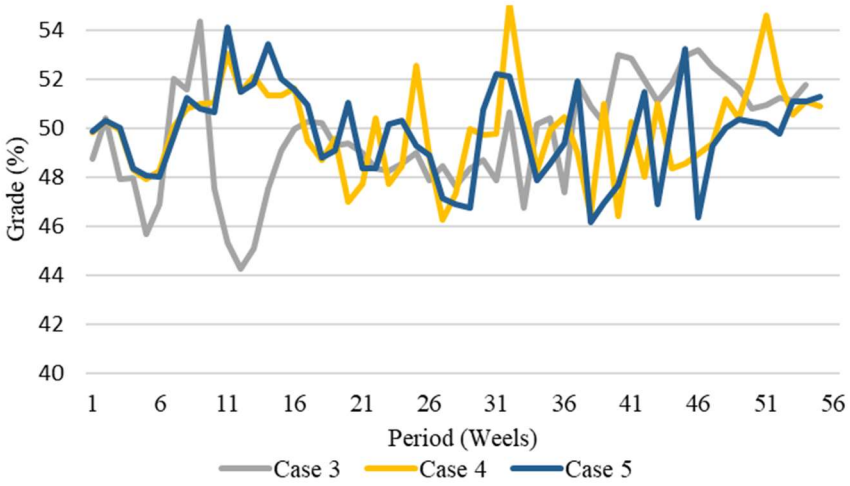


Fig. 41. Comparisons of experimental cases for ore mining grade.

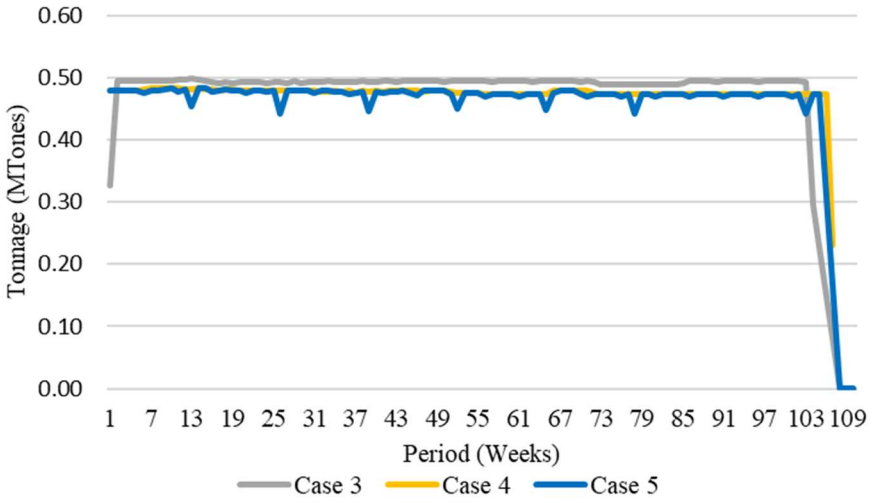


Fig. 42. Comparisons of experimental cases for ore tonnage processed.

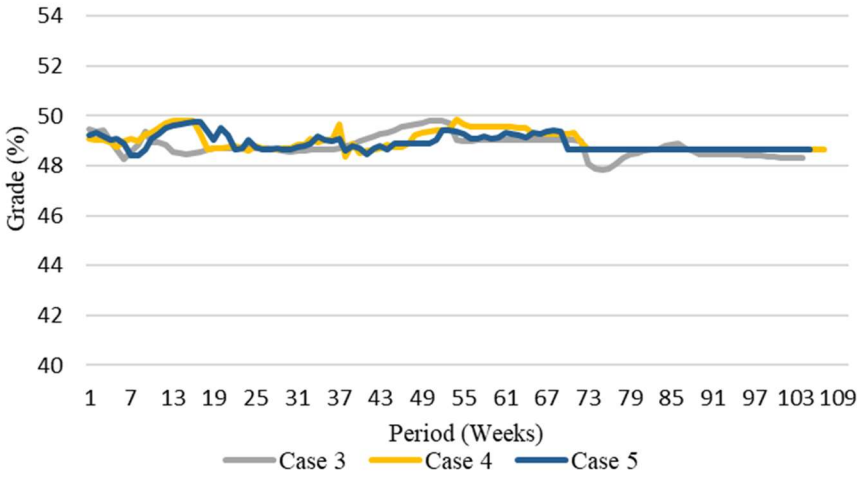


Fig. 43. Comparisons of experimental cases for processing plant head grade.

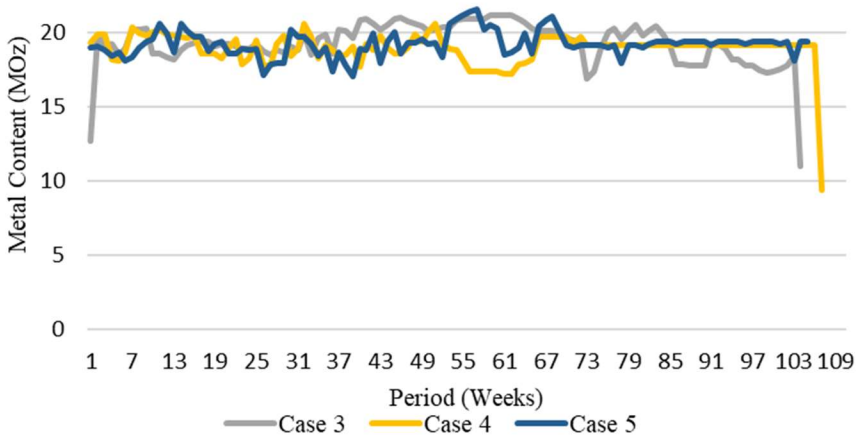


Fig. 44. Comparisons of experimental cases for metal content for ore processed.

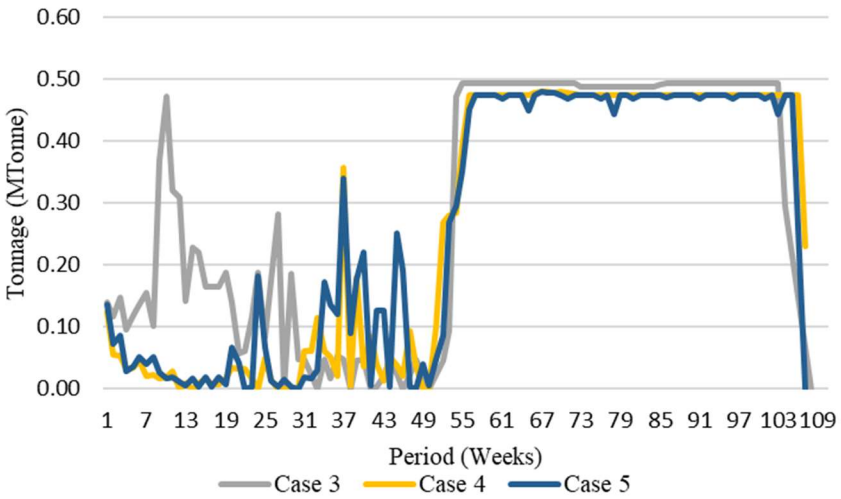


Fig. 45. Comparisons of experimental cases for stockpile material.

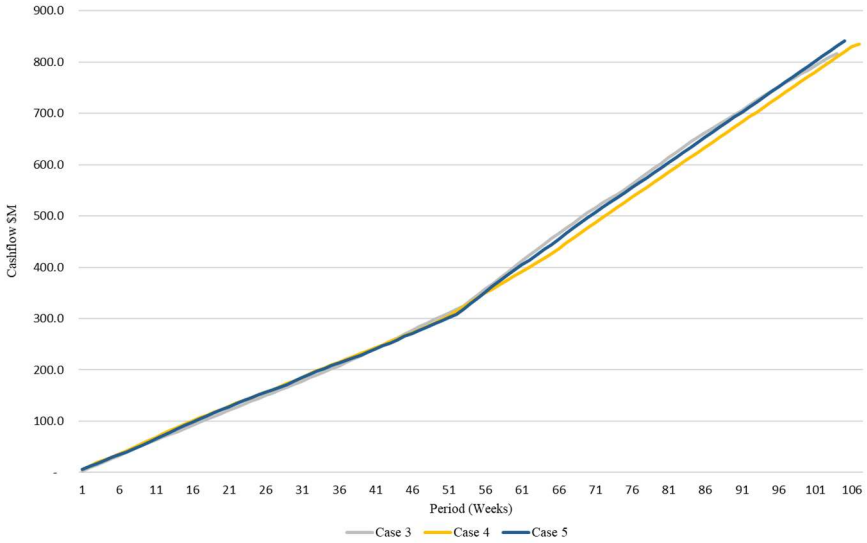


Fig. 46. Comparisons of experimental cases for cumulative cash flow.

The cumulative cash flows for various experimental cases over time are displayed in Table . For each experimental case, the cumulative cash flow rises over time, which is positive and demonstrates that income exceeds expenses. The Case 5 cash flow total is the highest at $840.9 million after 104 weeks. It appears from this that Case 5 is the most lucrative. The cumulative flows between the cases range from $815.9 million to $840.9 million, so the difference is not very significant. This suggests that the cases financial results are comparable.

Table 6. Cumulative cashflow for experimental cases.

Experimental Case	Period (Weeks)	Cumulative Cashflow ($M)
3	104	815.9
4	107	834.6
5	104	840.9

Fig. 47 to Fig. 50 illustrates truck and shovel utilizations for the experimental Cases 4 and 5. A steady utilization of shovels is observed in Case 4, since the shovels were always considered available, and mining continued until all blocks were exhausted. The utilization data for trucks and shovels ceases recording once mining is completed. Shovels 2 and 3 start to decline from Week 50 as all mining

zones have been exhausted except for the last zone which has been allocated to Shovel 1. A reduction in Case 5 compared to Case 4, mainly due to shovel availability, maintenance, and repairs.

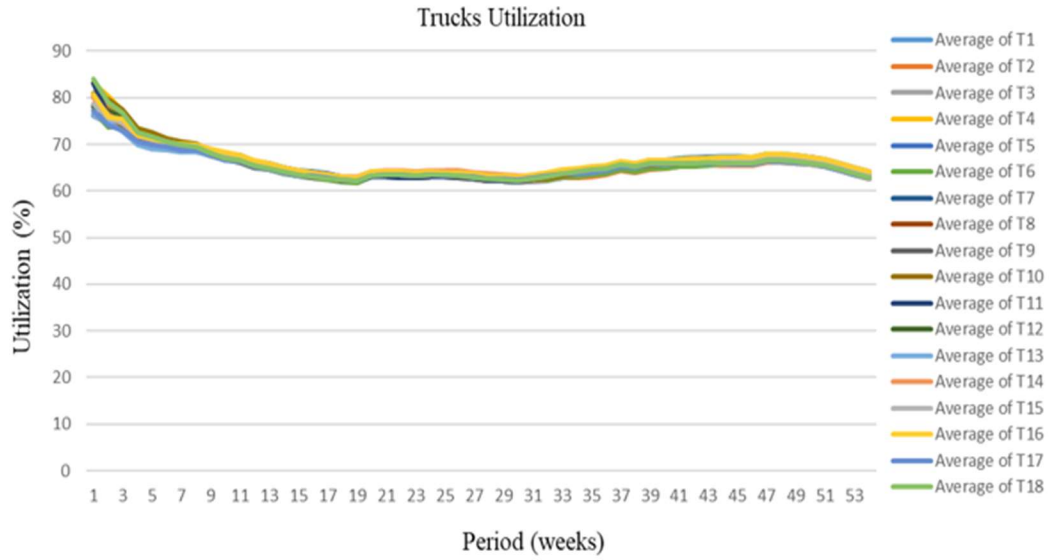


Fig. 47. Case 4 – Truck utilization.

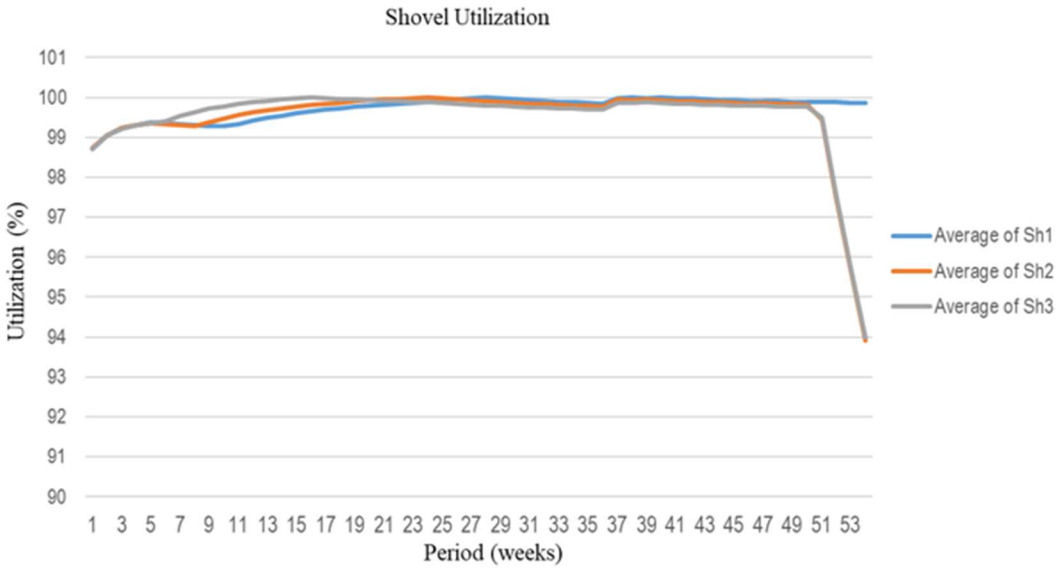


Fig. 48. Case 4 – Shovel utilization.

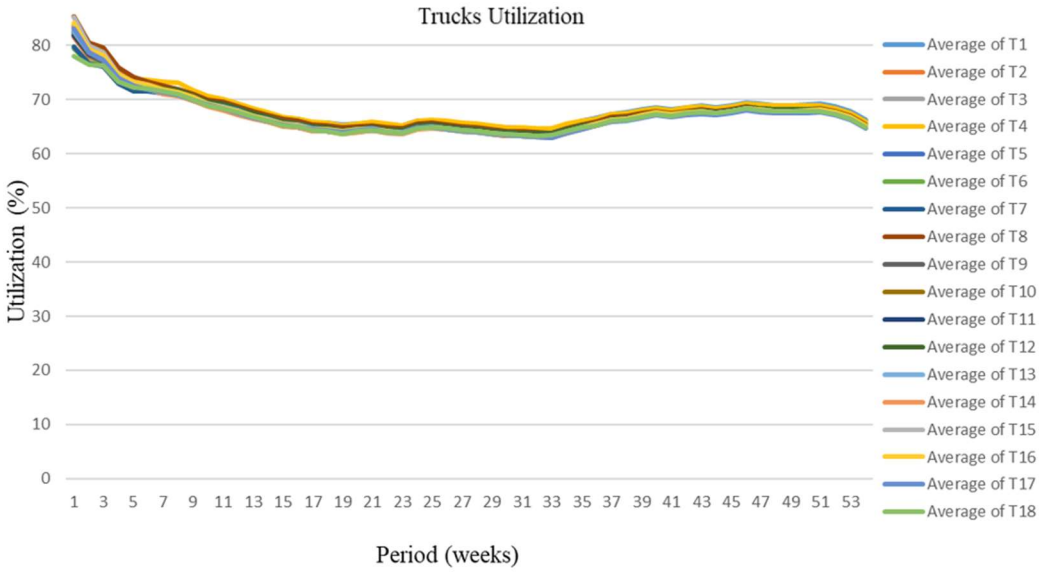


Fig. 49. Case 5 – Truck utilization.

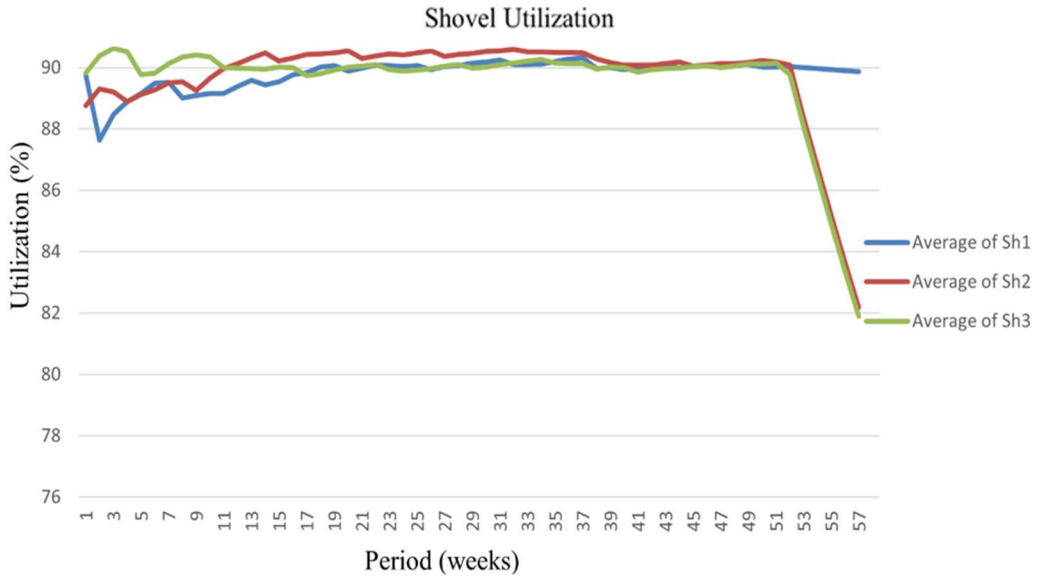


Fig. 50. Case 5 – Shovel utilization.

The outcomes showed how the Intelligent Supervisory Agent (ISA) could maintain and improve productivity even in the face of growing uncertainties and disruptions across the cases. Case 3 added more realism by including delays and uncertainties related to mining and processing parameters, but the activities were still completed according to the planned schedules. Case 4 demonstrated the ISA's abilities to monitor grade control, smooth mining production, and restore stockpiles in the face of variations. The ISA accomplished this by allocating resources dynamically by prioritizing zones based on ore tonnage and grade. By modifying shovel schedules and utilizing stockpiles to meet targets, Case 5 demonstrated the ISA's capacity to adapt to equipment failures and maintenance activities, resulting in the highest cashflow. When compared to Case 4, shovel utilization dropped in Case 5, but the overall output was still optimized. The development of the cases showed that relying solely on fixed schedules leaves no room for flexibility in the face of uncertainties, whereas intelligent systems like the ISA enable real-time adaptive decision-making to maintain productivity and increase cash flow. The importance of AI-driven technologies for efficiency in difficult mining environments is highlighted by this.

8. Conclusions

The simulation environment chosen for modelling Smart Mining Automation (SMA) involves a combination of discrete event simulation (DES) and an agent-based model (ABM). To train the intelligent supervisory agent (ISA) mentioned in this study, the selected reinforcement learning algorithm is the Deep Q network. The proposed SMA was implemented for a short-term mine plan and a bauxite mining operation, which included operational decisions taken on a weekly basis. Based on the results obtained, the following conclusions were drawn:

1. The proposed SMA can simulate a real-life mining operation, and with the integrated ISA, operational decisions such as block-sequencing and truck-shovel dispatching are made. The ISA performs block sequencing by prioritizing mining zones with more ore tons and high grades and relocating shovels to available mining zones when ore production is below the weekly KPI targets. Truck dispatching by the ISA is done based on the availability of working shovels.
2. The use of an ABM for modelling the mining resources (shovels, trucks, and plants) closes the gap of many input states fed to the neural network of the ISA. ABMs interact with each other as well as their environment. Since they already have individual states defining their behaviour, controlling the individual states with an integrated central neural network becomes robust.
3. The research demonstrates how operational decisions can be taken by a trained RL agent to maximize productivity without the intervention of human. Its significant contribution is the real-time decision-making capacity that it acquires as the mining simulation progresses through time.
4. The use of multiple stockpiles in the mining operation helped reduce the mining and processing times by storing high- and low-grade material when the crusher queue was larger than the set limit.
5. With the introduction of the ISA, fewer labor meaning less interaction between people and equipment, can be achieved, leading to improvements in health and safety records and financial savings.

9. References

[1] Alipour, A., Khodaiari, A. A., Jafari, A., and Tavakkoli-Moghaddam, R. (2018). Uncertain production scheduling optimization in open-pit mines and its ellipsoidal robust counterpart. *International Journal of Management Science and Engineering Management*, *13* (4), 245-253.

[2] AnyLogic (2021). Anylogic 8.7 Personal Learning Edition. Retrieved January 05, 2022, from: https://www.anylogic.com/

[3] Ares, G., Castañón Fernández, C., Álvarez, I. D., Arias, D., and Díaz, A. B. (2022). Open Pit Optimization Using the Floating Cone Method: A New Algorithm. in *Minerals*, vol. 12

[4] Askari-Nasab, H. (2006). Intelligent 3D interactive open pit mine planning and optimization. Ph.D Thesis, University of Alberta, Edmonton, Alberta, Pages 167.

[5] BANKS, J., 1939 2001. *Discrete-event system simulation*, Upper Saddle River, NJ : Prentice Hall.

[6] Bellman, R. E. and Dreyfus, S. E. (1962). *Applied dynamic programming.* Princeton University Press, Princeton, NJ, Pages 363.

[7] Bodon, P., Fricke, C., Sandeman, T., and Stanford, C. (2011). Modelling the mining supply chain from mine to port: A combined optimization and simulation approach. *Journal of Mining Science volume 47* (2), pp. 202-211.

[8] Brownlee, J. (2021). Deep Learning. Retrieved from: https://machinelearningmastery.com/

[9] Chaturvedi, M. (2021). What are dqn reinforcement learning models. Analytics India Magazine.
[10] Choudhary, A. (2019). A hands-on introduction to deep q-learning using openai gym in python. Analytics Vidhya. .
[11] DeepMind (2021). What if solving One problem could UNLOCK solutions to thousands more? Deepmind. . Retrieved from: https://deepmind.com/
[12] Gagniuc, P. (2017). *Markov Chains: From Theory to Implementation and Experimentation.* John Wiley & Sons, New Delhi, India, 1st Edición ed, Pages 256.
[13] Glockner, C. (2018). Simulators: The KEY training environment for applied deep reinforement learning. Retrieved from: https://towardsdatascience.com/simulators-the-key-training-environment-for-applied-deep-reinforcement-learning-9a54353f494f.
[14] Gomez, J.O., García, J.A.J., Arriaga, A.V.B. and Lira, A.J.R., 2018 (2018). Analysis of the impact of the increase of production volume on the material supply system and work in process through simulation scenarios. *International Journal of Supply Chain and Operations Resilience*, *3* (3), 260-273.
[15] Gou, S. (2019). DQN with Model-Based Exploration: Efficient Learning on Environments with Sparse Rewards.
[16] Grigoryev, I. (2019). AnyLogic in three days a quick course in simulation modelling, 5th ed.
[17] Hashemi, A. S. and Sattarvand, J. (2015). *Application of ARENA simulation software for evaluation of open pit mining transportation systems–a case study*. in Proceedings of Proceedings of the 12th International Symposium Continuous Surface Mining-Aachen 2014, Springer, pp. 213-224.
[18] Hebb, D. O. (2005). *The organization of behavior: A neuropsychological theory.* Psychology press.
[19] Holford, N. H., Hale, M., Ko, H., Steimer, J., Sheiner, L., Peck, C., Bonate, P., Gillespie, W., Ludden, T., and Rubin, D. (1999). Simulation in drug development: good practices. *Center for Drug Development Science (CDDS)*, *1* 23.
[20] Ben-Awuah, E. and Hosseini, N.S., 2017. An economic evaluation of a primary haulage system for a Bauxite mine: load and haul versus in-pit crushing and conveying. Min. Optim. Lab, 1, p.109.
[21] Hustrulid, W. A., Kuchta, M., and Martin, R. K. (2013). *Open pit mine planning and design, two volume set & CD-ROM pack.* CRC Press.
[22] Jovanoski, B., Polenakovik, R., Gecevska, V. and Minovski, R., (2014). *Applying a suitable simulation approach for processes on different management levels*. in Proceedings of XVI INTERNATIONAL SCIENTIFIC CONFERENCE ON INDUSTRIAL SYSTEMS, University of Novi Sad - Faculty of Technical Sciences Department of Industrial Engineering and Management, Novi Sad, Serbia., pp. 327-332.
[23] Kelton, W. D., Sadowski, R. P., & Zupick, N. B. (2015). *Simulation with arena.* McGraw-Hill Education, New York, N.Y., Sixth edition ed, Pages 635.
[24] Lazic, L. and Velasevic, D. (2004). Applying simulation and design of experiments to the embedded software testing process. *Software testing, verification & reliability*, vol. *14* (4), pp. 257-282.
[25] Lee, J., Won, J., and Lee, J. (2018). Crowd simulation by deep reinforcement learning. in *Proceedings of the 11th ACM SIGGRAPH Conference on Motion, Interaction and Games*. Limassol, Cyprus: Association for Computing Machinery
[26] Maeda, I. d., D.; Kitano, M.; Matsushima, H.; Sakaji, H.; Izumi, K.; Kato, A. (2020). Deep Reinforcement Learning in Agent Based Financial Market Simulation. *Journal of Risk and Financial Management.*, *13* (4), 71.
[27] Manríquez, F., Morales, N., Pinilla, G., and Piñeyro, I. (2019). Discrete event simulation to design open-pit mine production policy in the event of snowfall. *International Journal of Mining, Reclamation and Environment*, vol. *33* (8), pp. 572-588.

[28] McCulloch, W. S. and Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics*, vol. *5, pp.* 115-133.
[29] Minkah, E. A. (2014). Determination of optimized Inchiniso pit, Ghana Bauxite Company Limited. MSc Thesis, University of Mines and Technology, Tarkwa, Pages 86.
[30] Ozdemir, B. and Kumral, M. (2018). Appraising production targets through agent-based Petri net simulation of material handling systems in open pit mines. vol. *87,* pp. 138-154.
[31] Ramazan, S. and Dimitrakopoulos, R. (2013). Production scheduling with uncertain supply: a new solution to the open pit mining problem. *Optimization and Engineering*, *14* (2), 361-380.
[32] Samuel, A. L. (1962). Artificial intelligence: a frontier of automation. *The Annals of the American Academy of Political and Social Science*, vol. *340* (1), pp. 10-20.
[33] Shishvan, M. S. and Benndorf, J. (2019). Simulation-based optimization approach for material dispatching in continuous mining systems. *European Journal of Operational Research*, *275* (3), 1108-1125.
[34] Shiv Prakash, U. and Hooman, A.-N. (2018). Simulation and optimization approach for uncertainty-based short-term planning in open pit mines. *International journal of mining science and technology*, vol. *28* (2), pp. 153-166.
[35] Silver, D. (2009). Reinforcement learning and simulation-based search in computer Go.Thesis, University of Alberta.
[36] Systèmes, D. (2019). Geovia Whittle. Strategic mine planning software. Ver. 4.7.3, Vancouver. Ver.
[37] Systèmes, D. (2020). Geovia GEMS. Strategic mine planning software. Ver. 6.8.3, Vancouver. Ver.
[38] Train, K. E. (2009). *Discrete choice methods with simulation.* Cambridge university press,
[39] Turing, A. (1950). Computing machinery and intelligence. *Parsing the Turing Test*, 23-65.
[40] Vasquez-Coronado, P. P. (2014). Optimization of the haulage cycle model for open pit mining using a discrete-event simulator and a context-based alert system. MSc Thesis, The University of Arizona, Tucson, Pages 156.
[41] Vidhya, A. (2020). Reinforcement Learning via Markov Decision Process. .
[42] Wiki, A. (2021). Gradient Descent. Retrieved from: https://docs.paperspace.com/machine-learning/wiki/gradient-descent
[43] Wiki, A. (2021). Weights and Biases. Retrieved from: https://docs.wandb.ai/
[44] Xie, J., Ge, F., Cui, T., and Wang, X. (2022). A virtual test and evaluation method for fully mechanized mining production system with different smart levels. *International Journal of Coal Science & Technology*, vol. *9* (1), pp. 41.

Analyzing Trends and Challenges in Artificial-Intelligence-Based Fleet Management Systems for Open Pit Mines through Literature Review and Strategic Examinations

Arman Hazrathosseini and Ali Moradi Afrapoli
Mining Optimization Laboratory (MOL)
Université Laval, Québec City, Canada

ABSTRACT

Embracing the principles of Mining 4.0, transportation fleets, integral to open pit operations, recognize the importance of adopting autonomy, interoperability, virtualization, visualization, and interconnectivity. However, any novel transformation needs to be justified theoretically and strategically. To conform to the principle, the present work investigated into the limitations of conventional fleet management systems (FMSs) to establish the need for intelligent solutions. Following that, artificial-intelligence-based FMSs developed up to the present time were explored to track the latest status of this technological trend within the mining industry. Then, these frameworks were compared in terms of seven categories of features to pinpoint potential gaps and research directions. The popular SWOT analysis method was leveraged to outline the strengths, weaknesses, opportunities and threats associated with the advent of these smart controlling setups in mines of future. By and large, advantages outweighed disadvantages. Temporary obstacles are believed to be tackled by increasing pace of technological breakthroughs and propagation of the paradigm of cognitive management systems.

1. Introduction

Owing to extended operational lifecycles, substantial capital outlays, computational constraints (Upadhyay, 2017), mine planning tasks are categorized into three primary segments: strategic (encompassing long-term and medium-term planning), tactical (pertaining to short-term planning), and operational planning (involving fleet distribution and dispatching). The latter spans a time frame from seconds to a day, aligned with the designated planning horizon (Moradi Afrapoli and Askari-Nasab, 2020). Slightly over 50% of operational expenses, almost 30% of overall energy consumption, and approximately 10% of worldwide energy-linked greenhouse gas emissions are attributed to mining operations (Ahangaran et al., 2012; Siami-Irdemoosa and Dindarloo, 2015; Yokoi et al., 2022). These statistics highlight the significance of operational fleet management systems (FMSs), where even minor modifications result in significant economic and ecological advantages. In a mining setting, an FMS focuses on optimizing the loading-haulage process by making informed allocation and dispatch choices using computer algorithms, striving to function autonomously while bridging strategic plans with real-time production activities. The task of dynamically assigning vacant trucks is denoted as the dispatching issue. Dispatching mechanisms are categorized into three main types: manual, semi-automated, and fully automated. Manual dispatching adheres to a fixed or inflexible protocol, where a specific number of trucks are designated to a particular shovel for the entire work shift. The key contrast between the other two

ISBN: 978-1-55195-503-2

approaches lies in the requirement for human engagement within the semi-automated framework (Lizotte and Bonates, 1987). Contrary to the fixed allocation, flexible truck allocation involves trucks receiving fresh assignments from the dispatching system instead of being dedicated to a single shovel. This shift results in a productivity enhancement of around 10-15% (White et al., 1993). Literatures chiefly show 1-truck-for-n-shovels, m-trucks-for-1-shovel, and m-trucks-for-n-shovels assignment strategies (Alarie and Gamache, 2002). Truck allocation occurs through two primary systematic approaches: single-stage or multistage. In the single-stage method, assignments are made solely based on one or multiple heuristic rules (also known as dispatching criteria), without taking production requirements into account, namely fixed allocation (Lizotte and Bonates, 1987), minimizing the number of trucks (Munirathinam and Yingling, 1994), minimizing shovels' waiting time, minimizing trucks' cycle time, minimizing trucks' waiting time, minimizing shovel saturation (Kolonja et al., 1993). In contrast, the multistage approach solves three sequential sub-problems using operations research techniques: (1) Shortest path model, (2) Truck-shovel allocation optimization – upper stage and (3) Real-time truck assignment optimization – dispatching – lower stage (Moradi Afrapoli and Askari-Nasab, 2019). The multistage approach gains an advantage by addressing diverse constraints at the higher level, leading to enhanced efficiency in making dispatching decisions at the lower level.

Emerging as an idea at a German exhibition in 2011 and formally commencing its era in 2015, Industry 4.0 represents a transformative departure from conventional manufacturing methods. This evolution is founded on principles of interconnection, automation, autonomy, machine learning, and real-time data utilization (Munirathinam, 2020). Mining 4.0 can be defined as a digital revolution aimed at infusing intelligence into conventional mining activities. The objective is to establish robust and intelligent systems capable of adeptly managing dynamism, fostering interoperability, exhibiting autonomy, enabling monitoring, optimizing processes, predicting outcomes, making informed decisions, and providing virtualization and visualization. This transformation relies on foundational technologies like the Internet of Things, cloud computing, digital twins, artificial intelligence, and augmented reality. Given that load-and-haul machinery serves as the backbone of open pit mining operations, it necessitates a transformation in terms of embedded devices and management systems. This requirement arises not only from the overarching Mining 4.0 framework but also from various factors such as escalating operational intricacies and costs within and between value chains. However, the driving forces behind this change must initially be illuminated from both theoretical and strategic perspectives. This constitutes the primary objective pursued by the present paper. In other words, the article undertakes a literary examination to chart the attributes of conventional FMSs and their associated limitations, while highlighting the demand for alternative models. Subsequently, the study delves into intelligent FMSs developed within mining literature, aiming to provide a comprehensive overview of the prevailing trend and its current state by conducting a comparative analysis based on distinctive characteristics among previously published works. This analysis is envisioned to serve as a navigational guide for future research trajectories within the realm of mining FMSs. In order to conduct a strategic assessment, the widely recognized SWOT analysis technique is harnessed. This approach is employed to delineate the strengths, weaknesses, opportunities, and threats that warrant consideration in the practical implementation of such intelligent systems within open pit mining operations.

2. The Literary Analysis

Broken into two subsections, the literary analysis attempts to elicit the underlying need for move from conventional towards intelligent FMSs. In addition to the review of non-intelligent models, their main features addressed including contributing factors, parameters, and optimization goals are itemized to gain a deeper insight into these systems before bringing them under criticism. Upon establishing the need for change, intelligent FMSs are examined to draw the latest trajectory in the

mining scope as well as comparing features of the models proposed to date as a means to pinpoint research gaps for building up further works with the least amount of flaws possible.

2.1. Conventional FMSs

Conventional mine operational planning has mainly witnessed four approaches: operations research (OR), heuristics, queuing theory and simulation. Dijkstra is the most prevalent method in finding the shortest path in mining systems due to its simplicity (Dijkstra, 1959), and seen in commercial packages like DISPATCH®. Regarding the upper stage, Ercelebi and Bascetin (2009) created a truck allocation model capable of approximating the number of trucks, equipment idle time, and the processing plant's feed (Ercelebi and Bascetin, 2009). Nevertheless, the model assumes Markovian behavior for all uncertain parameters. Most of the thus far developed FMSs implement linear programming (LP) and mixed-integer linear programming (MILP) approach to solve the upper stage problem. White and Olson (1986) introduced a two-segment LP model to make optimal decisions on production requirements (White and Olson, 1986). While the first segment tries to ascertain shovels' digging rates, the second part allocates a minimum number of trucks to each active route to meet the routes' productivity rate. Bonates and Lizotte (1988) assumed a linear relation between shovels' production and the number of trucks in their LP model, which poses a problem in heterogeneous fleet (Bonates and Lizotte, 1988). Zhang et al. (1990) proposed another LP model for the optimal allocation of the flow of trucks in an open pit, yet the capacities of truck fleet were ignored (Zhang et al., 1990). With the aim of minimizing the total number of trucks required to meet the production schedule, Ta et al. (2013) developed an MILP model to solve the upper stage problem (Ta et al., 2013). In contrast, Chang et al. (2015) took transportation revenue into account for their MILP model tailored for a homogeneous fleet only (Chang et al., 2015). A pitfall of LP-based models is that to consider the limitations of the operation, such as the stripping ratio and required feed grade, the models have to define an acceptable range, pushing the operation far behind optimality (Moradi Afrapoli and Askari-Nasab, 2019). Elbrond and Soumis (1987), and Munirathinam and Yingling (1994) argue that the use of a nonlinear model at the upper stage instead of a linear one is preferable since truck waiting time does not follow a linear function, and NLP models search for the optimum solution over the entire feasible region instead of corners merely (Elbrond and Soumis, 1987; Munirathinam and Yingling, 1994). Temeng et al. (1998) formulated a goal programming model to enhance shovel production considering ore grade, shovel dig rate, dumping capacity and stripping ratio requirement (Temeng et al., 1998). They also allowed for fleet heterogeneity, but ignored other notable goals such as equipment movement costs. Anaraki and Afrapoli (2023) introduced a bi-objective mathematical model that integrates carbon emission reduction with allocation optimization. The model accounts for various factors influencing truck allocation decisions, including fleet size, truck velocity, and age groups. Through case studies in iron and copper mines with varying equipment quantities, the study demonstrated that the proposed model effectively improved production and emissions.

Despite the tremendous published models on the upper stage, the share of the lower stage has been limited. Noteworthy early works are enumerated as White and Olson (1986), Soumis et al. (1989), Li (1990), and Temeng et al. (1997) (White and Olson, 1986; Soumis et al., 1989; Li, 1990; Temeng et al., 1997). Then, the problem remained unattended for nearly two decades. Ahangaran et al. (2012) used a network analysis technique for routes finding and an MILP model for dynamic truck assignments by minimizing the total cost of loading and transportation in their two-stage algorithm (Ahangaran et al., 2012). They ignored traffic over the routes, though. Moradi-Afrapoli (2019) compared a benchmark model used in DISPATCH® with three simulation-integrated models for real-time dispatching, namely a multiple objective goal programming model, a stochastic mixed integer linear programming model, and a fuzzy linear programming model (Moradi Afrapoli, 2019). Results demonstrated that the developed models needed an average of 16.5% fewer trucks to meet production requirements. Afrapoli et al. (2018) presented a mixed integer linear programming solution for the surface mine truck dispatching problem. They

recognized the uncertainty in input parameters and employed a fuzzy approach to tackle it. Applying their model to a case study, they demonstrated its superiority over a benchmark model, requiring fewer trucks to meet production requirements. Moradi Afrapoli et al. (2022) proposed a nested fleet management system (N-FMS) for open-pit mining, connecting operations with strategic plans through shovel allocation and feed optimization. The N-FMS optimizes shovel and truck fleet efficiency using nested multiple-objective models. Application to a metal mining case revealed a substantial 14.6% increase in required truck fleet capacity for meeting production targets, surpassing locked-in approaches. Mirzaei-Nasirabad et al. (2023) addressed real-time truck dispatching in open-pit mining through a two-stage approach. They proposed a scenario-based method to estimate optimal truck sizes and introduced a multi-objective model to dynamically allocate trucks, minimizing waiting times and production deviations. The study evaluated their model using three heuristics and a copper ore mine simulation for comparison. Another fraction of authors has resorted to evolutionary algorithms and heuristics in an attempt to expedite the runtime of real-time dispatching models (He et al., 2010; Souza et al., 2010; Dabbagh and Bagherpour, 2019; Dabbagh and Bagherpour, 2019; Zhang et al., 2021; Pirmoradian et al., 2022).

Discrete-event simulation (DES) paradigm is applicable in material handling systems since they possess a discrete sequence of time-ordered events (loading, hauling, and dumping) (Blouin et al., 2007). Moradi-Afrapoli and Askari-Nasab (2022) proposed the need for constructing a simulation and optimization framework for mines, wherein the simulation component emulates operational processes, while the optimization facet replicates decision-making instruments. The credit for the first simulation in truck management in an open pit mine is given to Madge (1964) (Madge, 1964). In the 1970s, a slow computer language named Fortran was primarily used. In the next decade, more efficient simulation languages including GPSS and SLAM emerged and were endorsed by authors such as Sturgul and Harrison (1987) (Sturgul and Harrison, 1987), and Castillo and Cochran (1987) (Castillo and Cochran, 1987). In the 1990s, animation-based simulation found its way into fleet optimization frameworks by researchers, namely Forsman et al. (1993) (Forsman et al., 1993) and Jacobsen et al. (1995) (Jacobsen et al., 1995). In the third millennium, the most noticeable innovation has been the combination of simulation with optimization techniques. Askari-Nasab et al. (2014) applied a mixed integer linear goal programming to optimize four different goals (Askari-Nasab et al., 2014). Moreover, a DES model was developed to investigate the behavior of a truck-shovel haulage system in the presence of uncertainty within mining operations. Tabesh et al. (2016) proposed a complete dynamic package by incorporation of truck-shovel operations, road networks, processing plants, stockpiles, equipment failures, maintenance and capacity changes into a DES model (Tabesh et al., 2016). Moradi-Afrapoli et al. (2019) benchmarked their multiple objective mixed integer linear programming model against Modular Mining DISPATCH®, resulting in 13% reduction in the required truck fleet size (Moradi Afrapoli et al., 2019). Later, they made use of a fuzzy linear programming method, leading to a smaller fleet size of trucks to meet production targets (Moradi Afrapoli et al., 2021). A mixed-integer-linear goal programming model was formulated by Mohtasham et al. (2021) for fleet allocation, aiming at four major goals incorporating production, head grade, tonnage to the ore destinations, and fuel consumption of mining trucks (Mohtasham et al., 2021).

Main contributing factors, parameters, and optimization goals noticed in the previous non-intelligent fleet management works are categorized and listed in Table 1 for deeper insights. The selection of factors and parameters has a lot to do with the goal(s) targeted. Despite having sculpted a large fraction of research works, conventional methods are encountered with several drawbacks, and thereby requiring much attention. Speaking of OR, these methods pose a problem for large-size production scheduling in terms of complexity and runtime. Exact and numerical methods fall already short in present simplified problems, let alone in future cases, where more characteristics and sensory data must be taken into account. Another major ignored feature is stochasticity on account of inherent uncertainties present in most real-world problems. Deterministic approaches often lead to non-optimal results, and this pitfall is magnified excessively in equipment

dispatching. Queuing theory runs into trouble in uncertain and complex problems, and it also has a limited scope (Gurgur et al., 2011). Metaheuristics are exploited to alleviate the severity of the mentioned downsides, yet they are not perfect. There are more than 40 metaheuristic algorithms nowadays (Tilahun and Ong, 2015). The enormity in number baffles practitioners every so often as which method is more congruous with their need. Moreover, each method has some hyper-parameters needing sufficient tuning to act efficiently, and their adjustment is usually carried out by trial and error. Last but not least, they are problem-specific, and often yield excellent results for the problem they have been designed for, but they are not readily applicable to other variants of the same problem (Lamghari, 2017). As a whole, these disadvantages entail researchers to seek other potential tools. AI as a fast-growing field in all industries has the merit to peer through for its promising solutions. Utilizing AI-powered FMSs can offer a substantial boost to operational effectiveness by promptly making decisions informed by complex data analysis. This, in turn, can optimize routes for vehicles and curtails periods of inactivity. To elaborate, AI leverages ML algorithms to examine historical data and foresee maintenance needs, allowing for timely servicing that minimizes downtime. Furthermore, these systems heighten safety measures by utilizing predictive analytics to anticipate potential accidents, as well as by facilitating remote monitoring to avert personnel exposure to risky zones. To exemplify, the incorporation of AI into an FMS for an open pit mine enables the dynamic allocation of haul trucks, considering real-time variables like traffic congestion, weather conditions, and equipment status. The outcome is a smoother traffic flow, decreased fuel consumption, and a more secure operational environment.

Table 1. Summary of chief optimization components captured in the thus-far published works on FMSs.

No.	Items	Components
1	Contributing factors	1) Stripping ratio, 2) Heterogeneity, 3) The mill feed rate, 4) The mill head grade, 5) Geological uncertainties, 6) Operational uncertainties, 7) Uncertain truck failures, 8) Scheduled maintenance, 9) Scalability, 10) Linkage with short term plans, 11) Large equipment movement, 12) Traffic jam (bunching), 13) Grade blending requirements at stockpiles, 14) Shovel assignment, 15) Block precedence.
2	Parameters	1) Truck capacity, 2) Shovel capacity, 3) Shovel digging rate, 4) Mills' feed rate, 5) Mill's head grade, 6) Crusher capacity, 7) dump capacity, 8) All types of timing (Loading, hauling, spotting, dumping etc.), 9) Optimal flow rate for the path from a shovel to a dump based on upper stage decisions, 10) Loaded-and-empty truck velocity, 11) Road characteristics and distances, 12) utilization of trucks and shovels, 13) Grades of elements, 14) Vertical and horizontal precedence of blocks, 15) Number of trucks and shovels, 16) Match Factor, 17) availability of mining face.
3	Goals	1) Maximize production, 2) Maximize truck fleet utilization, 3) Maximize shovel fleet utilization, 4) Maximize shovel production, 5) Minimize plants' feed rate

	deviation, 6) Minimize deviations in head grade, 7) Minimize truck operation costs, 8) Minimize greenhouse gases, 9) distance minimization, 10) Minimize shovel movement costs, 11) minimize the summation of shovel idle times, 12) minimize the summation of truck wait times, 13) minimize the deviation in the path flow rate compared to the desired flow rate.

2.2. Intelligent FMSs

Artificial Intelligence (AI) involves the exploration of enabling computers to perform tasks that currently humans excel at (Rich, 1983). Machine Learning (ML), a significant component of AI, employs input data to accomplish a specific objective without explicit programming (hard coding). In other words, the algorithm autonomously adjusts its structure to advance its proficiency in achieving the desired task (El Naqa and Murphy, 2015). ML is divided into three primary learning approaches: supervised learning (SL), unsupervised learning (USL), and reinforcement learning (RL). In SL, both training and testing data are accessible, allowing the model to learn from labeled data for tasks such as regression or classification. Conversely, USL involves training a model using unlabeled data to identify patterns or associations. Unlike the first two strategies, where models learn from datasets, RL relies on trial and error or experiential learning. In other words, an agent engages with an environment to determine the best policy through a system of rewards and penalties. Common ML techniques include linear and nonlinear discriminant analysis, decision trees, random forests (RF), k-nearest neighbors (kNN), support vector machines (SVMs), artificial neural networks (ANNs), linear regression, principal component analysis (PCA), and Q-learning. Deep Learning (DL), categorized separately within Artificial Neural Networks (ANNs), holds a distinct position owing to its importance. Unlike conventional scenarios, human intervention doesn't directly influence the process of extracting features from input data. DL draws inspiration from the intricate structure of the human nervous system, and its formation is based on a complex network of neurons that interact across input, hidden, and output layers. DL experienced a period of twenty years marked by limited progress, primarily due to inadequate availability of substantial datasets and suitable software/hardware. However, its resurgence commenced with renewed vigor during the ImageNet challenge of 2012. Since then, this field of study has undergone remarkable and rapid evolution. Notably, in 2017, Gartner forecasted that the domains of DL and ML would advance significantly within a span of 2 to 5 years, reaching a point of high productivity (Gartner Inc., 2017). During the second decade of the 21st century, SVM and DL are recognized as the prevailing methods, while RL is progressively expanding its presence within the mining sector (Jung and Choi, 2021; Noriega and Pourrahimian, 2022). During the mining exploitation phase, ML applications can primarily be categorized into production scheduling, drilling/blasting, and equipment management.

Various Machine Learning approaches become apparent when considering equipment management. Wang et al. (2019) juxtaposed four ML techniques to construct a driving style identification model for open-pit mine truck drivers, and reduce diesel consumption, where RF was found to be the most effective tool (Wang et al., 2019). Choi et al. (2021) compared six ML techniques for predicting ore production through truck haulage using Internet of Things (IoT) as a data collector, with the SVM model exhibiting the most superior performance (Choi et al., 2021). In another study, they predicted the performance of a truck-haulage system in the ore transportation process in open-pit mines using a combination of Harris hawks optimization and SVM before comparing it with RF and ANNs (Choi et al., 2022). Choudhury and Naik (2022) made a comparison among three models i.e., SVM, kNN and RF to predict the travelling time of trucks, thereby minimizing the cycle time and allocating an optimized number of dumpers to one shovel

(Choudhury and Naik, 2022). RF was recognized as the most suitable algorithm with least errors. Then, a linear programming model was developed to minimize the total number of trucks. The model is inclusive of constraints such as time-related attributes, truck condition, driver experience, atmospheric condition, and route profiles. These same algorithms were employed by Sun et al. (2018) for prediction of the real-time link travel time of open-pit trucks, where SVM and RF resembled in accuracy (Sun et al., 2018). To optimize the type of loader and the number of trucks required to meet the processing plant's throughput, Nobahar et al. (2022) compared five algorithms including linear regression, decision tree, kNN, RF, and gradient boosting algorithm, with the latter being indicated as the most precise (Nobahar et al., 2022).

However, SL is incapable to capture and model real-time changes (Lin et al., 2018), especially in mining environments, where high-dimensional dynamic and stochastic events govern. On the other hand, an RL agent strives to discover the optimal route that yields the greatest reward. An intriguing parallel can be drawn between this overarching concept and the challenge of route optimization encountered in the mining sector. Indeed, wherever the quest for an optimal pathway emerges – whether it pertains to determining the sequence for block extraction in production scheduling or mapping out the most efficient routes for the mining fleet – RL emerges as a suitable methodology. In scenarios involving agent-based truck dispatching dilemmas, each truck functions as an individual agent that collaborates within the mining system, all aimed at optimizing a specific objective. Bastos et al. (2011) were one of the first employers of agent-based approaches in truck dispatching at mines, where they proposed a single-dependent agent approach based on time-dependent Markov decision processes (Bastos et al., 2011). Comparison of their model with two heuristics in a DES simulator showed a superiority in the amount of materials hauled. Icarte Ahumada et al. (2020) utilized a negotiation mechanism for task sharing called the Contract Net Protocol, under the supervision of which trucks, shovels, and unloading points as individual agents interact in a shared mine environment through exchanging their schedules in an attempt to accomplish production goals at the minimum cost (Icarte Ahumada et al., 2020). Benchmarking the model against a heuristic brought about 18% decline in expenses. However, the scheduling process requires up to 16 minutes computational time on a standard device. Later, their work was extended to allow for truck failures rescheduling (Icarte Ahumada et al., 2021). Zhang et al. (2020) proposed an experience-sharing deep Q-learning network for dynamic truck allocation considering constraints such as truck capacity, expected wait time, total capacity of waiting trucks, activity time of delayed trucks, and capacity of delayed trucks (Zhang et al., 2020). Sharing the same network, trucks are able to be added or removed readily. To speed up the training, they only eliminated learning-complicating experiences. Additionally, a memory-tailoring algorithm was scripted to cope with the problem of trucks cutting lines of others. Finally, the model was put to the test against two dispatching heuristics in an event-based simulator developed in SimPy™, resulting in above 5% increase in productivity. In spite of all the creativity that their model enjoys, the impact of downstream units such as crushers or processing plants has been ignored. De Carvalho and Dimitrakopoulos (2021) integrated a discrete event simulation (DES) model with a deep double Q-learning network for truck dispatching at mines with various configurations (De Carvalho and Dimitrakopoulos, 2021). The simulator emulates operational interactions between shovels, trucks and dumping locations to create a vector consisting of inputs such as queue sizes, availability, down times, crusher/plant requirements, and past experiences. These parameters together with a reward function are used to generate experiences, and to train the network for future truck assignments. The model outperformed two dispatching schemes at a copper–gold mining complex in terms of ore recovery, daily mill throughput and queue sizes. Speaking of strengths, the model allowed for heterogeneous fleet (both shovels and trucks), machinery failures, capacities of plants, and geological uncertainties. However, changes in block sequence extraction, destinations, and fleet size require a 4-hour retraining. Huo et al. (2023) applied an AI-powered intelligent dispatching system with the aim of greenhouse gas emissions minimization in open-pit mining operations (Huo et al., 2023). They paid attention to constraints including payload, traffic,

queueing, and maintenance conditions in their multi-agent Q-learning algorithm. The model was benchmarked by two reference dispatching solutions (fixed allocation and fixed scheduling) in a simulator developed in the OpenAI™ framework. The RL-based dispatching scheme could reduce the emissions per unit production by over 30%. It also outperformed the fixed allocation solution by nearly one-third in fleet production and fuel efficiency. However, they assumed the fleet to be homogenous and small-sized. That's why the Q-table was utilized instead of a deep Q-learning network, and this decision affects the program solving time in larger-fleet cases. Processing plants' role was left out, too. Due to significant injuries and fatalities of mining trucks, the idea of autonomous trucks has also been addressed in literature. Ali and Frimpong (2021) developed a framework named DeepHaul consisting of two major components: first, inducing an object recognition ability using CNNs, and second, an RL-based algorithm for the steering action decision-making ability (Ali and Frimpong, 2021). The algorithm allegedly exhibited a remarkable accuracy score regarding safety, haulage efficiency and overall effectiveness.

Scrutinizing the components described in Table 1 unveils the fact that all the factors and parameters are reducible to seven chief features: (1) Rock mass (e.g., grade, production rate, stripping ratio, block precedence), (2) Shovel (e.g., capacity, digging rate, number, loading time, movement time), (3) Truck (e.g., capacity, velocity, loading time, hauling time, spotting time, number), (4) Operational (e.g., heterogeneity, scalability, failures, traffic jam, weather condition), (5) Processing plants (e.g., head grade, feed rate, capacity), (6) Stockpiles and waste dumps (capacities and grade requirements), (7) Linkage to strategic plans. Table 2 draws a distinction among previously-published works in RL-based fleet systems in terms of these features. As it is obvious, codes 5, 6 and 7 are the least addressed features. Rock mass and operational features are partially paid attention to in the literature. These bottlenecks highlight the necessity for more probe into the artificial world in the hope of bridging the research gap as much as possible. However, one should be cognizant of the fact that an ideal intelligent FMS incorporating all viable features might not be in the realm of possibility, at least at the moment due to hardware or software restrictions. On the other hand, rapid advancements in technology, especially quantum computing, are tantamount to an encouragement for practitioners to pass the ideality milestone in the foreseeable future.

Table 2. Salient RL-based proposed FMSs in the literature and features addressed.

No.	Authors	Features
1	Bastos et al. (2011)	1(production rate), 2,3, 4 (heterogeneity)
2	Icarte Ahumada et al. (2020)	1(production rate), 2, 3
3	Icarte Ahumada et al. (2021)	1(production rate), 2, 3, 4 (failures)
4	Zhang et al. (2020)	1(production rate), 2, 3, 4 (failures, scalability, heterogeneity)
5	De Carvalho and Dimitrakopoulos (2021)	1(production rate, grade), 2, 3, 4 (heterogeneity, failures), 5 (capacity)

6	Huo et al. (2023)	1(production rate, grade), 2, 3, 4 (failures, scalability)

3. The SWOT Analysis

Despite its unclear origins and lack of specific development timeframe (Helms and Nixon, 2010), the SWOT analysis method has gained widespread recognition for evaluating both internal (controllable: strengths and weaknesses) and external (uncontrollable: opportunities and threats) aspects influencing an entity. It employs a strategic matrix to systematically analyze these factors, aiding decision-making processes (Ghazinoory et al., 2011). SWOT integrates both internal and external factors that contribute to the effectiveness of an industry, a company, individuals, or even a new system transformation. Strengths identify the areas where an organization excels and what sets it apart from its rivals. Weaknesses, conversely, hinder the organization from operating optimally; hence, addressing them becomes crucial to maintain market presence. Opportunities encompass external factors that can provide the organization with a competitive edge to capitalize on or invest in. In contrast, threats encompass external elements that could potentially harm the organization and jeopardize its success. The SWOT diagram for the analysis of intelligent FMSs is illustrated in Fig. 1. Each of these components is elaborated upon as follows:

Strengths: The main supremacy of RL algorithms lies in their capability to address the dynamicity involved in a mining site. The RL agent is trained by trial and error to immediately acclimate to timely-changes in the environment as a way to be prepared for real-time rerouting and rescheduling. Another strength point relates to their ability for surmounting large-sized problems relatively to conventional methods. In other words, judging on the mere solving methodology, they alleviate the computational complexity and runtime by looking for near optimal solutions. This feature should not be confused with the temporary hardware-processing-power-restriction defect commented by some critics. The next significant merit is autonomy and self-awareness, thus reducing human interventions and mistakes.

Weaknesses: RL-based systems are suffering from a few temporary impediments. Firstly, hardware restrictions pose a problem in extremely high-dimensional environments unless the quantum-computing technology emerges rapidly with affordable costs. Secondly, the theoretical background for artificial intelligence, particularly RL is both obscure and deficient in maturity. A significant variety of algorithms comes to notice in the literature with increasing complexity. Furthermore, the effective design of an RL framework has a lot to do with the developer's knowledge, experience and hardware. Nonetheless, these barriers are tractable through the advancements in technology and academic texts.

Opportunities: Research works report an average productivity increase of 5 to 30% as a result of a smart FMS application (Zhang et al., 2020; De Carvalho and Dimitrakopoulos, 2021; Huo et al., 2023). An agent-based system for truck dispatching in open-pit mines is said to be capable of nearly 17% decrease in truck costs (Icarte Ahumada et al., 2021). Minimization of fuel, idling and maintenance costs as well as working hours of vehicles and employees are merely the direct benefits of intelligent systems, not to mention of indirect asset-management merits including equipment tracking, security, utilization, predictive maintenance, and life extension of vehicles via timely repairs. Another strength is ascribed to operational efficiency, specifically agile dispatching, proficient rescheduling induced by failures, weather conditions, or change in ore destinations, as well as bringing an organized procedure and smooth implementation, automation, autonomy and self-awareness. Regarding environmental aspects, RL-aided dispatching could diminish the greenhouse gas emissions per unit production by one-third in a three-shovel mine (Huo et al., 2023). Safety and health practices can be upgraded to higher standards through road conditions monitoring, traffic accidents prevention, driver's behavior surveillance (e.g., speeding or sleeping), and analysis of received sensory data for finding potential defects in vehicles. Professional

documentation and data reporting (e.g., 3D visualization by HoloLens), and less paperwork are also promised. For instance, in some underdeveloped mines, the onus of tracking the cycle of trucks and their load quality rests upon an in-field human controller, which is not only laborious in the task itself but also erroneous in data, especially in inclement weathers. Another dimension worth attention is culture. The less human interactions exist in a jobsite, the less conflicts will occur. That is to say, a truck driver may became involved in an altercation with a foreman over discharging the load in a wrong dump; however, it might not be the case in an intelligent framework where the ore destination path is displayed on a compact monitor installed at the driver's fingertips.

Threats: In this analysis, the word Threat means all the external factors hindering the successful implementation of an intelligent FMS. First of all, the capital investment required for intelligent systems is significant due to their need for infrastructure and speedy hardware, and the restricted knowledge behind these solutions. Another threat seems to be the persuasion of shareholders regarding the added value of such systems and the return promised over a medium-to-long run. A cost-benefit analysis is thus proposed to be conducted in such occasions for catching a deeper insight into this transformation. Governmental policies can also stand in the way, especially in countries with restrictive communication rules, which overshadows telematics. Last but not least, hackers might gain unauthorized access to the fleet control unit. However, the cybersecurity science has evolved proportionally by introducing up-to-the-minute firewalls.

Internal factors (strengths and weaknesses) are correlated to intrinsic features of intelligent systems (e.g. algorithm and hardware), whereas external factors (opportunities and threats) consider constructive and destructive forces imposed extrinsically. In another perspective, these four components are itemized as negative (weaknesses and threats) and positive (strengths and opportunities) classes. Fig. 1 illustrates that the diagram is on the positive side, implying that the advantages outweigh the disadvantages when it comes to incorporating intelligent FMSs into open pit mining operations.

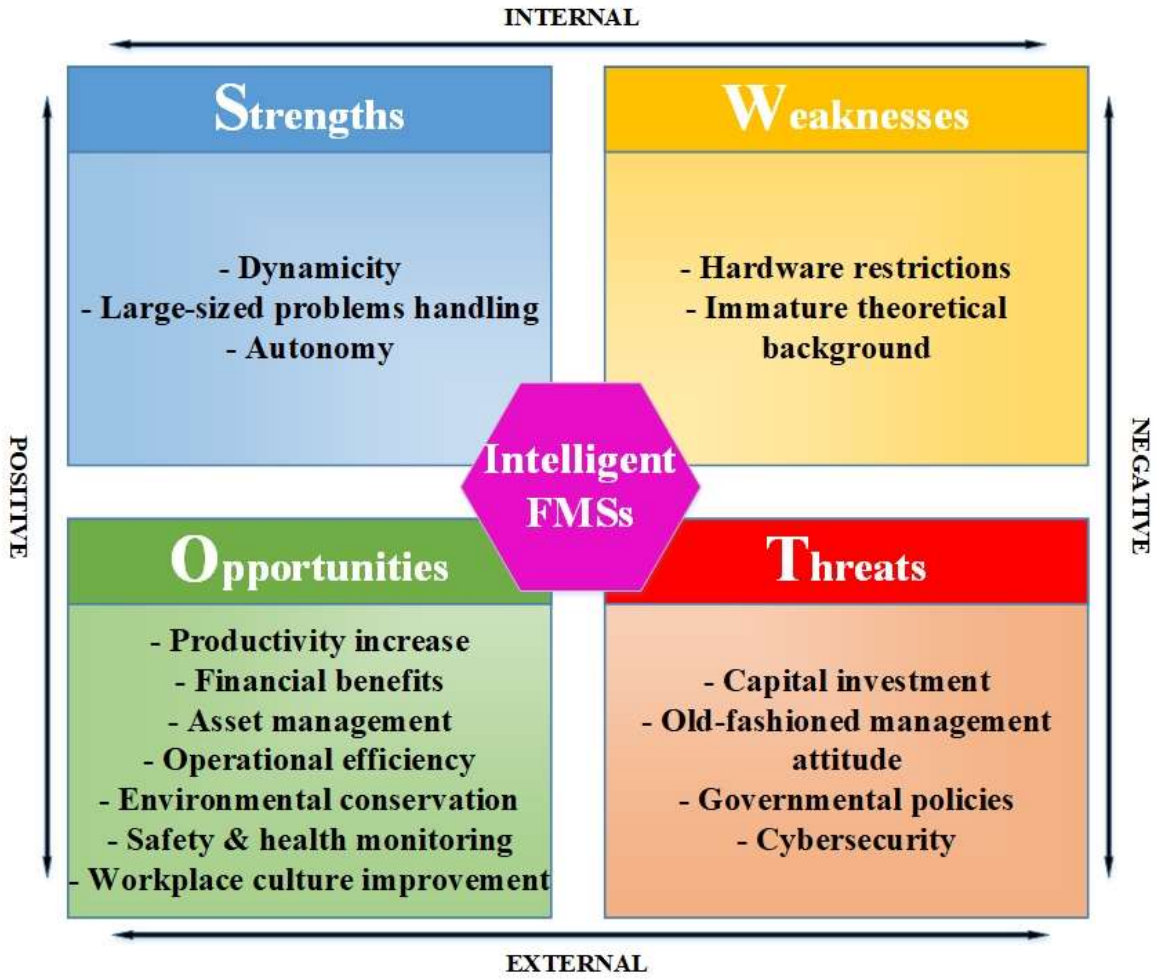


Fig. 1. The SWOT analysis diagram for intelligent fleet management systems (FMSs) in open pit mining.

4. Discussion and Conclusion

In mining publications, fleet management is traceable in diverse equipment-related aspects such as production optimization, dispatching, maintenance, fuel conservation, environmental impacts, weather conditions, the vehicle's operator monitoring, and health/safety aspects. The most prevalent algorithms applied are classifiable as conventional and intelligent. A variety of factors, parameters and goals has been attended to in conventional texts to capture dispatching and fleet-related issues. Nevertheless, the absence of scalability and dynamicity is noticed in real-life implementation of such models, entailing a quest for alternative solutions, which seems not to be a demanding task, with the Industry 4.0 ideology prevailing ubiquitously. Its translation into the mining context known as Mining 4.0 highlights the need for dynamism, one of the main tools of which in fleet routing is RL. This agent-based method has a rosy future ahead as hardware obstacles vanish. The trace of RL in mining FMSs literature is noticeable from the year 2011. Since then, RL has witnessed new developments in terms of underlying algorithms, and continues its evolutionary trajectory similarly to any new phenomenon.

RL empowers systems to acquire insights from their interactions with the environment, gradually streamlining decision-making processes for enhanced results. This innovation holds significant potential for elevating fleet management protocols, enabling systems to dynamically adjust and

optimize operations in response to real-time circumstances. For instance, the realm of truck dispatching, where RL algorithms can develop proficiency in making optimal choices by scrutinizing a spectrum of variables including shovel availability, traffic patterns, haul road conditions, and ore demand. These algorithms continuously fine-tune dispatching strategies, thereby curtailing wait times, minimizing unproductive runs, and refining overall truck deployment efficiency. In the larger scheme, the integration of RL into fleet management bears the potential for a myriad of advantages. Augmented production efficiency and reduced operational expenses stem directly from optimized dispatching and maintenance, which concurrently extend the functional longevity of equipment. Moreover, through dynamic adjustments to evolving conditions and drawing insights from historical data, RL-driven fleet management systems can bolster safety protocols by preemptively detecting and mitigating potential hazards. As the technology advances and mining enterprises harness its capabilities, prospects for advanced applications are foreseeable, culminating in heightened productivity, more effective resource utilization, and the promotion of sustainable mining practices within surface mining operations. The characteristics-based comparison revealed the status quo and research directions for addressing more features, especially processing plants, ore/waste dumps, and linkage to strategic plans. Now, RL programmers are challenged into developing holistic algorithms capable of satisfying all the requirements in the scope of mining FMSs. After proving theoretically the underlying need for intelligent systems, a strategic mechanism was needed to uncover all the related aspects of this type of transition. Herein, the SWOT analysis generated strengths (dynamicity, large-sized problem handling, autonomy), weaknesses (hardware restrictions and immature theoretical backgrounds), opportunities (productivity, finance, environment, safety and culture) and threats (investment, persuasion of shareholders, governmental deterrents and cybersecurity) associated with introducing intelligence into mining FMSs. These weaknesses appear to be tractable as time goes on. The required capital investment and outdated attitudinal issues are manageable by elaborating on the potential opportunities that intelligent setups can open up for shareholders. Overall, the plate for positive factors weighs more in favor of smart fleet systems. To recapitulate, the present study corroborated the need for intelligent FMSs using literary and SWOT analyses.

5. References

[1] Afrapoli, A. M., Upadhyay, S., and Askari-Nasab, H. (2018). A Fuzzy Logic Approach towards Truck Dispatching Problem in Surface Mines1. *Mining Optimization Laboratory*, *1* (780), 131.

[2] Ahangaran, D. K., Yasrebi, A. B., Wetherelt, A., and Foster, P. (2012). Real–time dispatching modelling for trucks with different capacities in open pit mines. *Archives of Mining Sciences*, *57* (1),

[3] Alarie, S. and Gamache, M. (2002). Overview of solution strategies used in truck dispatching systems for open pit mines. *International Journal of Surface Mining, Reclamation and Environment*, *16* (1), 59-76.

[4] Ali, D. and Frimpong, S. (2021). DeepHaul: a deep learning and reinforcement learning-based smart automation framework for dump trucks. *Progress in Artificial Intelligence*, *10* (2), 157-180.

[5] Anaraki, M. G. and Afrapoli, A. M. (2023). Sustainable open pit fleet management system: integrating economic and environmental objectives into truck allocation. *Mining Technology*, 1-11.

[6] Askari-Nasab, H., Upadhyay, S., Torkamani, E., Tabesh, M., and Badiozamani, M. (2014). *Simulation optimisation of mine operational plans*. in Proceedings of Orebody Modelling and Strategic Mine Planning Symposium, Perth, WA Australia,

[7] Bastos, G. S., Souza, L. E., Ramos, F. T., and Ribeiro, C. H. (2011). *A single-dependent agent approach for stochastic time-dependent truck dispatching in open-pit mining*. in Proceedings of 2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC), IEEE, pp. 1057-1062.

[8] Blouin, S., Guay, M., and Rudie, K. (2007). An application of discrete-event theory to truck dispatching. *Central European Journal of Operations Research*, *15* (4), 369-391.

[9] Bonates, E. and Lizotte, Y. (1988). A computer simulation model to evaluate the effect of dispatching. *International Journal of Surface Mining, Reclamation and Environment*, *2* (2), 99-104.

[10] Castillo, D. and Cochran, J. K. (1987). A microcomputer approach for simulating truck haulage systems in open pit mining. *Computers in Industry*, *8* (1), 37-47.

[11] Chang, Y., Ren, H., and Wang, S. (2015). Modelling and optimizing an open-pit truck scheduling problem. *Discrete Dynamics in nature and Society*, *2015*

[12] Choi, Y., Nguyen, H., Bui, X.-N., and Nguyen-Thoi, T. (2022). Optimization of haulage-truck system performance for ore production in open-pit mines using big data and machine learning-based methods. *Resources Policy*, *75* 102522.

[13] Choi, Y., Nguyen, H., Bui, X.-N., Nguyen-Thoi, T., and Park, S. (2021). Estimating ore production in open-pit mines using various machine learning algorithms based on a truck-haulage system and support of internet of things. *Natural Resources Research*, *30* (2), 1141-1173.

[14] Choudhury, S. and Naik, H. (2022). *Use of Machine Learning Algorithm Models to Optimize the Fleet Management System in Opencast Mines*. in Proceedings of 2022 IEEE 7th International conference for Convergence in Technology (I2CT), IEEE, pp. 1-8.

[15] Dabbagh, A. and Bagherpour, R. (2019). Development of a match factor and comparison of its applicability with ant-colony algorithm in a heterogeneous transportation fleet in an open-pit mine. *Journal of Mining Science*, *55* (1), 45-56.

[16] Dabbagh, A. and Bagherpour, R. (2019). Investigating the Applicability of Imperialist Competitive Algorithm in the Problem of Allocating Truck to the Open Pit Mine. *Rudarsko-geološko-naftni zbornik*, *34* (2),

[17] De Carvalho, J. P. and Dimitrakopoulos, R. (2021). Integrating production planning with truck-dispatching decisions through reinforcement learning while managing uncertainty. *Minerals*, *11* (6), 587.

[18] Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. *Numerische mathematik*, *1* (1), 269-271.

[19] El Naqa, I. and Murphy, M. J. (2015). *What is machine learning?* Springer, Pages 3-11.

[20] Elbrond, J. and Soumis, F. (1987). Towards integrated production planning and truck dispatching in open pit mines. *International Journal of Surface Mining, Reclamation and Environment*, *1* (1), 1-6.

[21] Ercelebi, S. G. and Bascetin, A. (2009). Optimization of shovel-truck system for surface mining. *Journal of the Southern African Institute of Mining and Metallurgy*, *109* (7), 433-439.

[22] Forsman, B., Rönnkvist, E., and Vagenas, N. (1993). Truck dispatch computer simulation in Aitik open pit mine. *International Journal of Surface Mining, Reclamation and Environment*, *7* (3), 117-120.

[23] Gartner Inc. (2017). Gartner hype cycle for emerging technologies in 2017. https://www.gartner.com/ (accessed 01 April 2023).

[24] Ghazinoory, S., Abdi, M., and Azadegan-Mehr, M. (2011). SWOT methodology: a state-of-the-art review for the past, a framework for the future. *Journal of business economics and management*, *12* (1), 24-48.

[25] Gurgur, C. Z., Dagdelen, K., and Artittong, S. (2011). Optimisation of a real-time multi-period truck dispatching system in mining operations. *International Journal of Applied Decision Sciences*, *4* (1), 57-79.

[26] He, M.-X., Wei, J.-C., Lu, X.-M., and Huang, B.-X. (2010). The genetic algorithm for truck dispatching problems in surface mine. *Information technology journal*, *9* (4), 710-714.

[27] Helms, M. M. and Nixon, J. (2010). Exploring SWOT analysis–where are we now? A review of academic research from the last decade. *Journal of strategy and management*,

[28] Huo, D., Sari, Y. A., Kealey, R., and Zhang, Q. (2023). Reinforcement Learning-Based Fleet Dispatching for Greenhouse Gas Emission Reduction in Open-Pit Mining Operations. *Resources, Conservation and Recycling*, *188* 106664.

[29] Icarte Ahumada, G., Berrios, P., Castillo, R., and Herzog, O. (2020). *A multiagent system for truck dispatching in open-pit mines*. in Proceedings of International Conference on Dynamics in Logistics, Springer, pp. 363-373.

[30] Icarte Ahumada, G., Diaz Pinto, J., and Herzog, O. (2021). *A dynamic scheduling multiagent system for truck dispatching in open-pit mines*. in Proceedings of International Conference on Agents and Artificial Intelligence, Springer, pp. 132-148.

[31] Jacobsen, W., Sturgul, J., Ritter, K., and Fliess, T. (1995). *A Simulation Model of the Waste Handling System Proposed for the Lihir Project in Papua New Guinea*. in Proceedings of APCOM XXV 1995 Conference, 9-14 July 1995, Brisbane, pp. 333-344.

[32] Jung, D. and Choi, Y. (2021). Systematic review of machine learning applications in mining: Exploration, exploitation, and reclamation. *Minerals*, *11* (2), 148.

[33] Kolonja, B., Kalasky, D. R., and Mutmansky, J. M. (1993). *Optimization of dispatching criteria for open-pit truck haulage system design using multiple comparisons with the best and common random numbers*. in Proceedings of Proceedings of the 25th conference on Winter simulation, pp. 393-401.

[34] Lamghari, A. (2017). Mine planning and oil field development: a survey and research potentials. *Mathematical Geosciences*, *49* (3), 395-437.

[35] Li, Z. (1990). A methodology for the optimum control of shovel and truck operations in open-pit mining. *Mining science and technology*, *10* (3), 337-340.

[36] Lin, K., Zhao, R., Xu, Z., and Zhou, J. (2018). *Efficient large-scale fleet management via multi-agent deep reinforcement learning*. in Proceedings of Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 1774-1783.

[37] Lizotte, Y. and Bonates, E. (1987). Truck and shovel dispatching rules assessment using simulation. *Mining Science and Technology*, *5* (1), 45-58.

[38] Madge, D. (1964). Simulation of truck movement in an open pit mining operation. *Canadian Operation Research Society*, *11* 32-41.

[39] Mirzaei-Nasirabad, H., Mohtasham, M., Askari-Nasab, H., and Alizadeh, B. (2023). An optimization model for the real-time truck dispatching problem in open-pit mining operations. *Optimization and Engineering*, 1-25.

[40] Mohtasham, M., Mirzaei-Nasirabad, H., Askari-Nasab, H., and Alizadeh, B. (2021). A multi-objective model for fleet allocation schedule in open-pit mines considering the impact of prioritising objectives on transportation system performance. *International Journal of Mining, Reclamation and Environment*, *35* (10), 709-727.

[41] Moradi-Afrapoli, A. and Askari-Nasab, H. (2022). Advanced Analytics for Surface Extraction. in *Advanced Analytics in Mining Engineering: Leverage Advanced Analytics in Mining Industry to Make Better Business Decisions*, Springer, pp. 181-203.

[42] Moradi Afrapoli, A. (2019). A Hybrid Simulation and Optimization Approach towards Truck Dispatching Problem in Surface Mines.Thesis, The University of Alberta, Canada., Canada,

[43] Moradi Afrapoli, A. and Askari-Nasab, H. (2019). Mining fleet management systems: a review of models and algorithms. *International Journal of Mining, Reclamation and Environment*, *33* (1), 42-60.

[44] Moradi Afrapoli, A. and Askari-Nasab, H. (2020). A stochastic integrated simulation and mixed integer linear programming optimisation framework for truck dispatching problem in surface mines. *International Journal of Mining and Mineral Engineering*, *11* (4), 257-284.

[45] Moradi Afrapoli, A., Tabesh, M., and Askari-Nasab, H. (2019). A stochastic hybrid simulation-optimization approach towards haul fleet sizing in surface mines. *Mining Technology*, *128* (1), 9-20.

[46] Moradi Afrapoli, A., Upadhyay, S., and Askari-Nasab, H. (2021). Truck dispatching in surface mines-Application of fuzzy linear programming. *Journal of the Southern African Institute of Mining and Metallurgy*, *121* (9), 505-512.

[47] Moradi Afrapoli, A., Upadhyay, S. P., and Askari-Nasab, H. (2022). A nested multiple-objective optimization algorithm for managing production fleets in surface mines. *Engineering Optimization*, 1-14.

[48] Munirathinam, M. and Yingling, J. C. (1994). A review of computer-based truck dispatching strategies for surface mining operations. *International Journal of Surface Mining and Reclamation*, *8* (1), 1-15.

[49] Munirathinam, S. (2020). Industry 4.0: Industrial internet of things (IIOT). *Advances in computers*, *117* (1), 129-164.

[50] Nobahar, P., Pourrahimian, Y., and Mollaei Koshki, F. (2022). Optimum Fleet Selection Using Machine Learning Algorithms—Case Study: Zenouz Kaolin Mine. *Mining*, *2* (3), 528-541.

[51] Noriega, R. and Pourrahimian, Y. (2022). A systematic review of artificial intelligence and data-driven approaches in strategic open-pit mine planning. *Resources Policy*, *77* 102727.

[52] Pirmoradian, H., Monjezi, M., Askari-Nasab, H., Nikbakhsh, E., and Mousavi Nogholi, A. (2022). Development of a local search algorithm for solving allocation and dispatching problem of transportation fleet in open pit mines. *Journal of Mineral Resources Engineering*,

[53] Rich, E. (1983). *Artificial intelligence.* McGraw-Hill, Inc.,

[54] Siami-Irdemoosa, E. and Dindarloo, S. R. (2015). Prediction of fuel consumption of mining dump trucks: A neural networks approach. *Applied Energy*, *151* 77-84.

[55] Soumis, F., Ethier, J., and Elbrond, J. (1989). Evaluation of the new truck dispatching in the mount wright mine. *Application of Computers and Operations Research in the Mineral Industry*, 674-682.

[56] Souza, M. J., Coelho, I. M., Ribas, S., Santos, H. G., and Merschmann, L. H. d. C. (2010). A hybrid heuristic algorithm for the open-pit-mining operational planning problem. *European Journal of Operational Research*, *207* (2), 1041-1051.

[57] Sturgul, J. and Harrison, J. (1987). Using a special computer language for simulating coal mines. *Coal J.(Australia);(Australia)*, *18*

[58] Sun, X., Zhang, H., Tian, F., and Yang, L. (2018). The use of a machine learning method to predict the real-time link travel time of open-pit trucks. *Mathematical Problems in Engineering*, *2018*

[59] Ta, C. H., Ingolfsson, A., and Doucette, J. (2013). A linear model for surface mining haul truck allocation incorporating shovel idle probabilities. *European journal of Operational research*, *231* (3), 770-778.

[60] Tabesh, M., Upadhyay, S. P., and Askari-Nasab, H. (2016). Discrete Event Simulation of Truck-Shovel Operations in Open Pit Mines1. *MOL Annual Report Seven 2015/2016 (ISBN: 978-1-55195-367-0)*, *7* 77-93.

[61] Temeng, V. A., Otuonye, F. O., and Frendewey, J. O. (1998). A nonpreemptive goal programming approach to truck dispatching in open pit mines. *Mineral Resources Engineering*, *7* (02), 59-67.

[62] Temeng, V. A., Otuonye, F. O., and Frendewey Jr, J. O. (1997). Real-time truck dispatching using a transportation algorithm. *International Journal of Surface Mining, Reclamation and Environment*, *11* (4), 203-207.

[63] Tilahun, S. L. and Ong, H. C. (2015). Prey-predator algorithm: a new metaheuristic algorithm for optimization problems. *International Journal of Information Technology & Decision Making*, *14* (06), 1331-1352.

[64] Upadhyay, S. P. (2017). Simulation optimization of mine operations for uncertainty based short term and operational planning in open pit mines.Thesis, University of Alberta, Canada,

[65] Wang, Q., Zhang, R., Wang, Y., and Lv, S. (2019). Machine learning-based driving style identification of truck drivers in open-pit mines. *Electronics*, *9* (1), 19.

[66] White, J. and Olson, J. (1986). Computer-based dispatching in mines with concurrent operating objectives. *Min. Eng.(Littleton, Colo.);(United States)*, *38* (11),

[67] White, J. W., Olson, J., and Vohnout, S. (1993). On improving truck/shovel productivity in open pit mines. *CIM bulletin*, *86* (973), 43-49.

[68] Yokoi, R., Watari, T., and Motoshita, M. (2022). Future greenhouse gas emissions from metal production: gaps and opportunities towards climate goals. *Energy & Environmental Science*, *15* (1), 146-157.

[69] Zhang, C., Odonkor, P., Zheng, S., Khorasgani, H., Serita, S., Gupta, C., and Wang, H. (2020). *Dynamic dispatching for large-scale heterogeneous fleet via multi-agent deep reinforcement learning*. in Proceedings of 2020 IEEE International Conference on Big Data (Big Data), IEEE, pp. 1436-1441.

[70] Zhang, X., Chen, L., Ai, Y., Tian, B., Cao, D., and Li, L. (2021). *Scheduling of Autonomous Mining Trucks: Allocation Model Based Tabu Search Algorithm Development*. in Proceedings of 2021 IEEE International Intelligent Transportation Systems Conference (ITSC), IEEE, pp. 982-989.

[71] Zhang, Y., Li, S., and Cai, Q. (1990). Optimization criteria for computer-controlled truck dispatching system. *Computer and operations research in the mineral industries*, 295-306.

Truck Fleet Dispatching in Open Pit Mines Using Artificial Intelligence Methods

Roberto Noriega and Yashar Pourrahimian
Mining Optimization Laboratory (MOL)
University of Alberta, Edmonton, Alberta, Canada

ABSTRACT

Truck fleet dispatching plays a key role in reducing operational costs and fulfilling operational targets in open-pit mining operations and is subject to large uncertainty arising from the operating cycles of trucks and loading equipment. In this research, we propose a reinforcement learning-based truck dispatching system. Reinforcement learning is a machine learning area that deals with learning an optimal sequential decision-making strategy in an uncertain environment. An open-pit load-and-haul simulation is developed that also captures the truck movements and interactions in the shared road network, and a Neural Network is successfully trained to suggest truck dispatching decisions in real-time.

1. Introduction

A truck dispatching system aims to assign trucks to their next destination after completing an operating cycle. An open-pit is a complex and dynamic production environment where trucks haul material between mining faces and different material destinations, travelling across a shared haul road network. A truck dispatching system must provide real-time assignments as trucks complete their cycles, based on the current state of the mine, to contribute towards the shift production targets. The operating cycle of trucks, comprising of hauling empty towards a shovel, receiving its payload, hauling the payload, and dumping it at a given destination, is subject to operational uncertainties at every step. These arise from equipment characteristics, equipment and road condition, and operator skill, amongst other factors. Furthermore, traffic rules such as no overtaking and different equipment sizes and production rates make the truck dispatching problem challenging to model and solve in a real-time manner.

The problem is usually modelled and solved in two stages, as proposed by White and Olson (1986) [1] and Olson et al. (1993) [2], where a first or upper stage defines a simplified model of the open-pit production environment and uses linear programming (LP) to obtain shovel digging rates and tonnage of material to be moved between different paths between mining faces and destinations in the pit. A lower stage refers to the real-time dispatch of trucks in operations and is solved using a heuristic rule to match trucks to shovels to meet the path tonnages established in the upper stage section. New developments have focused on more complex optimization models and using simulations (Temeng et al. (1998) [3], Ta et al. (2005) [4], Topal and Ramazan (2012) [5], Ahangaran et al. (2015) [6], Moradi Afrapoli et al. (2018) [7], Moradi Afrapoli et al. (2019) [8], Moradi-Afrapoli and Askari-Nasab (2020) [9], Moradi-Afrapoli et al. (2021) [10], Mohtasham et al. (2022) [11], Pirmoradian et al. (2022) [12], Moradi-Afrapoli et al. (2022) [13], Mirzaei-Nasirabad et al. (2023) [14], Ghasempour and Moradi-Afrapoli (2023) [15]). For a more detailed review of truck dispatching systems, readers are directed to Moradi Afrapoli and Askari-Nasab (2019) [16]. However, approaches based on linear optimization have a limited ability to capture the dynamics of the pit

ISBN: 978-1-55195-503-2

operations requiring significant simplifications or a large model that is incurring in large computing times. Moreover, these models make decisions based on estimates of equipment activity times which are highly uncertain, and simulation models have only been used to evaluate the performance of the dispatching model rather than to integrate the uncertainty into the optimization process directly.

This paper proposes an artificial intelligence (AI) based truck dispatching agent trained in an open-pit simulation environment that captures all the equipment cycle and interaction uncertainties. This allows the agent to learn from the system's uncertainties and directly incorporate them into the optimization process. The truck dispatching agent is trained to meet target shovel digging target rates in tonnes-per-hour (tph) and target tonnage targets to be delivered at the different destinations during a production shift. Furthermore, the training process is linked with the monthly production schedule and projected pit development to ensure the truck dispatching model performs optimally for the next month of production.

The truck dispatching agent is trained using Reinforcement Learning (RL). RL is a branch of Machine Learning (ML) that implements a computational approach to learning an optimal policy, a decision-making strategy, through interactions with an environment (Sutton and Barto (2018) [17]). In an RL framework, an agent, an abstraction for the decision-maker, interacts with an environment at different time steps. At any time-step t where the agent must act, it observes the current state of the system, s_t, and makes an action, a_t based on it. The environment then responds to this action by transitioning into a new state in the next time step s_{t+1}, and providing a reward R_{t+1} for the agent (Figure 1).

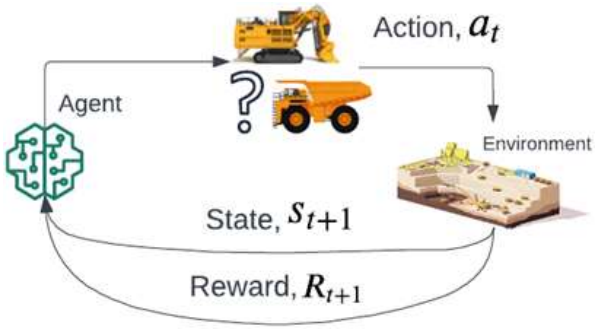


Figure 1. Reinforcement learning conceptual framework.

RL goal is to enable the agent to learn an optimal decision-making policy that maximizes the cumulative reward received throughout its interaction. The objective function that RL algorithms optimize is the total discounted reward accumulated by the agent by interacting with the environment. The RL agent seeks to learn a relation, or a function, from state-action pairs, (s, a), to the expected return of taking action a from state s, denominated Q-value, $Q(s, a)$. The Q-value is a function defined as the expected cumulative discounted reward achieved by the agent by taking an action a from a state s, following the same function for the next steps until the end of an episode (Equation 1). The cumulative nature of the return allows the agent to understand the impact of actions over long sequences rather than acting greedily at every step.

$$Q(s,a) = E\left[\sum_n \gamma^n R_n \middle| s_t = s, a_t = a\right] \quad (1)$$

The use of Deep Neural Networks (DNN) as function approximators in RL frameworks to learn the Q-value function provides the ability to learn complex and non-linear relations between environment states, agent actions, and returns. This framework has been used to develop complex scheduling and routing systems for complex real-world industrial applications in manufacturing plants (Lian et al.

(2022) [18]), chemical production plants (Hubbs et al. (2020) [19]), and vehicle routing platforms (Qin et al. (2020) [20]).

Machine Learning and Reinforcement Learning frameworks have also been explored for truck dispatching in open-pit mining (Noriega and Pourrahimian (2022) [21], Nobahar et al. (2022) [22]). Zhang et al. (2020) [23] proposed a deep Q-learning model that maximizes the total fleet productivity in open-pit operations, considering a truck fleet of heterogeneous capacities. However, the system does not consider potential production targets at different destinations, making it impractical for real-world operations where ore and waste targets can vary depending on the different processing methods applied in the mine. Moreover, the system is trained and evaluated for a single production shift. de Carvalho and Dimitrakopoulos (2021) [24], on the other hand, proposed a deep Q-learning that can dispatch trucks to meet different ore and waste production targets; however, the simulation that is used to train the agent is relatively simple and would not be able to fully capture the dynamics of a real-world operation which could lead to significant discrepancies in a potential real-world application. Furthermore, the authors train their system for only three days of production, and the evaluation indicates that the performance significantly degrades after five days suggesting that the model would need to be continuously retrained. This paper aims to address these limitations by training the agent in a detailed open-pit simulation environment and linking the training process with the production schedule to obtain optimal and consistent performance for a month of production.

2. METHODS

A discrete event simulation (DES) model is used to build a simulated open-pit production environment to train the truck dispatching agent. DES models have been widely used to evaluate mining fleet productivity and the impact of changes to the mining production environment (Upadhyay et al. (2021) [25], Moradi-Afrapoli et al. (2022) [26]) and provide an approximation of the impact of truck dispatching decisions in the open-pit system state. The DES is built using information about the mine layout to model the haul road network, mining faces and destination locations, and other relevant features. Equipment dispatch and mine planning databases are used to model the uncertainties in equipment activities as probability distributions. The DES then simulates the movement of trucks and their interaction with shovels and dumping destinations keeping track of different key production indicators (KPIs) and productivity rates. Whenever a truck dispatching decision is required, control in the DES is yielded to the AI truck dispatching agent, which observes the current state of the mine, described as a vector, and outputs a dispatching action. The agent is a neural network (NN), trained by interacting multiple times with the environment, receiving a feedback signal, the Q-value cumulative discounted returns. The feedback signal is designed to encourage the agent to meet desired goals, in this case, maximizing equipment utilization and meeting the different shift production targets. Figure 2 presents the methodology proposed in this paper. Due to the extensive AI packages available, the DES model is implemented in Python, an open-source programming language. The training loop is executed using PyTorch's deep learning framework.

2.1. Open-pit environment

The open-pit DES environment simulates a shift of production where trucks move between shovels and dumping destinations across a shared haul road network. Stochasticity is considered in each component of the truck operating cycle: hauling empty, getting loaded, hauling loaded and dumping. With queues forming based on the limited serving capacity of both shovels and dumping destinations. The DES is based on the models described by (Goris Cervantes et al. (2019) [27]). At the start of each shift simulated, shovels are assigned to a mining face based on the mine plan which also dictates the destination of the material being loaded there. Truck dispatching actions are required every time a truck dumps its payload, where the system's current state is given as input to the AI dispatched to

obtain a truck-shovel assignment for its next cycle. Figure **3** shows the general logic of the DES environment and its interaction with the AI dispatcher agent.

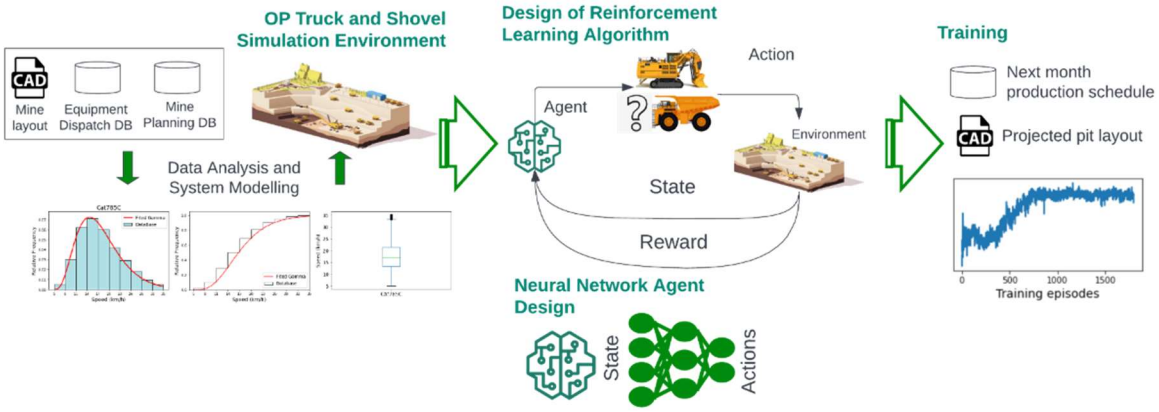


Figure 2. General methodology proposed for the development of an AI based truck dispatching agent.

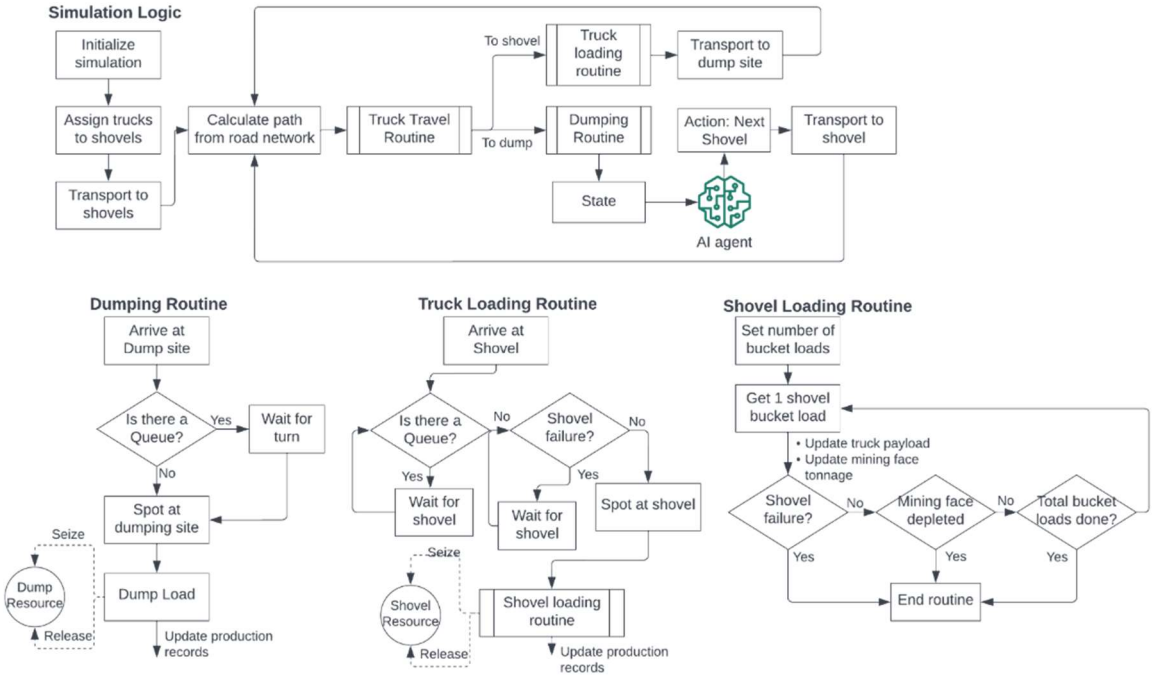


Figure 3. Interaction between the open-pit DES environment and the AI dispatcher agent.

When a truck starts traveling across the road network towards either a shovel or a dump destination, it is assigned a path, a collection of connected road segments from the network that is the shortest path between the current location of the truck and its next destination. Each road segment in this path contains information about the segment's rolling resistance, grade resistance, and length and maintains a queue of trucks that are traveling across it which is used to model truck bunching. Moreover, each segment has a maximum speed limit v_{road} that constrains the speed of any truck traveling through it.

Each truck traverses its path by moving along each road segment. Truck velocities are estimated using the equipment dispatch database to model each truck type's empty flat haul movement distribution. This refers to the velocity of trucks when hauling empty over flat segments and provides a good baseline then to include the effects of payload and road resistance. After entering a segment, the truck enters the road segment truck's queue and is assigned a velocity based on its truck type

empty flat haul velocity distribution adjusted by the road resistance and payload based on the truck manufacturer's rimpull curves. While travelling through the different road segments, trucks are not allowed to overtake and bunch behind, adopting its leading truck's velocity.

2.2. Truck Dispatching Agent

The implementation and training of the AI dispatcher agent require the definition of state, action, rewards, and the NN architecture. The decision on these components is based on the goals that the AI agent must reach. In this paper, we design the agent to dispatch trucks to meet given shovel digging rate targets for each shovel, expressed in tonnes-per-hour (tph), meet target tonnes dumped at the different destinations by the end of the shift and maximize equipment utilization.

To handle large truck fleets and improve generalization, each truck is considered an individual agent that collects state, action, next state, reward transitions, or experiences. However, a centralized truck dispatching policy is used to avoid incurring in training many individual agents, which severely suffers from scalability and implementation issues. Each truck pushes its experiences to a shared buffer that is used to train one general truck dispatching NN agent. Therefore, each transition between states of the pit encodes information about dispatching a single truck and its impact on the production environment after completing its cycle.

Considering an open-pit with m shovels and n destinations, the state of the system refers to an observation of useful features that the agent can use to correlate with the expected return of actions. In this case, the state is a vector that encodes information available by processing real-time data based on equipment tracking systems, production targets, and monitoring of shift progress. The AI agent's action is assigning the truck to a shovel for its next operating cycle. This action is encoded as a one-hot vector, a vector with a dimension equal to the number of shovels where the index or position of each element is tied to a shovel in the system. All its elements are 0 except for one element with a value of 1 where its position indicates the shovel assignment.

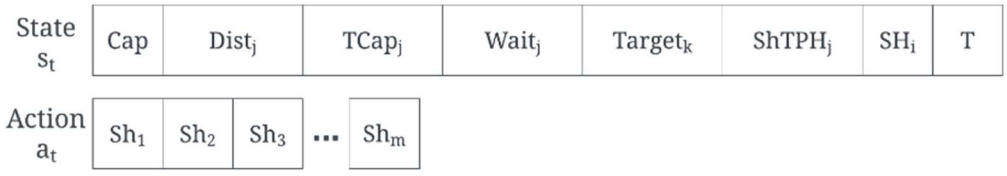


Figure 4. State and action representation for the truck dispatching agent.

In the state and action descriptuion the i, j, k indices refer to trucks, shovels and destinations respectively. The $Cap \in \mathbb{R}$ component is a real number indicating the capacity of the current truck being dispatched; this allows the agent to handle fleets with trucks of different sizes better. $Dist_j \in \mathbb{R}^m$ is a vector containing the total distance to be travelled along the road network for the next operating cycle between the location of the current truck and each shovel j. $TCap_j \in \mathbb{R}^m$ is a vector that contains information about the total truck capacity currently in route, at the queue and being serviced at each shovel, and its obtained based on the current truck's shovel assignments. $Wait_j \in \mathbb{R}^m$ elements contain the expected waiting for the current truck to be loaded at each shovel and is estimated based on path length, number of trucks in route, at the queue and being serviced by each shovel. $Target_k \in \mathbb{R}^n$ indicates the current progress of the target tonnage to be dumped at each destination. $ShTPH_j \in \mathbb{R}^m$ vector contains the current shovel's tph. $SH_i \in \mathbb{R}^m$ is a one-hot encoded vector that indicates the last shovel assignment of the current truck and $T \in \mathbb{R}$ is a real number indicating the current time of the shift. Each component is scaled to avoid the dominance of a single component due to large quantities.

The reward signal is designed to direct the agent to meet the desired goals. Once the agent dispatches a truck to a shovel and this completes its operating cycle by dumping its load at a destination point, a transition is completed and a reward, r_t, is provided as the truck waits for a new assignment. The reward function is shown in Equation 2.

$$r_t = \sum_j tph_j^- + (1 - qt_i) + \frac{Cap_i}{MaxCap}\delta_k + \delta_T \sum_k c_k^- \quad (2)$$

In the first component, tph_j^- indicates the current negative deviation, or shortfall, from the target tph of shovel j, expressed as a ratio. Adding all shovel production shortfalls encourages the agent to keep all shovels at the target rates, or higher. The second component rewards the agent for obtaining efficient truck cycles, where qt_i indicates the fraction of time the current truck spent at queues both at shovel and destination in its last cycle because of the action taken. The third component rewards the agent for every truck payload delivered, weighing by how large relative to the maximum truck size, where Cap_i is the capacity of the current truck, $MaxCap$ is the maximum truck capacity in the system and δ_k is a binary indicator for meeting the tonnage target to be delivered at the destination where the current truck dumped. This reward component only applies to destinations whose targets have not been met, using the binary indicator, to create a reward gradient with respect to other destinations with unmet targets and encourage the agent to meet all production targets. Finally, the last component of the reward is only applied at the end of an episode, where δ_k is a binary indicator that takes the value 1 when the shift ends, and penalizes the agent for not meeting the shift targets at each destination, where c_k^- is the shortfall from the target tonnes delivered at destination k at the end of the shift, expressed as a ratio.

The agent is implemented as a neural network (NN), which takes a state observation and estimates the Q-value for each action; that is, the expected discounted cumulative reward for taking each dispatching action from the given state up to the end of the shift. The action with the highest Q-value is then selected. The NN implemented in this paper is a feedforward network with five layers and 200 neurons in each layer using the ReLU function as the activation function.

2.3. Training Process

The AI dispatching agent is trained using the Deep Q-learning algorithm described by Mnih et al. (2015) [28], with the Double Q-learning modification proposed by van Hasselt et al. (2016) [29]. The training process refers to the iterative adjustment of the agent's NN weights, θ, to better predict the action-values, Q-value, for taking each action from a given state of the system.

The training process in deep Q-learning relies on the agent interacting with the environment storing experience vectors, $e_t = (s_t, a_t, r_t, s_{t+1})$ that represent each transition observed, in a memory replay buffer which serves as the training dataset for every training update of the NN agent. The role of the replay buffer is to break the correlation between consecutive experiences obtained from sequential time steps in the environment. The Q-values are estimated recurrently from the experience vectors by calling the NN to estimate the Q-value of the next state from the transition.

At every NN training step, a batch of experiences is drawn randomly from the replay buffer, and the NN weights are trained to minimize the prediction loss $L_i(\theta_i)$ defined as the mean square error (MSE) between the observed return (target) and the predicted return from the network at training step i, as shown in Equation 3.

$$L_i(\theta_i) = (r + \gamma max_{a_{t+1}} Q(s_{t+1}, a_{t+1}; {\theta_i}^{tgt}) - Q(s_t, a_t; \theta_i))^2 \quad (3)$$

Where θ_i^{tgt} refers to a NN used to evaluate target returns not trained at every step but synced with the online network defined by θ_i every C steps, called the target network, which helps stabilize the training process. The original Q-learning tends to overestimate the value of actions, which is harmful for training stability. Double Q-learning alleviates this problem by making the simple modification of using the training NN to choose actions but evaluating the next state Q-values using the target network and has been found to overperform the original implementation. Stochastic gradient descent (SGD) is used to update the NN weights to minimize the loss function. This process is controlled by a learning rate parameter, α, that scales the magnitude of the update in the direction of the loss gradients.

A training episode consists of a production shift and the agent's NN is updated at each transition, a truck operating cycle, as described above. To develop a dispatching model for the next month of production, at the start of the training shift the location of the shovels and the mine road layout is chosen randomly based on the production schedule and the projected pit development. That is the shift to be simulated and used for training is representative of one of the projected shifts for the next month. This helps avoid prohibitively long training episodes, as each episode is still one shift, and learn a general dispatching policy as the policy learned must be optimal for the whole month.

3. Results

3.1. Case Study

The AI truck dispatching agent was tested in a case study based on an iron ore mining operation. The mining operation uses a total of five shovels to load material from mining faces: 2 Hitachi 2500 shovels for ore production and 3 Hitachi 5500 Ex shovels for waste production. A fleet of 38 trucks is employed to haul the material from the pit to their destination, either one of two crushers or a waste dump. The mine uses 22 CAT785C, with a payload of 140 tonnes, and 16 CAT793C, with a payload of 218 tonnes. Two crushers are available, which both require 25,000 tonnes of ore to be delivered every shift. Figure 5 shows a plan view of the mine layout, in addition to the crusher and waste dump locations and the access to the mining faces areas. From the mining faces access, it is assumed that the distance to each mining face is the linear distance between its digging coordinate and the closest access point in the road network.

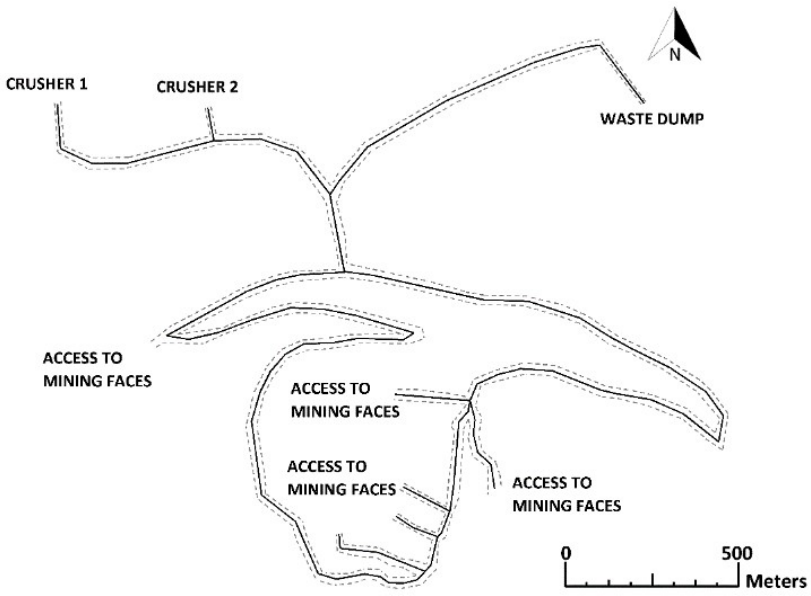


Figure 5. Case study iron ore open-pit layout.

Equipment activity records are available in the form of a Leica Jigsaw equipment dispatch database. This database is used to fit probability distributions to each shovel, truck operating activities, and truck haul speeds to build the stochastic DES open-pit for the case study. This probability fitting section is considered out of scope, not presenting any novelty, and not included to avoid a lengthy paper.

3.2. Training Results

The dispatcher agent is trained by interacting with the environment multiple times, simulating production shifts randomly based on the production schedule and pit layout. The agent's NN is updated to identify the best actions to take to maximize the total cumulative reward obtained at the end of the simulated shift. An epsilon greedy exploration strategy was used to encourage the agent

to explore and discover better dispatching strategies. When an action is required, there is a probability, ε, that the agent will select a completely random action. This probability starts high but decreases linearly as training progresses and the agent has experienced more episodes. The parameters used for the training of the AI truck dispatcher are shown in Table 1. The ε probability of taking random actions starts at 80% and decreases linearly to 1% during 500,000 environment transitions.

Table 1. Parameters used for the training of the truck dispatching agent.

Replay buffer size	200,000
Batch size for NN training updates	32
Discount factor, γ	0.99
Learning rate, α	5×10^{-6}
Iteration update frequency of target network	25,000

The system was trained in Google Colab platform, which provides powerful GPU cloud nodes to develop deep learning models. The training took about 4 hours and 20 minutes until convergence was achieved in the total cumulative reward obtained by the agent. Figure 6 shows the training performance, total production, average truck fleet cycle times, and average truck utilization as the agent learns an optimal dispatching policy.

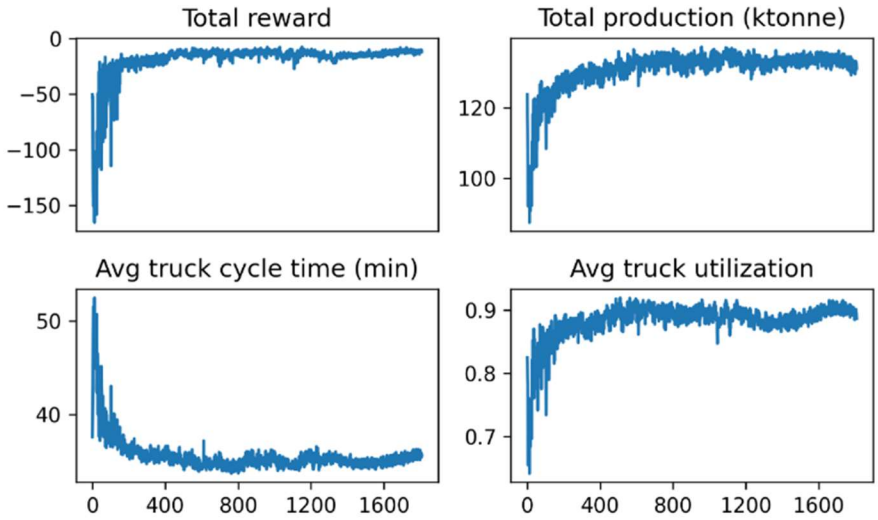


Figure 6. Training performance of the AI truck dispatching agent.

As training progresses, the agent improves its performance as measured by the total cumulative reward obtained at the end of each episode. After about 1000 training episodes, the agent can consistently achieve a high total cumulative reward over all simulated shifts randomly drawn considering the next production month. Since the agent receives a penalty for failing to keep the shovels at the target tph, total negative rewards indicate irregular shovel production. By the end of the training, the agent maintains a consistent production at all shovels, as its total cumulative reward approaches zero, where the small shortfall is caused due to the first hours of production when the trucks are starting their initial trips. The improvement in the performance of the agent can also be observed in the total production obtained, the improvement in the average truck cycle times and truck fleet utilization.

3.3. Performance Evaluation

During the training process, the performance of the dispatcher was measured based on a single shift drawn from the projected configurations of the pit during the next month. To evaluate the performance of the AI dispatcher, the entire month is simulated in one run. The DES is modified to allow shovel movement between mining faces as their current working areas are depleted. When this happens, a shovel is marked as unavailable, and the AI dispatcher is asked to re-dispatch all trucks currently assigned to it. Once the shovel arrives at its new working area, it is marked as available again.

The agent is tested for a month of production in the case study described above, using a mixed fleet of 22 CAT 785C and 16 CAT 793C trucks, 2 HIT 2500 shovels for ore production and 3 HIT 5500EX shovels for waste stripping. A total of 20 replications of the production month are used to obtain an average value for the different KPIs.

The agent managed to meet the shift production target and obtain extra daily production over the month as shown in Figure 7. The dips in material correspond to time slots where the shovels finish mining their current working area and move to the next one based on their schedule, where they are unavailable to constrain the system.

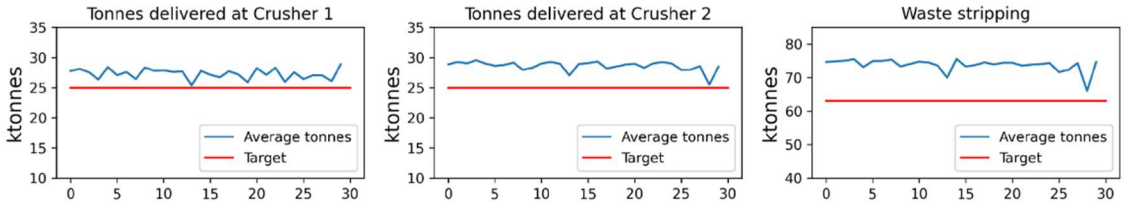


Figure 7. Average daily tonnes delivered at the destination over the month of production by the AI truck dispatching agent.

The AI agent also managed to meet the different shovel productivity rates, expressed as tonnage-per-hour (tph) loaded, as shown in Figure 8. The agent not only manages to maximize the total productivity of the system but also consistently meets the different shovel-loading targets at the different mining faces established from the mine plan, to ensure the projected advance in the ore mining faces and waste stripping requirements.

Moreover, the truck dispatching also achieves high average utilization rates for the equipment fleet. Figure 9 shows the average utilizations achieved for the shovel and truck fleet. The shovel fleet achieves an average of 90% utilization across the month which indicates the agent manages to keep all the shovels reasonably busy throughout the shift. The truck fleet utilization hovers around 85%, which could indicate some inevitable queues formed at the shovels.

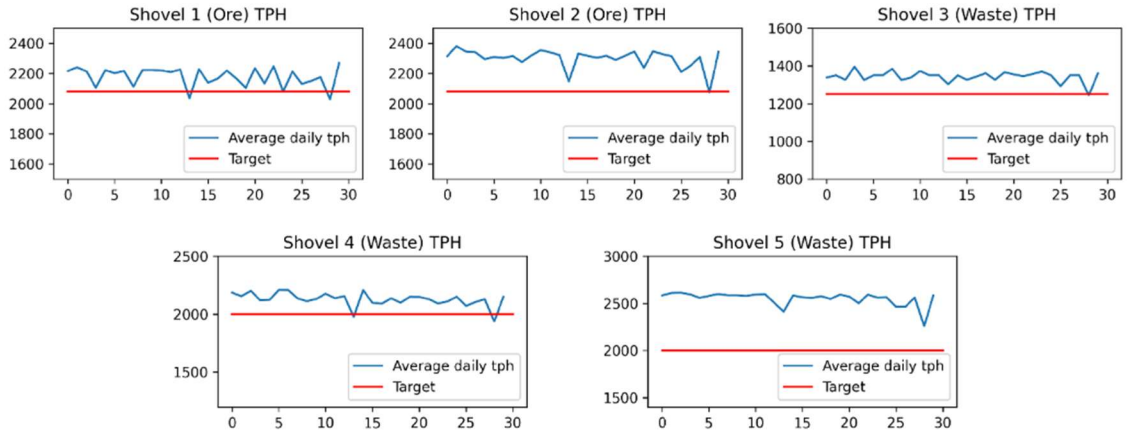


Figure 8. Average daily shovel tonnes-per-hour (tph) rate over the month of production obtained by the AI truck dispatching agent.

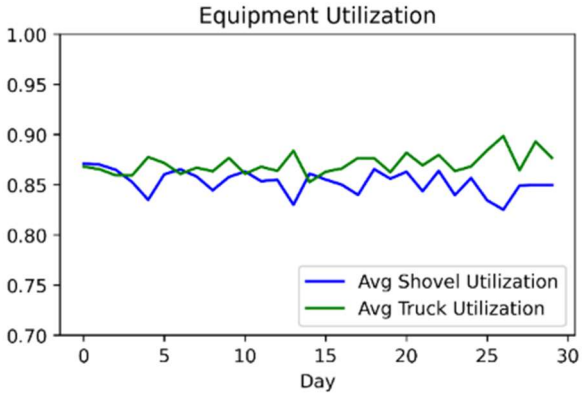


Figure 9. Average equipment fleet utilization achieved by the AI truck dispatching agent over the month of production.

4. Conclusions

This paper proposed an Artificial Intelligence (AI) based truck dispatching agent for open-pit mining. The agent is trained using a Deep Reinforcement (DR) Learning algorithmic framework, which has seen successful application in other production industries. The AI truck dispatcher is trained in a discrete simulation model of the open-pit operation, that considers stochasticity at every stage of the truck and shovel operating cycles. This allows the agent to learn the uncertainties in the behavior of the system and discover efficient dispatching strategies. The agent is trained to maximize equipment utilization and meet shovel productivity rates and destination rates, including ore delivered to crushers and waste stripping. After the agent is trained, obtaining a truck assignment is fast as it only requires a forward pass through a neural network, which takes a fraction of a second, making it appealing for real-time truck dispatching.

The framework is evaluated in an iron open-pit operation, where the simulation environment was built using the mine planning database, the mine layout, and the equipment dispatch database to model the stochasticity in the equipment activities. The agent was trained to learn a dispatching strategy for the next month of production and successfully met all the targets while maximizing equipment utilization and overall production.

The use of data-driven AI-based truck dispatching systems would allow the efficient use of multiple real-time data streams to take full advantage of new developments in monitoring systems for open-pit operations and digital twin technologies. Although the system currently takes about 4 hours and

a half to train for one month of production, future research will focus on extending the time over which the truck dispatching system operates and developing efficient training strategies to minimize computational effort—additionally, incorporating extra data streams such as equipment health and shovel bucket load sensors to provide better real-time dispatching solutions.

5. Rerences

[1] J. W. White and J. P. Olson, “Computer-based dispatching in mines with concurrent operating objectives,” Min. Eng., vol. 38, no. 11, pp. 1045–1054, 1986.

[2] J. P. Olson, S. I. Vohnout, and J. White, “On improving truck/shovel productivity in open-pit mines,” CIM Bull., vol. 86, no. 973, pp. 43–49, 1993.

[3] V. Temeng, F. Otuonye, and J. Frendewey, “A Nonpreemptive Goal Programming Approach to Truck Dispatching in Open-pit Mines,” Miner. Resour. Eng., vol. 07, no. 2, 1998.

[4] C. H. Ta, J. V. Kresta, J. F. Forbes, and H. J. Marquez, “A stochastic optimization approach to mine truck allocation,” Int. J. Surf. Mining, Reclam. Environ., vol. 19, no. 3, pp. 162–175, 2005, doi: 10.1080/13895260500128914.

[5] E. Topal and S. Ramazan, “Mining truck scheduling with stochastic maintenance cost,” J. Coal Sci. Eng., vol. 18, no. 3, pp. 313–319, 2012, doi: 10.1007/s12404-012-0316-4.

[6] D. K. Ahangaran, A. B. Yasrebi, A. Wetherelt, and P. Foster, “Real -time dispatching modelling for trucks with different capacities in open-pit mines,” Arch. Min. Sci., vol. 57, no. 1, pp. 39–52, 2012, doi: 10.2478/v10267-012-0003-8.

[7] R. Noriega and Y. Pourrahimian, “A systematic review of artificial intelligence and data-driven approaches in strategic open-pit mine planning”, Resources Policy, 2022, Vol. 77-102727

[8] A. Moradi Afrapoli, M. Tabesh, and H. Askari-Nasab, “A multiple objective transportation problem approach to dynamic truck dispatching in surface mines,” Eur. J. Oper. Res., vol. 276, no. 1, pp. 331–342, 2019, doi: 10.1016/j.ejor.2019.01.008.

[9] A. Moradi Afrapoli, S. Upadhyay, H. Askari-Nasab, "A Fuzzy Logic Approach towards Truck Dispatching Problem in Surface Mines ", International Journal of Mechanical and Production Engineering (IJMPE) , vol. 6, no.12, pp. 79-84, 2018.

[10] A. Moradi Afrapoli and H. Askari-Nasab, “A stochastic integrated simulation and mixed integer linear programming optimisation framework for truck dispatching problem in surface mines”, International Journal of Mining and Mineral Engineering, vol.11, no.4, 2020.

[11] M. Mohtasham, H. Mirzaei-Nasirabad, H. Askari-Nasab, and B. Alizadeh, “Multi-stage optimization framework for the real-time truck decision problem in open-pit mines: a case study on Sungun copper mine,” Int. J. Mining, Reclam. Environ., vol. 36, no. 7, pp. 461–491, 2022, doi: 10.1080/17480930.2022.2067709.

[12] A. Moradi-Afrapoli, S. Upadhyay, and H. Askari-Nasab. “Truck dispatching in surface mines -Application of fuzzy linear programming”, Journal of the Southern African Institute of Mining and Metallurgy, vol. 121, no. 9, pp. 505-512. https://dx.doi.org/10.17159/2411-9717/522/2021

[13] H. Pirmoradian, M. Monjezi, H. Askari-Nasab, E. Nikbakhsh, and A. Mousavi Nogholi. Development of a local search algorithm for solving allocation and dispatching problem of transportation fleet in open pit mines. Journal of Mineral Resources Engineering, 2022.

[14] A. Moradi Afrapoli, S. Prakash Upadhyay & H. Askari-Nasab, "A nested multiple-objective optimization algorithm for managing production fleets in surface mines", Engineering Optimization, 2022, DOI: 10.1080/0305215X.2022.2153840

[15] Mirzaei-Nasirabad, H., Mohtasham, M., Askari-Nasab, H. et al. An optimization model for the real-time truck dispatching problem in open-pit mining operations. Optimization and Engineering, 2023.

[16] A. Moradi Afrapoli and H. Askari-Nasab, "Mining fleet management systems: a review of models and algorithms," Int. J. Mining, Reclam. Environ., vol. 33, no. 1, pp. 42–60, 2019, doi: 10.1080/17480930.2017.1336607.

[17] R. Sutton and A. Barto, Reinforcement Learning An Introduction, 2nd Editio. MIT Press, 2018.

[18] Y. Liang et al., "Lenovo Schedules Laptop Manufacturing Using Deep Reinforcement Learning," Interfaces (Providence)., vol. 52, no. 1, pp. 56–68, 2022, doi: 10.1287/inte.2021.1109.

[19] C. D. Hubbs, C. Li, N. V Sahinidis, I. E. Grossmann, and J. M. Wassick, "A deep reinforcement learning approach for chemical production scheduling," Comput. Chem. Eng., vol. 141, p. 106982, 2020, doi: 10.1016/j.compchemeng.2020.106982.

[20] Z. Qin et al., "Ride-hailing order dispatching at DiDi via reinforcement learning," Interfaces (Providence)., vol. 50, no. 5, pp. 272–286, 2020, doi: 10.1287/INTE.2020.1047.

[21] M. Ghasempour Anaraki and A. Moradi Afrapoli, "Sustainable open pit fleet management system: integrating economic and environmental objectives into truck allocation", Mining Technology, 2023, DOI: 10.1080/25726668.2023.2233230

[22] P. Nobahar, Y. Pourrahimian and F. Mollaei Koshki, "Optimum Fleet Selection Using Machine Learning Algorithms—Case Study: Zenouz Kaolin Mine", Mining, vol. 2, no. 3, pp. 528-54, DOI: https://doi.org/10.3390/mining2030028

[23] C. Zhang, P. Odonkor, S. Zheng, H. Khorasgani, S. Serita, and C. Gupta, "Dynamic Dispatching for Large-Scale Heterogeneous Fleet via Multi-agent Deep Reinforcement Learning," arXiv:2008.10713v1, p. 9, 2020.

[24] J. P. de Carvalho and R. Dimitrakopoulos, "Integrating production planning with truck-dispatching decisions through reinforcement learning while managing uncertainty," Minerals, vol. 11, no. 6, 2021, doi: 10.3390/min11060587.

[25] S. Upadhyay, M. Tabesh, M. Badiozamani, A. Moradi Afrapoli, and H. Askari-Nasab, "A simulation-based algorithm for solving surface mines' equipment selection and sizing problem under uncertainty," CIM J., vol. 12, no. 1, pp. 36–46, 2021.

[26] A. Moradi-Afrapoli, H. Askari-Nasab, "Advanced Analytics for Surface Extraction". In: Soofastaei, A. (eds) Advanced Analytics in Mining Engineering. Springer, Cham., 2022, https://doi.org/10.1007/978-3-030-91589-6_8

[27] E. Goris Cervantes, S. Upadhyay, and H. Askari-Nasab, "Improvements to production planning in oil sands mining through analysis and simulation of truck cycle times," CIM J., vol. 10, no. 1, pp. 39–52, 2019.

[28] V. Mnih et al., "Human-level control through deep reinforcement learning," Nature, vol. 518, no. 7540, pp. 529–533, 2015, doi: 10.1038/nature14236.

[29] H. van Hasselt, A. Guez, and D. Silver, "Deep Reinforcement Learning with Double Q-Learning," in Proceedings of the AAAI Conference on Artificial Intelligence (AAAI-16), 2016, pp. 2094–20100, doi: https://doi.org/10.1609/aaai.v30i1.10295.

Benefits of Discrete Event Simulation in Modeling Mining Processes

Sandra Katharina Fahl and Hooman Askari-Nasab
Mining Optimization Laboratory (MOL)
University of Alberta, Edmonton, Canada

ABSTRACT

Discrete event simulation is a stochastic mathematical modeling tool. In modern mining operations maximizing productivity by effective decision making is essential. Discrete event simulation is used to conduct "what if" analysis supporting mining engineers and management in decision making. This paper discusses benefits of discrete event simulation compared to other analysis techniques like spreadsheet analysis. Discrete event simulation can model uncertainty and time changing events. It can be used to model complex systems. A case study example of a stochastic framework for equipment selection is presented to elaborate an example of the applicability of discrete event simulation in modeling and optimizing mining processes. A summary of the results is presented.

1. Introduction

Our modern lifestyle is based on the consumption of mineral resources. From cradle to grave we are surrounded by consumer products created out of stones and rocks. A growing world population, economic growth in developing and emerging countries and a constant need for further innovation increases the demand for mineral resources. The constant optimization of mining operations is vital to cope with the global challenges linked to the rising demand for mineral resources. This paper introduces the concept of Discrete Event Simulation and its application in modeling and optimizing processes in the mining industry. Recent literature is reviewed to acknowledge the variety of applications of Discrete Event Simulation. The analysis of Discrete Event Simulation models is compared to traditional spreadsheet analysis. Advantages and disadvantages of Discrete Event Simulation are evaluated. A brief case study of the application of Discrete Event Simulation in the gypsum quarry industry is presented. Recent limitations of Discrete Event Simulation applied in the mining industry are outlined. Further topics of research are suggested.

2. Benefits of Discrete Event Simulation

Discrete Event Simulation has evolved as a powerful decision making tool after the appearance of fast and inexpensive computing capacity. (Upadhyay et al. 2015) Discrete event simulation enables the study of systems which are discrete, dynamic and stochastic. Discrete Event Simulation models are dynamic simulation models. Time evolvement plays an important role in the analyzed system. Stochastic simulation models are run several times to generate a distribution of outcomes that can be analyzed. (Law, 2015) Additional literature about the utilization of Discrete Event Simulation in the mining industry includes but is not limited to (Ben-Awuah et al., 2010), Paravarzar et al. (2018), Moradi-Afrapoli & Askari-Nasab (2020), Moradi-Afrapoli & Askari-Nasab (2022), Noriega & Pourrahimian (2022) and Hazrathosseini & Moradi-Afrapoli (2023).

ISBN: 978-1-55195-503-2

Discrete Event Simulations are typically used to analyze queuing problems. Although it fits many applications in mining, the optimization of the load-haul-dump cycle, both above and underground, is most critical for achieving higher efficiency and cost reduction. Fluctuating cycle times represent the queuing behavior and performance is measured in delay, waiting time, throughput and resource utilization. (Coronado & Tenorio 2015) (Fishman 2001, p.6)

Discrete Event Simulations have been used for a number of purposes in optimizing mine haulage management. The purposes include but are not limited to: the improvement of equipment utilization, reducing waiting and queuing time, to evaluate cost reduction ideas, to minimize the effects of breakdowns, to understand the impact of mixed fleet interactions.

The scope of each Discrete Event simulation model analysis is defined prior to designing the simulation model. (Price, 2014) All methods of successful performance of discrete event simulation include quality control. Procedures of quality control include verification (checking whether the simulation model works as intended) and validation (checking whether the simulation model reflects the real system adequately). (Rabe et al., 2008)

A summary of the most important benefits of Discrete Event Simulation models is given below:

- In a capital intensive industry the possibility to perform what if analysis by the means of simulation and evaluate systems before they are introduced is an essential benefit. Mining engineers are able to study the behavior of systems in order to evaluate design alternatives, improvements or to justify costs. Every aspect of the system can be tested without committing resources for the acquisition of for example new equipment. (Both, 2015)
- Various levels of detail and complexity can be modeled according to the grade of accuracy and detail needed for the decision-making process. According to Price 2014: “Discrete Event simulation models are very useful when components of systems change […] at discrete points in time as a result of specific events. For example, the state of a truck will normally change at discrete points during a haulage cycle.” (Price, 2014)
- Uncertainties and dynamic (time-changing) behavior of the real system can be modeled. Stochastic variables that influence haulage fleet management are for example: waiting times, loading time, spotting time and the haulage time. These factors will vary depending on the road conditions, the type of material loaded, the skills of the operators, the weather and other uncontrollable and sometimes different to predict conditions. (Price, 2014)
- Phenomena can be sped up or slowed down in the simulation. An entire shift can be analyzed in minutes. (Dindarloo et al., 2016)
- The question why a phenomenon occurs in a real system is often asked by managers. Reconstructing the scene with a simulation and analyzing the system microscopically can answer why a phenomenon occurs. (Dindarloo et al., 2016)
- New policies and different operating procedures or new methods can be analyzed in the simulation model. Meanwhile the real system is not disrupted by experiments. The system is modified on the computer rather than modifying the real system. (Dindarloo et al., 2016)
- The simulation model can be used to train new staff. The new operators make their decisions in the simulation model to learn and gain experience before operating the real system. When they make mistakes they can learn from this experience while the real system is not disrupted. (Dindarloo et al., 2016)
- Simple haulage models used to estimate fleet requirements make a large number of assumptions and can not model complex systems. Decisions made based on these simple models do not represent accurate solutions for complex models. Inaccuracies in the haulage models and under-optimized haulage systems is a severe consequence. (Price, 2014)

- Discrete Event simulation models model how complex real systems actually operate. They include the variability, interactions and dependencies of the real system. Thus, decisions such as to invest in new infrastructure or equipment can be made with more certainty. (Price, 2014)

Major shortcomings of Discrete Event Simulations are:

- Discrete Event Simulation can only be applied if the simulation model can replicate the reality to a sufficient extent. (Upadhyay et al. 2015)
- Stochastic skills and an adequate level of experience and knowledge is needed for the creation of a simulation model. This time consuming simulation approach is therefore limited to larger mining companies that have the financial capacities to invest in simulation. (Basu, 1999)
- It is difficult to keep mine models up to date due to the highly dynamic nature of mining. For example, does the design of haul road networks change almost daily. If mine simulation models are not managed by the mine planning team of the mining company onsite but are prepared externally the mine simulation models will become out of date soon. (Price, 2014)
- Like numerical mathematical models and traditional spreadsheet analysis, Discrete Event Simulation only provides estimations for the model outcomes. (Price, 2015)

More areas in mining operations and mineral processing that can be modeled with Discrete Event Simulation need further research. (Dindarloo et al., 2016) There is no comprehensive Discrete Event Simulation program adjusted for mining applications available on the market. Further research should focus on the development of low-cost simulation tools with an easy usable User-interface.

3. Case Study Castellina Gypsum Quarry

For the work presented in this case study the Discrete Event Simulation software Plant Simulation, a product developed by Siemens was used. The software was adapted to develop a simulation tool that can be used on a cross-project basis in the mining industry. The development of the Discrete Event Simulation model followed the general procedure adapted from the Association of German Engineers (VDI), which is shown in Figure 1. (Both, 2016)

Objective of the case study was the optimization of ore transport in the Castellina Marittima gypsum quarry operation. The quarry is located in the south-west of the Italian province of Pisa. The ore is mined by drilling and blasting. At the time of raw data collection for the case study four levels were in operation. The mining equipment in operation included two 3.2 m3 shovels and two articulated dump trucks with a capacity of 27 and 23 tonnes. (Both, 2016)

In the case study the benefit of stockpiling is analyzed in comparison to conventional ore transport. Aim of the case study is to find the most cost effective transportation setup comparing a stockpiling and non-stockpiling scenario with varying equipment. The daily operating costs are used as key performance indicators (KPI). The results of the Discrete Event Simulation model are verified and compared to a deterministic spreadsheet calculation of the same problems. Figure 2 gives an overview of the complexity of the topographical network layer for the simulation model of the case study. (Both, 2016)

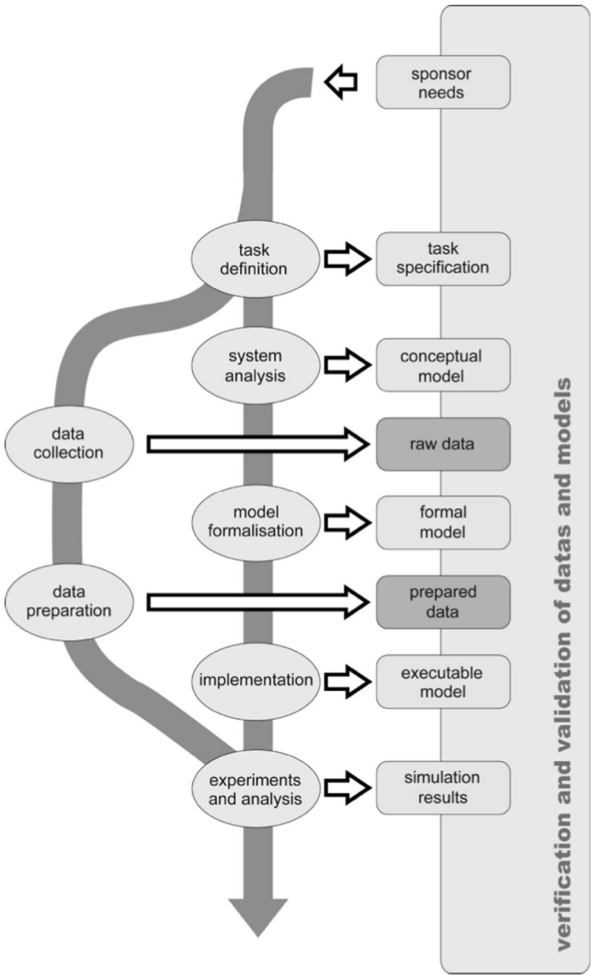


Figure 1. Procedure model for Discrete Event Simulations of VDI, translated to English by (Both, 2016).

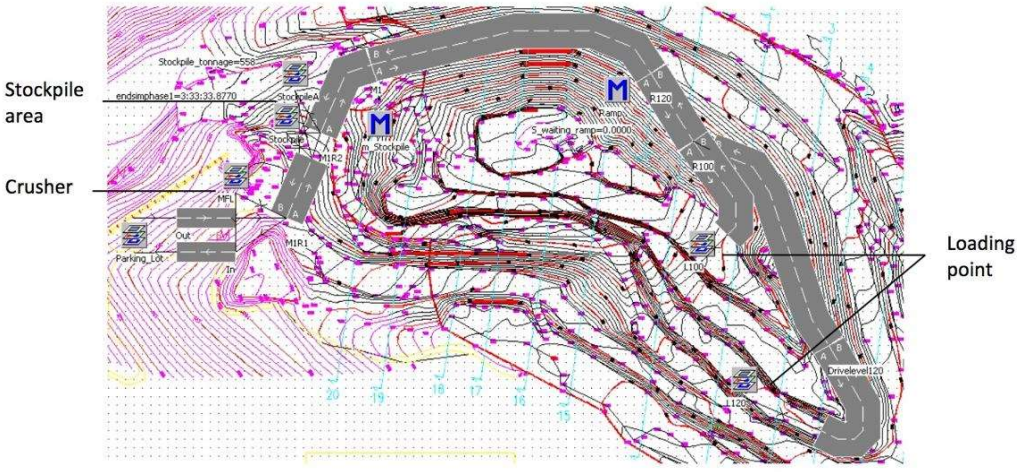


Figure 2. Topographical network layer for the simulation model of the case study (Both, 2016).

In summary, the assessment of the case study results showed that the Discrete Event simulation approach is superior to the deterministic spreadsheet calculation if the case study includes unpredictable interactions of equipment. (Both, 2016) One example stated by Both (2016) is “the

basic examination of stockpile profitability using different equipment combinations in the [] case study. While the exact amount of ore placed on the stockpile was difficult to determine by spreadsheet calculation, the Discrete Event Simulation model could benefit from decision-making based on the filling level of the crusher bunker, which reproduces the behavior of the real transport system."

4. Conclusion

Discrete Event simulation is a powerful decision making tool. Discrete Event Simulation enables the study of systems that are discrete, dynamic and stochastic. Discrete Event Simulation is ideal to optimize mine haulage management. Major benefits of Discrete Event Simulation include but are not limited to: a flexible and varying level of detail and complexity of the simulation model. As well as the possibility to model uncertainties and the dynamic behavior of the real system. What if analysis of different scenarios and training of new staff can be performed on the simulation model without disrupting the real system and committing resources for the acquisition of for example new equipment. In a capital intensive industry this is an essential benefit. New policies and new operating procedures can be tested at low cost.

To achieve this the Discrete Event Simulation model must replicate the real system to a sufficient extent. Effort is necessary to keep the mine models up to date and the simulation model validated. The application of Discrete Event Simulation is still limited to larger mining companies that have the necessary financial capacities. Further research should focus on the development of low-cost simulation tools with an easy usable User-interface adjusted to the mining industry to open up the possibility of Discrete Event Simulation to smaller companies. The comparison of the case study results achieved by simulation to the deterministic spreadsheet approach shows that simulation is beneficial when the interaction of the equipment pieces is hard to predict and the real system depends on dynamic processes. More areas in mining operations that can be modeled with Discrete Event Simulation in addition to haulage fleet management need further research.

5. References

[1] Basu (1999) – Discrete event simulation of mining systems. Current practice in Australia. In: *International Journal of Surface Mining, Reclamation and Environment 13 (2),* pp. 79-84. DOI:10.1080/09208119908944214

[2] Ben-Awuah, Kalantari, Pourrahimian & Askari-Nasab (2010) – Hierarchical mine production scheduling using discrete-event simulation.. In: *International Journal of Mining and Mineral Engineering 2 (2), 137-158*.

[3] Both (2016) – Review of the Applicability of Discrete Event Simulation for Process Optimization in Mining. *Master Thesis. Delft University of Technology, August, 2016.*

[4] Coronado & Tenorio (2015) – Optimization of Open Pit Haulage Cycle Using a KPI Controlling Alert System and a Discrete-Event Operations Simulator. In Bandopadhyay (Ed.): *Application of computers and operations research in the mineral industry. Englewood, Colo., Society for Mining Metallurgy & Exploration Inc. (SME).*

[5] Dindarloo & Siami-Irdemossa (2016) – Merits of Discrete Event Simulation in Modeling Mining Operations. *At SME Annual Meeting, Feb. 21- 24, 2016, Phoenix AZ*.

[6] Fishman (2001) – Discrete-event simulation. Modeling, programming, and analysis. New York, Springer. ISBN: 0387951601

[7] Hazrathosseini & Moradi-Afrapoli (2023) – The advent of digital twins in surface mining: Its time has finally arrived. *Resources Policy 80, 2023.*

[7] Law (2015) – Simulation modeling and analysis. 5. Ed. New York, McGraw-Hill Education *(McGraw-Hill series in industrial engineering and management science*). ISBN: 9780073401324

[8] Moradi-Afrapoli & Askari-Nasab (2020) – A stochastic integrated simulation and mixed integer linear programming optimisation framework for truck dispatching problem in surface mines. *International Journal Mining and Mineral Engineering, Vol. 11, No. 4, 257-284*.

[9] Moradi-Afrapoli & Askari-Nasab (2022) – Advanced Analytics for Surface Extraction. *Advanced Analytics in Mining Engineering. Leverage Advanced Analytics in Mining Industry to Make Better Business Decisions.* Edited by Soofastaei A., Springer.

[10] Noriega & Pourrahimian (2022). A systematic review of artificial intelligence and data-driven approaches in strategic open-pit mine planning. *Resources Policy, 1-13.*

[11] Paravarzar, Pourrahimian & Askari-Nasab (2018) – Short-Term Underground Mine Planning: A Review. *MOL Report Nine.*

[12] Price (2014) – Discrete-event haulage simulation. Making better decisions with reduced uncertainty. In: Runge Pincock Minarco. *Perspectives. Issue No. 123, April, 2014.* Retrieved from: http://www.rpmglobal.com/wp-content/uploads/2015/08/Issue123-Discrete-Event-Haulage-Simulation.pdf On: Dec. 7. 2017

[13] Rabe, Spiekermann & Wenzel (2008) – Verifikation und Validierung für die Simulation in Produktion und Logistik. Vorgehensmodelle und Techniken. Berlin, Heidelberg, Springer. ISBN: 978-3-540-25281-5.

[14] Upadhyay, Askari-Nasab, Tabesh & Badiozamani (2015) – Simulation & Optimization in Open Pit Mining. In Bandopadhyay (Ed.): *Application of computers and operations in research in the mining industry.* Englewood, Colo., Society for Mining Metallurgy & Exploration Inc. (SME).

Application of Simulation in Truck Fleet Selection and Sizing in Open-Pit Mining: With and Without Truck Failure Effect

Mohammadreza Kazemi Ashtiani[a], Ali Moradi Afrapoli[b], John Doucette[c] and Hooman Askari-Nasab[a]

Mining Optimization Laboratory (MOL)

[a] University of Alberta, Edmonton, Canada

[b] Université Laval, Québec City, Canada

[c] Department of Mechanical Engineering, University of Alberta, Canada

ABSTRACT

In this study, a novel simulation model is introduced to assess and determine the optimal configuration of truck fleet type and size for mining operations. The aim is to improve operational efficiency, productivity, and sustainability. The study investigates the performance of both homogeneous and heterogeneous fleets in various scenarios. The findings reveal that the heterogeneous fleet outperforms the homogeneous fleet in terms of meeting production targets and minimizing fuel consumption, thereby striking an effective balance between productivity and sustainability. Conversely, the homogeneous fleet exhibits higher total fuel consumption and fuel consumption per ton production. Additionally, smaller trucks in the fleet offer greater flexibility in transferring ore materials and prove advantageous in scenarios involving truck failures, with reduced average downtime. Therefore, homogenous fleet of smaller trucks outperforms the heterogenous fleet when truck failure is considered. The study emphasizes the importance of considering factors such as fleet type and sizing, truck failures, fuel consumption, and production rates in optimizing fleet performance and material flow in mining operations. These insights contribute to the development of strategies for improving overall mining efficiency and reducing costs.

Keywords: *Truck fleet selection and sizing, Open-pit mine, Sustainability, Truck failure, Simulation*

1. Introduction

Open-pit mining presents a variety of substantial challenges requiring solutions. These encompass mine design, road network analysis, infrastructure optimization, fleet management, truck quantity and type determination, and truck allocation. Achieving an efficient truck fleet size is crucial for a cost-effective hauling system in mining, ensuring production needs are met while minimizing expenses. Choosing the quantity and types of trucks for the fleet is a substantial financial commitment, given its non-reversible nature (Salhi and Rand, 1993). Within the mining system, an excess of trucks can lead to over-trucking, with trucks waiting for shovels, while too few trucks result in under-trucking, causing shovels to wait (Ataeepour and Baafi, 1999). Having the right fleet size is crucial for efficient transportation. Having too few or too many trucks can cause delays and underutilization. A shortage of trucks reduces production, while an excess raises GHG emissions. Achieving the optimum number of trucks maintains a balance between meeting production needs and minimizing GHG emissions.

ISBN: 978-1-55195-503-2

Simulation modeling proves potent for testing alternative actions, offering insights into optimal outcomes. In mining, these models predict the impact of new ideas and policies. Monte Carlo Simulation and specialized languages have simplified discrete event model creation, aiding analysis of production capacities, bottleneck identification, and resource utilization (Knights and Bonates, 1999). Manríquez et al. (2019) highlighted discrete event simulation's role in designing mining systems, including transportation routes and equipment types. For truck allocation, simulation has long been valued. Maran and Topuz (1988) stressed its importance, especially when traditional methods fall short. Discrete event simulation is widely used in optimizing truck and shovel systems due to its capacity to model randomness and complexity (Que et al., 2016).

This study employs Arena simulation software to develope a discrete event simulation model, evaluating fleet truck sizing and selection's influence on production rates and GHG emissions in open-pit mining. Truck allocation in the simulation model relies on a multi-objective optimization model aiming to minimize deviations from target production, shovel idle time, truck wait time, and fuel consumption. The study also examines the impact of truck failures in production and truck fleet selection.

In the upcoming sections, following a literature review, this research will introduce the simulation model and the integrated optimization model. Subsequently, a detailed explanation of the case study, including key performance indicators (KPIs), will be provided. Shifting to the results, the paper will analyze and compare the performance of different scenarios related to truck selection, sizing, and the impact of failures within a case study. Lastly, the paper will engage in a comprehensive discussion of the results, drawing conclusions, and outlining potential directions for future research.

2. Literature Review

The use of simulation techniques is crucial for effectively addressing fleet management and haulage systems within open-pit mining. Through the creation of a dynamic virtual environment, simulation empowers researchers and engineers to comprehensively analyze the impact of truck fleet selection and sizing in mining operations, production rate, and GHG emissions. As a result, decision-makers gain the insights needed to make informed choices. Simulation serves as a reliable tool for evaluating trade-offs and alternative scenarios, ultimately providing decision-makers with a clearer perspective, and enhancing efficiency, sustainability, and resource utilization. In what follows, a series of studies are presented that address the fleet selection and sizing challenge in open pit mining, followed by application of simulation in this context.

Bozorgebrahimi et al. (2003) reviewed critical parameters of fleet sizing in open pit mining. On the other hand, Burt and Caccetta (2018, 2014) explored fleet selection problem in mining, supported by case studies. They reviewed fleet selection problem challenges, applications, and solution approaches within the context of open-pit mining.

Over the years, various techniques have been used in fleet selecting and sizing in open-pit mining. Markeset and Kumar (2000) introduced the Lifecycle costing technique, followed by Samanta et al. (2002) who combined the Analytical Hierarchy Process and Life-cycle costing. Different approaches like the match factor concept (Burt and Caccetta, 2007; Douglas, 1964), queuing theory (Ercelebi and Bascetin, 2009), linear programming (Edwards et al., 2001; Ta et al., 2013), and machine repair modeling (A. Krause and Musingwini, 2007) have been used conventionally. In addition, innovative computer-based algorithms, including expert systems, fuzzy set theory, genetic algorithms, multiple criteria decision-making, and machine learning algorithms have also emerged (Bandopadhyay and Venkatasubramanian, 1987; Bazzazi et al., 2011; Li and Song, 2009; Marzouk and Moselhi, 2004; Nobahar et al., 2022). To address uncertainties in the selection of surface mining fleet, it is necessary to create a stochastic model. Discrete event simulation, pioneered by Rist (1961) for mine haulage, offers a solution by considering stochastic parameters. Noteworthy applications of this simulation method can be found in various mining studies (Ataeepour and Baafi, 1999; Baafi and Ataeepour,

1998; Chaowasakoo et al., 2017; Kolonja and Mutmansky, 1994; Que et al., 2016; Yuriy and Vayenas, 2008; Zeng et al., 2019; Zhang et al., 2022). However, these models often lack accuracy with respect to real-world fleet management systems and underestimate production capacity effects. To address these limitations, Moradi Afrapoli et al. (2019) presented an integrated simulation model encompassing mining, processing, and dispatching systems. Subsequently, several studies utilized the integration of simulation and dispatch optimization modeling to predict the optimal solution for the fleet selection and sizing problem in the presence of uncertainty (Mirzaei-Nasirabad et al., 2023; Mohtasham et al., 2021; Moradi-Afrapoli et al., 2021; Moradi-Afrapoli and Askari-Nasab, 2020; Moradi Afrapoli et al., 2022; Upadhyay et al., 2021; Yeganejou et al., 2022). Nevertheless, their model fails to account for energy efficiency, greenhouse gas (GHG) reduction, and truck failure. In this study, an integrated framework is established that integrates simulation and optimization, considering production capacity, energy efficiency, and GHG mitigation as well as truck failure.

3. Methodology

The integrated simulation and optimization model in this research relies on various input parameters and data, which encompass the short-term production schedule, the mine's road network, specifications for shovels and trucks detailing capacities and performance, information about dumping locations and their capacities, as well as the count of dumping points per dump location. Moreover, fitted probability distributions are necessary for numerous input variables, including loading and dumping times, hauling durations, empty travel times, backing times, spot times, shovel bucket capacities, and truck loading capacities. The majority of these inputs are stochastic, which makes them particularly challenging. Consequently, historical data for such random variables were employed to fit diverse probability density functions.

3.1. Multi-Objective Optimization Model

The truck dispatching optimization model utilized in this research is centered around four primary objectives: reducing deviations from target path flow rates, minimizing fuel consumption (and GHG emissions), minimizing shovel idle time, and minimizing truck wait time. Since these four objectives exist in varying dimensions, it is necessary to transform them into dimensionless forms. An efficient operation requires the satisfaction of several constraints. Furthermore, certain estimated parameters are utilized within the constraints, and their estimation methods (formulas) are presented in the equalization constraints of the mathematical model. Several indices, parameters, and decision variables are available within the optimization model. The indices are as follows:

t	Index for set of trucks: $t = \{1, \dots, T\}$
s	Index for set of shovels: $s = \{1, \dots, S\}$
d	Index for set of dumping points: $d = \{1, \dots, D\}$
d'	Index for set of locations where trucks are required to dump their load before traveling to the new shovel: $d' = \{1, \dots, D\}$
w	Index for set of weights assigned to individual goals: $w = \{1, 2, 3, 4\}$
g	index for the group of trucks that are currently waiting in a queue of the shovel: $g = \{1, \dots, NTWS\}$

The parameters are introduced below:

IT_{tsd}	Idle time for shovel s if truck t is assigned to transport material from shovel s to the dumping point d
WT_{tsd}	Wait time for truck t if it is assigned to transport material from shovel s to the dumping point d
N_w	Normalized weights of individual goals based on priority
AF	A factor balancing available trucks with the required capacity of plants
PC_d	Capacity of the plant d: $d = \{1, \dots, P\} \subset \{1, \dots, \mathrm{D}\}$
SC_s	Production capacity of shovel s
MP_{sd}	Path flow rate for the path from shovel s to the dumping point d that the production operation has met so far
TC_t	Actual capacity of truck t (tonne)
NTC_t	Nominal capacity of truck t (tonne)
P_{sd}	Path flow rate for the path from shovel s to the dumping point d
TR_{tsd}	Next time truck t reaches shovel s, if truck t is assigned to transport material from shovel s to the dumping point d
SA_{tsd}	Next time shovel s is available to serve truck t, if truck t is assigned to transport material from shovel s to the dumping point d
TNOW	Current time of the operation/simulation
$LD_{td'}$	The distance truck t must travel to reach the dumping point d' to dump its load
$ED_{td's}$	The distance truck t must travel from the dumping point d' to the next expected shovel s
ALT_t	Average loading time of truck t
APL_t	Average payload of truck t
$LV_{td's}$	Average loaded velocity of truck t traveling to dumping point d' and will travel to shovel s after dumping its load
$EV_{td's}$	Average empty velocity of truck t traveling from dumping point d' to the next expected shovel s
$DQ_{td'}$	Queue time for truck t in the queue of the dumping point d'
$DT_{td'}$	Dump time for truck t to dump its material in dumping point d'

$NTWS_s$	Number of trucks waiting in queue at shovel s
ST_g	Spotting time for the truck g in the queue
LT_g	Loading time for the truck g in the queue
α_t	Intercept of truck t for the fuel consumption
β_t	Payload coefficient of truck t for the fuel consumption
γ_t	Loading time coefficient of truck t for the fuel consumption
τ_t	Idle time coefficient of truck t for the fuel consumption
ω_t	Empty traveling time coefficient of truck t for the fuel consumption
φ_t	Loaded traveling time coefficient of truck t for the fuel consumption
SIT_{tsd}	Shovel idle time coefficient, by assigning truck t to the path of shovel s to dumping point d
TWT_{tsd}	Truck wait time coefficient, by assigning truck t to the path of shovel s to dumping point d
F_{tsd}	Truck fuel consumption coefficient, by assigning truck t to the path of shovel s to dumping point d

Below are the decision variables:

x_{tsd}	Binary variable equals to 1 if truck t assigns to the path of shovel s to dumping point d , and 0 otherwise
y_{sd}^{-}	Negative deviation of the met path flow rate and the desired path flow rate for the path between shovel s and dumping point d
y_{sd}^{+}	Positive deviation of the met path flow rate and the desired path flow rate for the path between shovel s and dumping point d

The model has the following objective functions:

$$f_1 = \sum_{s=1}^{S}\sum_{d=1}^{D}(y_{sd}^{-} + y_{sd}^{+}) \tag{1}$$

$$f_2 = \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{d=1}^{D} F_{tsd}x_{tsd} \tag{2}$$

$$f_3 = \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{d=1}^{D} SIT_{tsd}x_{tsd} \tag{3}$$

$$f_4 = \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{d=1}^{D} TWT_{tsd}x_{tsd} \tag{4}$$

The following two formulas are used to normalize the objective functions and to present the normalized weighted sum objective function, respectively.

$$\bar{f_i} = \frac{f_i - U_i}{N_i - U_i} \qquad \forall i \in \{1,2,3,4\} \tag{5}$$

$$f = N_1\bar{f_1} + N_2\bar{f_2} + N_3\bar{f_3} + N_4\bar{f_4} \tag{6}$$

The constraints of the model are expressed below:

$$\sum_{s=1}^{S}\sum_{d=1}^{D} TC_t x_{tsd} \le NTC_t \qquad \forall t \in \{1,\dots,T\} \tag{7}$$

$$\sum_{t=1}^{T}\sum_{s=1}^{S} TC_t x_{tsd} \ge AF \times PC_d \qquad \forall d \in \{1,\dots,P\} \tag{8}$$

$$\sum_{t=1}^{T}\sum_{d=1}^{D} TC_t x_{tsd} \le SC_s \qquad \forall s \in \{1,\dots,S\} \tag{9}$$

$$\sum_{t=1}^{T} TC_t x_{tsd} + MP_{sd} + y_{sd}^{-} - y_{sd}^{+} = P_{sd} \qquad \forall s \in \{1,\dots,S\} \,\&\, \forall d \in \{1,\dots,D\} \tag{10}$$

$$AF = \frac{\sum capacity\ of\ available\ trucks}{\sum required\ flow\ rate\ at\ paths} \tag{11}$$

$$TR_{tsd} = TNOW + \frac{LD_{td'}}{LV_{td's}} + DQ_{td'} + DT_{td'} + \frac{ED_{td's}}{EV_{td's}} \tag{12}$$
$$\forall t \in \{1,\dots,T\} \,\&\, \forall s \in \{1,\dots,S\} \,\&\, \forall d \in \{1,\dots,D\} \,\&\, \forall d' \in \{1,\dots,D\}$$

$$SA_{tsd} = TNOW + \sum_{g=1}^{NTWS_s} \left(ST_g + LT_g\right) \tag{13}$$
$$\forall t \in \{1,\dots,T\} \,\&\, \forall s \in \{1,\dots,S\} \,\&\, \forall d \in \{1,\dots,D\}$$

$$SIT_{tsd} = \max\left(0, TR_{tsd} - SA_{tsd}\right) \tag{14}$$
$$\forall t \in \{1,\dots,T\} \,\&\, \forall s \in \{1,\dots,S\} \,\&\, \forall d \in \{1,\dots,D\}$$

$$TWT_{tsd} = \max\left(0, SA_{tsd} - TR_{tsd}\right) \tag{15}$$
$$\forall t \in \{1,\dots,T\} \,\&\, \forall s \in \{1,\dots,S\} \,\&\, \forall d \in \{1,\dots,D\}$$

$$F_{tsd} = \alpha_t + \beta_t \times APL_t + \gamma_t \times ALT_t + \tau_t \times TWT_{tsd} + \omega_t \frac{ED_{td's}}{EV_{td's}} + \varphi_t \frac{LD_{td'}}{LV_{td's}} \quad (16)$$

$$\forall t \in \{1, \dots, T\} \,\&\, \forall s \in \{1, \dots, S\} \,\&\, \forall d \in \{1, \dots, D\} \,\&\, \forall d' \in \{1, \dots, D\}$$

$$x_{tsd} \in \{0,1\} \qquad \forall t \in \{1, \dots, T\} \,\&\, \forall s \in \{1, \dots, S\} \,\&\, \forall d \in \{1, \dots, D\} \quad (17)$$

$$y_{sd}^{-} \geq 0 \qquad \forall s \in \{1, \dots, S\} \,\&\, \forall d \in \{1, \dots, D\} \quad (18)$$

$$y_{sd}^{+} \geq 0 \qquad \forall s \in \{1, \dots, S\} \,\&\, \forall d \in \{1, \dots, D\} \quad (19)$$

The first objective employs a goal programming approach to minimize deviations from path flow rates, which is computed using Eq. (1). The second objective function seeks to minimize the total fuel consumption of active trucks using Eq. (2). The third objective centers on minimizing the idle time of active shovels using Eq. (3). The fourth objective is to decrease truck wait time during operations, calculated using Eq. (4). To achieve the model's solution, the four objectives are made dimensionless using Nadir and Utopia points (Grodzevich and Romanko, 2006), defining lower and upper limits. This process scales objectives from 0 to 1 using Eq. (5). Priority weights for the weighted sum method are based on normalized versions of objectives from Eqs. (1) to (4) in Eq. (6). There are several constraints in the model. Constraint (7) restricts a truck's payload to its nominal capacity for tonnage transport in one cycle. In constraint (8), the material transported to processing plants via all trucks must fulfill processing targets set by each plant, adjusted by the AF factor (calculated in Eq. (11)). Only the AF portion of plant requirements can be fulfilled. Constraint (9) limits haulage capacity to a shovel's nominal digging rate, while constraint (10) calculates path flow rate deviations for paths linking a shovel as a source and a dumping location as a destination. Eq. (12) is employed to ascertain the arrival time of each truck for loading by a shovel. Shovel availability is determined using Eq. (13), predicting the next time the shovel will be available to load the truck. The coefficients for the three optimization objectives are computed through Eqs. (14), (15), and (16), corresponding to shovel idle time, truck wait time, and fuel consumption objective functions, respectively. Lastly, constraint (17) guarantees the binary nature of the first set of decision variables, while constraints (18) and (19) ensure non-negativity for the goal programming variables.

3.2. Integrated Simulation and Optimization Framework

The simulation section of the framework employs a step-by-step approach, as depicted in Figure 1. Initially, the model identifies trucks awaiting assignment to operational shovels and destinations. Subsequently, the multi-objective optimization model comes into action, efficiently allocating unassigned trucks. This ensures that all available trucks are effectively assigned their respective tasks. Throughout the simulation, the optimization model is recalibrated in response to specific events, such as truck initiation, dumping completion, or truck reactivation following a failure. These occurrences trigger a reassessment of the optimal assignment for each truck. The optimization process for assigning available trucks persists throughout the simulation runtime until the predefined time period for the simulation is reached. The input data for the framework encompasses the quantity and types of trucks present within the system. As a result of this input, the framework generates Key Performance Indicators (KPIs) statistical report, which will be elaborated upon in the subsequent section. Figure 2 depicts the hauling procedure executed by trucks in open-pit mining. The sequence commences at the terminal, where trucks are designated to ore or waste shovels, determined by considerations like production goals, travel durations, queue statuses, and processing periods. Following this, the trucks journey to either the waste dump or one of the crushers/plants, contingent on their cargo and the hopper capacities at each plant. Ultimately, the trucks are reassigned to a different shovel based on the timetable and objective functions, and this cycle persists. Finally, Figure 3 presents a flowchart of a truck status during the operation. Once a failed truck has been repaired, it becomes imperative to reassign it to a new loading or unloading point.

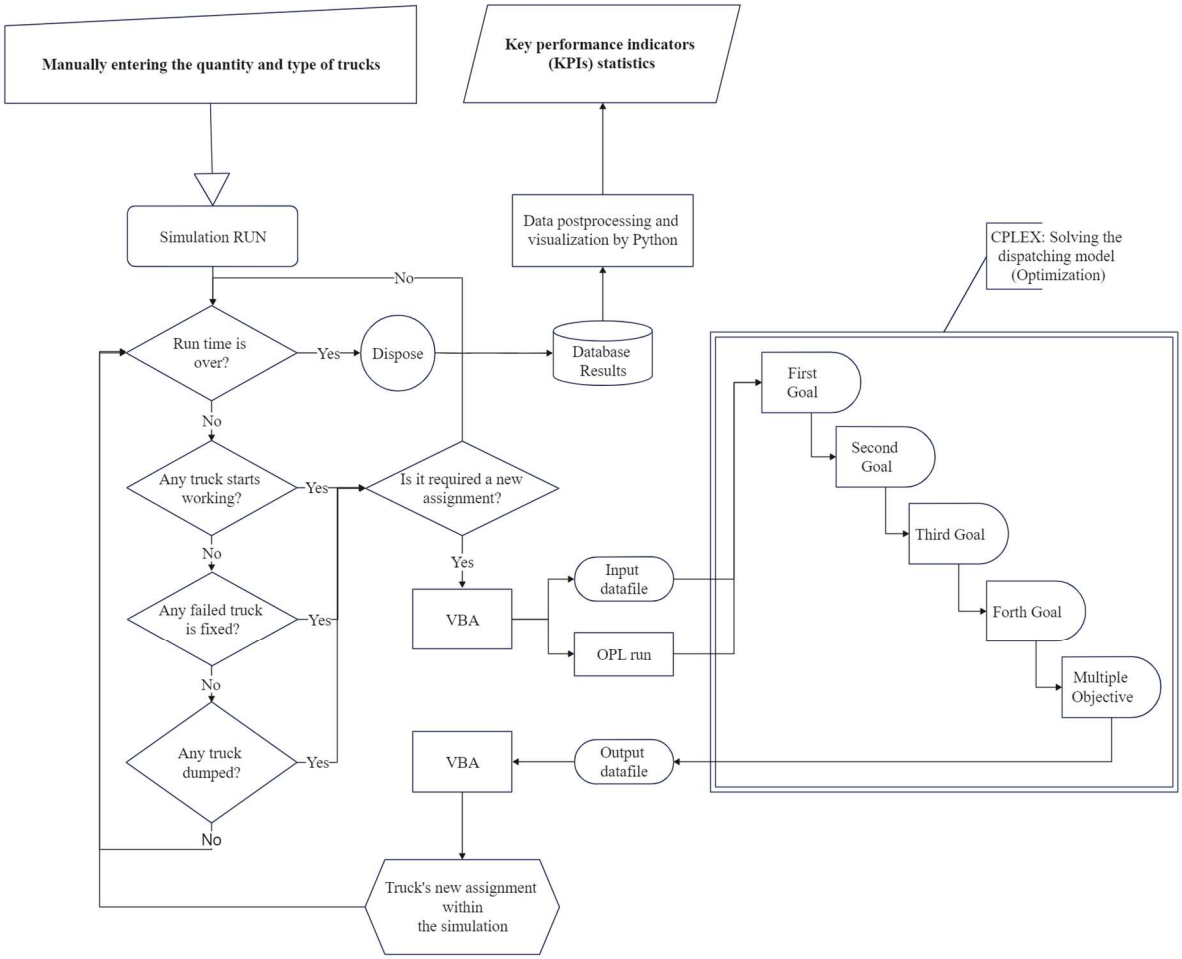


Figure 1. An overview of the simulation and optimization integration process.

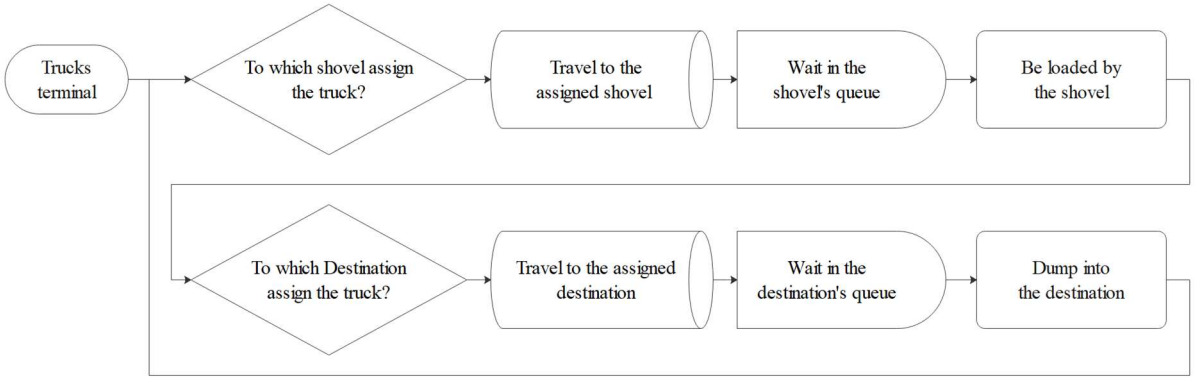


Figure 2. An active truck's operations.

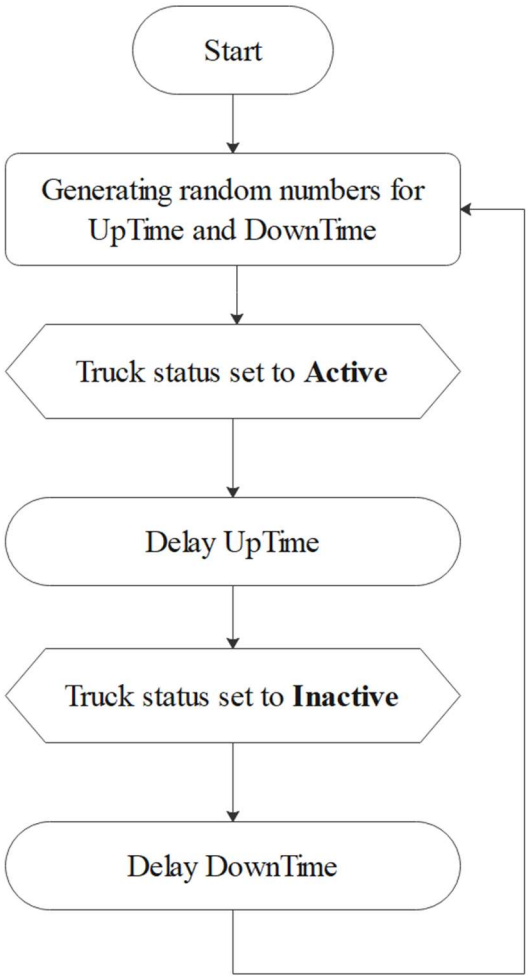


Figure 3. Truck status flowchart.

3.3. Key Performance Indicators (KPIs)

Variables below are introduced as KPIs in this study. Collectively, these variables wield a substantial influence in evaluating and optimizing truck dispatching within mining operations, facilitating improved decision-making, heightened operational efficiency, and enhanced profitability.

- Total ore tonnage production: This metric reflects the overall volume of ore transported to processing plants, directly impacting the mining operation's profitability and productivity.
- Total ore and waste tonnages mined and delivered: Monitoring the total quantities of both ore and waste materials offers insights into mining process efficiency and facilitates resource utilization optimization.
- Utilization of ore and waste shovels: Evaluating the usage of shovels dedicated to ore and waste handling ensures optimal deployment and helps identify potential operational bottlenecks or underutilized equipment.
- Total and average queue times for trucks: Tracking queue times for trucks awaiting loading or unloading provides operational efficiency information and reveals areas where delays might occur.

- Trucks' fuel consumption: Effective fuel management is vital for cost control and environmental sustainability. Monitoring and optimizing fuel usage aids in minimizing operational expenses and carbon emissions.
- Fuel consumption of a truck per tonne of production: This measure offers insights into trucks' fuel efficiency relative to the amount of material transported. It identifies opportunities for enhancing fuel efficiency and reducing operational costs.
- Ore TPGOH (tonne per gross operating hour): This gauge quantifies mining productivity by calculating extracted ore per equipment operation hour. Higher TPGOH values signify better efficiency and productivity.
- Stripping ratio: This ratio compares waste material removal volume to ore extraction volume, shedding light on the balance between ore production and waste elimination.
- Trucks' availabilities and downtimes: Monitoring truck availability and tracking downtimes identifies potential equipment failures, planned maintenance activities, and minimizes mining operation disruptions. Additionally, it can significantly impact TPGOH.

4. Design of Experiments, and Results

This study includes a case study utilizing historical data from the Gol-E-Gohar iron ore open-pit mine in Iran to assess the developed framework. The evaluation aims to analyze the performance of different truck fleets in terms of their truck's types and quantities, and also to investigate the impact of truck failures on each fleet scenario. Figure 4 depicts the arrangement of loading and dumping points, as well as the operational road network. At the loading points, there are five active shovels, with two designated for ore extraction and three for waste. At the dumping points, there are three destinations including two processing plants and a waste dump.

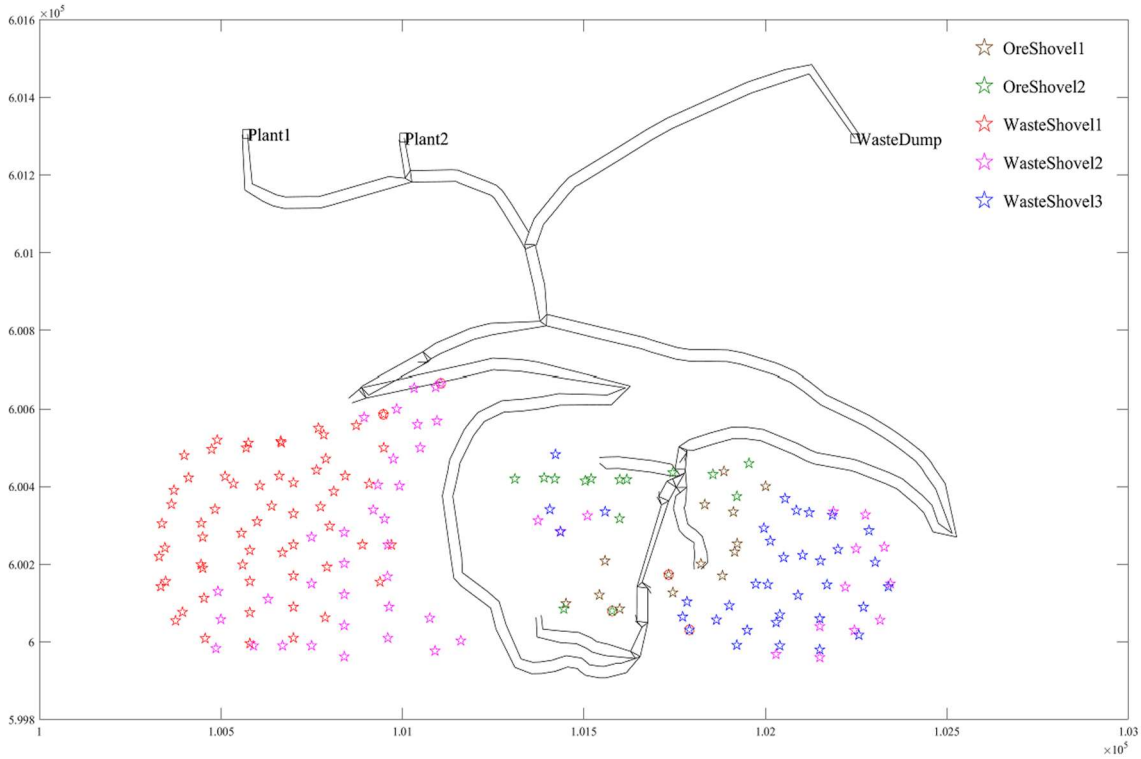


Figure 4. Gol-E-Gohar iron ore mine network.

The equipment present in the case study comprises Hitachi EX2500 and Hitachi EX5500 shovels, as well as Caterpillar 785C and Caterpillar 793C trucks for the transportation operations. The mining

activities involve three distinct destinations: two processing plants equipped with two hoppers each, and a waste dump featuring multiple dumping points. The distribution of shovels and trucks to the excavation and dumping locations is outlined in Table 1.

Table 1. Equipment distributions.

Origin	Destination	Shovel Type	Truck Type
Shovel 1	Plant 1 Plant 2	Hitachi EX2500	Cat 785C Cat 793C
Shovel 2	Plant 1 Plant 2	Hitachi EX2500	Cat 785C Cat 793C
Shovel 3	Waste Dump	Hitachi EX5500	Cat 785C Cat 793C
Shovel 4	Waste Dump	Hitachi EX5500	Cat 785C Cat 793C
Shovel 5	Waste Dump	Hitachi EX2500	Cat 785C Cat 793C

There is deterministic and stochastic information included in the case study's input data. The Arena Input Analyzer tool (Rockwell Automation, 2019) has been utilized in (Moradi Afrapoli, 2018) for the establishment of stochastic input distributions based on historical data. Each processing plant has a feeding rate target (capacity limit) of 2300 tonnes per hour.

The calculation of fuel consumption for individual CAT 785C trucks is performed using Eq. (20) obtained from (Dindarloo and Siami-Irdemoosa, 2016):

$$F(\frac{l}{cycle}) = 1.37071 + 0.00483 \times PL + 0.00398 \times LT + 0.00499 \times ES + 0.01471 \times ETR + 0.00278 \times LS + 0.0519 \times LTR \quad (20)$$

F: fuel consumption per cycle (liters)

PL: payload (tonnes)

LT: loading time (seconds)

ES: empty idle time (seconds)

ETR: empty travel time (seconds)

LS: loaded idle time (seconds)

LTR: loaded travel time (seconds)

The fuel consumption for the CAT 793C truck type is determined through Eq. (21), where a specific coefficient from the Caterpillar handbook (Caterpillar Performance Handbook Edition 29, 1999) is multiplied with it. This coefficient accounts for factors such as load and haul conditions, road conditions, grades, and rolling resistance. As a result, the CAT 793C's fuel consumption is approximately 1.59 times that of CAT 785C. Thus, Eq. (21) outlines the formula utilized to compute the fuel consumption for CAT 793C trucks in each operational cycle.

$$F(\frac{l}{cycle}) = 2.17943 + 0.00768 \times PL + 0.00633 \times LT + 0.00793 \times ES + 0.02339 \times ETR + 0.00442 \times LS + 0.0825 \times LTR \quad (21)$$

The simulation encompassed a duration of 10 days, involving 12 hours of operation per day, with the goal of achieving a satisfactory ore production of 550,000 tonnes for the planned mining operations over this period.

The operational efficiency, productivity, cost-effectiveness, and sustainability of a mining fleet are significantly impacted by the number and varieties of trucks within it. It is crucial to carefully consider the right quantity of trucks, select appropriate truck types, and efficiently manage their dispatch. This plays a vital role in developing a productive and financially viable fleet system. Through analysis of these factors and implementing fleet management approaches,, mining companies can streamline operations, boost productivity, and reduce expenses and environmental impacts. This research presents 40 scenarios based on different truck types and quantities. The first nine scenarios focus on a homogenous fleet of CAT 785C trucks.. Subsequently, the following eight scenarios involve a homogenous fleet of CAT 793C trucks, each with varying quantities. The remaining scenarios encompass a diverse fleet arrangement, incorporating both CAT 785C and CAT 793C trucks (heterogenous fleet) within the system. Within the Appendix, there is a comprehensive table (Table A. 1) that presents the key performance indicators (KPIs) for each distinctive scenario involving diverse combinations of truck types and quantities. Among the scenarios, scenario 6 with a homogenous fleet of 30 CAT 785C trucks, scenario 13 featuring 18 CAT 793C trucks in a homogenous fleet, and scenario 24 that combines 20 CAT 785C trucks with 5 CAT 793C trucks in a heterogenous fleet, demonstrate the best performance in terms of achieving production goals and reducing fuel usage as shown in Figure 5, Figure 6, and Figure 7.

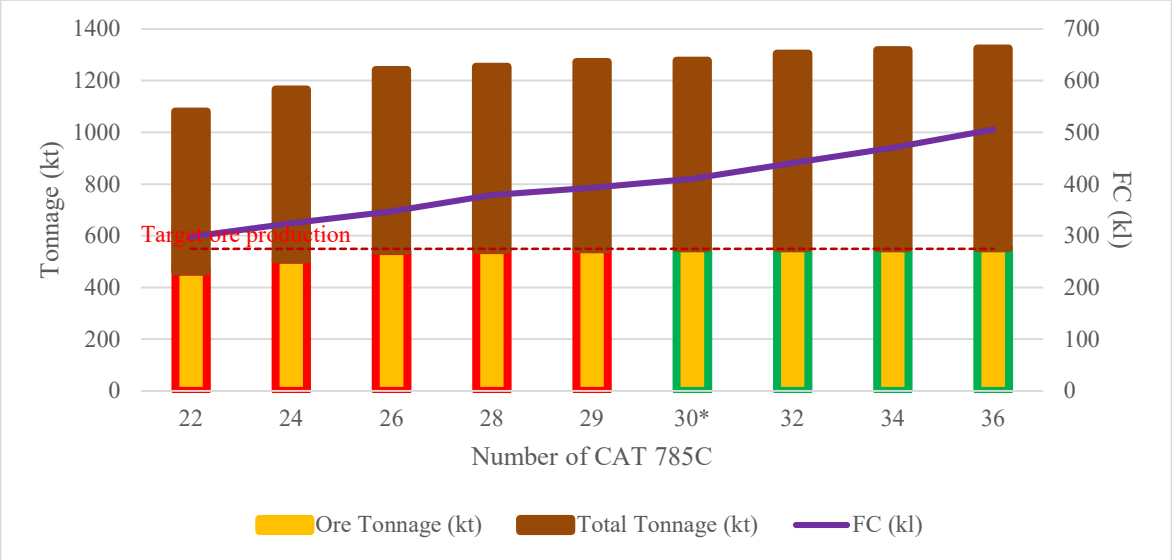


Figure 5. Production and fuel consumption in homogenous fleet of CAT 785C.

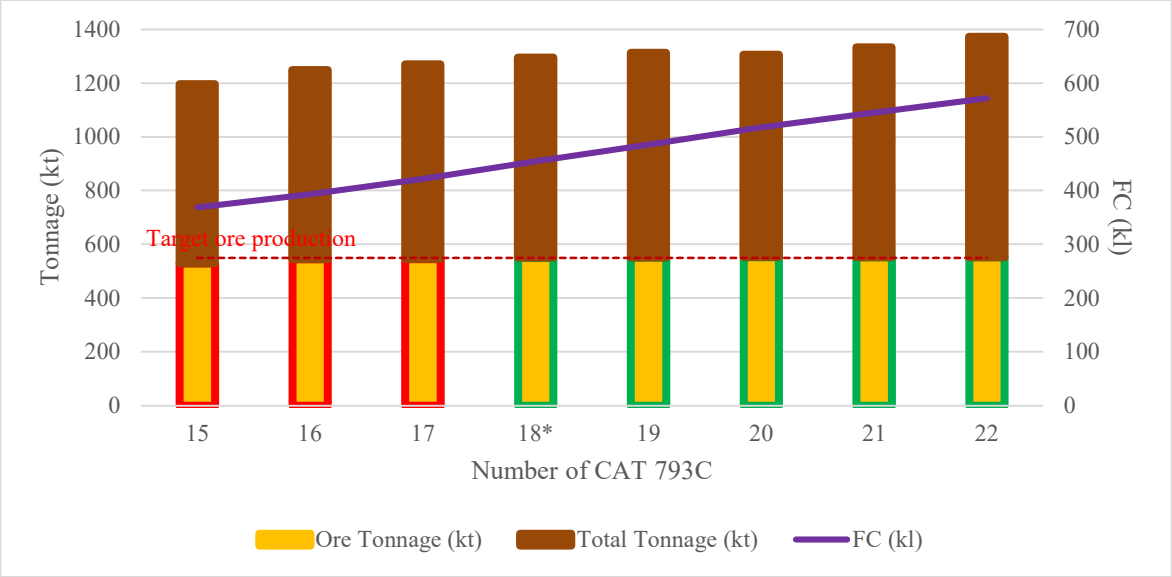


Figure 6. Production and fuel consumption in homogenous fleet of CAT 793C.

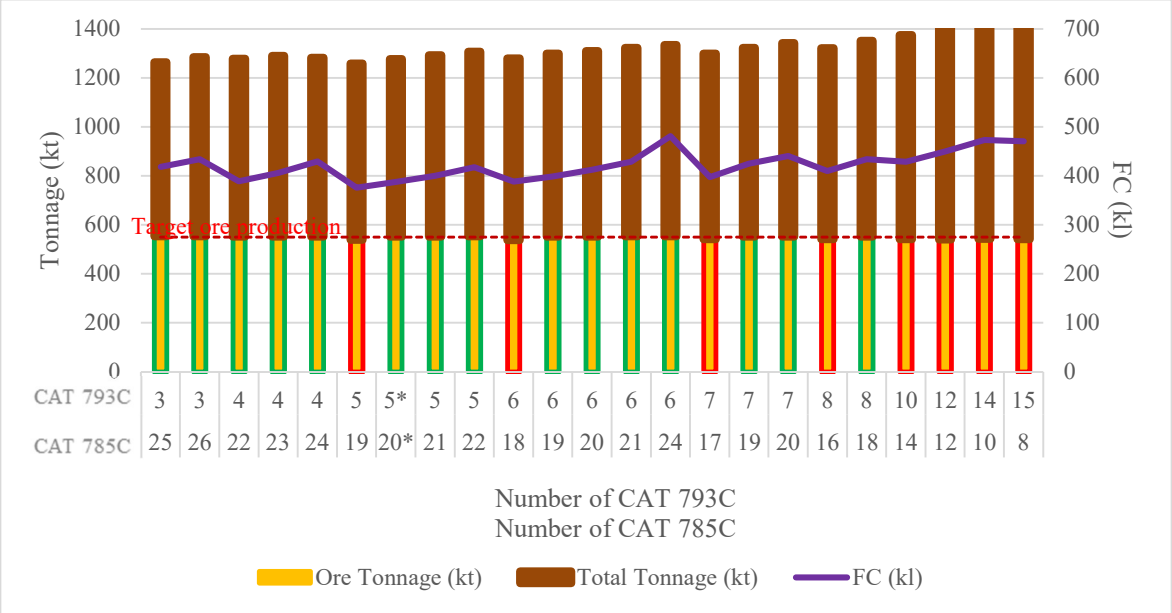


Figure 7. Production and fuel consumption in heterogenous fleet of CAT 785C and CAT 793C.

With the central aim being the maximization of production, scenario 24 emerges as the optimal selection by simultaneously achieving production targets, minimizing fuel usage, and reducing carbon emissions. This configuration involves a fleet composition comprising 20 smaller trucks (CAT 785C) and 5 larger trucks (CAT 793C). This choice effectively strikes a balance between the demand for high productivity and the imperative to curtail fuel consumption and environmental impact, aligning seamlessly with the sustainability objectives outlined in this study. Scenario 6 boasts the highest utilization of ore and waste shovels, closely followed by scenario 24. Among the three scenarios, scenario 13 demonstrates the lowest utilization of shovels. When considering average truck queue times, scenario 6 holds the record for the longest, followed by scenario 24. Scenario 13 displays the shortest average truck queue time among the three scenarios. All three scenarios achieve acceptable ore tonnage, with scenario 6 slightly surpassing in ore tonnage, and scenario 13 slightly lagging. Surprisingly, scenario 13 showcases the highest total tonnage, standing notably higher than

the other scenarios, followed by scenario 6. In contrast, scenario 24 presents a slightly lower total tonnage when compared to scenario 6. In terms of fuel consumption, a comparison between scenario 6, scenario 13, and the lowest fuel consumption recorded in scenario 24 reveals a clear distinction. Scenario 6 shows a 5.83% higher fuel consumption ratio, while scenario 13 exhibits a significantly higher ratio difference of 17.35%.

Table 2 details the average cycle numbers for each shovel and destination for every truck in scenario 24. Moreover, it provides the OreCycles%, which is the percentage of times a truck transports ore material of the total cycles. Similarly, it presents the WasteCycles%, representing the percentage for waste material transport.

Table 2. Heterogenous fleet cycles of scenario 24.

Truck Type	Truck#	SH1	SH2	SH3	SH4	SH5	P1	P2	WD	Ore Cycles (%)	Waste Cycles (%)
785C	1	84	82.2	50.4	56.6	51.6	82.8	83.4	158.6	51	49
	2	82.8	77.8	54.4	58.8	55.4	79.4	81.2	168.6	49	51
	3	75.4	78.4	60.4	59.8	58	74.8	79	178.2	46	54
	4	79.8	76.4	60.8	63.4	53	81.2	75	177.2	47	53
	5	80.6	74.6	61.6	67	52.6	75.6	79.6	181.2	46	54
	6	81.6	65.4	60.2	76	57.2	68.8	78.2	193.4	43	57
	7	84.2	67.6	65.8	71.8	51.2	69.6	82.2	188.8	45	55
	8	72.6	71.4	71.4	69.2	57.4	66.8	77.2	198	42	58
	9	81.6	65	66.6	83	51	69.4	77.2	200.6	42	58
	10	71.8	68.4	67.2	85.6	56.4	65.2	75	209.2	40	60
	11	72.2	70.8	77.4	82.4	47.6	69.8	73.2	207.4	41	59
	12	73.6	63.4	72	85.4	54	66.4	70.6	211.4	39	61
	13	73.4	65.8	76.6	88	48.2	67	72.2	212.8	40	60
	14	68.4	68	78.2	88.6	53	67.2	69.2	219.8	38	62
	15	71.4	64.6	79.4	82.8	55.2	63.8	72.2	217.4	38	62
	16	77	64.8	84.2	83.2	45.8	65.2	76.6	213.2	40	60
	17	78.4	64	73.2	80.2	50.2	67.6	74.8	203.6	41	59
	18	76.2	76	78.6	75	43.4	74	78.2	197	44	56
	19	70.6	77.6	78	84.4	41.4	67.6	80.6	203.8	42	58
	20	76	78.2	79	75.6	41	74	80.2	195.6	44	56
793C	21	47.8	67.8	48.4	44.8	95.8	67.4	48.2	189	38	62
	22	45.4	60.4	58.4	39	104.2	61.8	44	201.6	34	66
	23	48.2	61	53.8	42.6	98	61.4	47.8	194.4	36	64
	24	52.2	57	54.4	44.4	101.4	58.2	51	200.2	35	65
	25	51.4	61.6	46.8	39.4	103.2	61.8	51.2	189.4	37	63

The findings highlight that CAT 793C trucks transport larger quantities of waste in comparison to CAT 785C trucks. While waste dumping isn't constrained by hourly capacity, plants have specific hourly hopper limits. Trucks with lower capacities offer greater flexibility for transferring ore materials within the system, making them a more suitable choice for assignment to ore shovels. Furthermore, a significant distinction is observed in the assignment of large trucks to waste shovel

5. This difference primarily arises from the fact that shovel 5 boasts a higher digging rate and capacity than the other waste shovels.

In Table 3, the KPIs for the most promising scenarios, accounting for truck failures, are shown. These scenarios, previously discussed without factoring in truck failures. Considering truck failures, scenario 6, featuring a homogeneous CAT 785C truck fleet with 30 number of trucks, stands out for its remarkable tonnage transportation, production rate, and shovels' utilization. Although its fuel consumption isn't the lowest, its rate per tonne of production is acceptable.. Examining the impact of truck failures, it becomes evident that a fleet with a higher number of smaller trucks holds advantages in achieving the hourly ore production rate. Despite their smaller capacities, the flexibility of smaller trucks enhances their effectiveness Moreover, these smaller trucks (CAT 785C) experience reduced downtime when compared to the larger trucks (CAT 793C), further enhancing their performance in the context of truck failures.

Table 3. KPIs of the Best Scenarios with the Trucks failure, and differences' percentages in KPIs.

Scenario	Util. Ore (%)	Util. Waste (%)	Average Q time (Mins)	Total Q time (Hrs)	FC (KL)	Ore Tonnage (KT)	Total Tonnage (KT)	Ore TPGOH (T)	SR
6(F)	78.1	53.5	3.4	527	361	531	1222	4421	1.30
13(F)	66.6	43.3	2.3	190	389	512	1180	4264	1.31
24(F)	71.8	50.1	2.9	378	343	502	1171	4181	1.33
(%) Diff. 6(F) and 6	-3.8	-4.8	-11.4	-15.3	-12.0	-4.0	-4.4	-4.0	-0.8
(%) Diff. 13(F) and 13	-7.0	-10.2	-11.0	-17.4	-14.4	-7.0	-8.9	-7.0	-3.0
(%) Diff. 24(F) and 24	-8.8	-7.1	-15.7	-21.8	-11.4	-9.0	-8.3	-9.0	1.5

Scenario 6 stands out with the least variation in KPIs compared to other scenarios. This suggests that incorporating a larger number of smaller trucks in the fleet can minimize production losses in the event of unplanned failures. However, when considering the presence of a stockpile or several stockpiles in the system and a slightly higher number of trucks in both types, a heterogenous fleet still outperforms homogenous fleets.

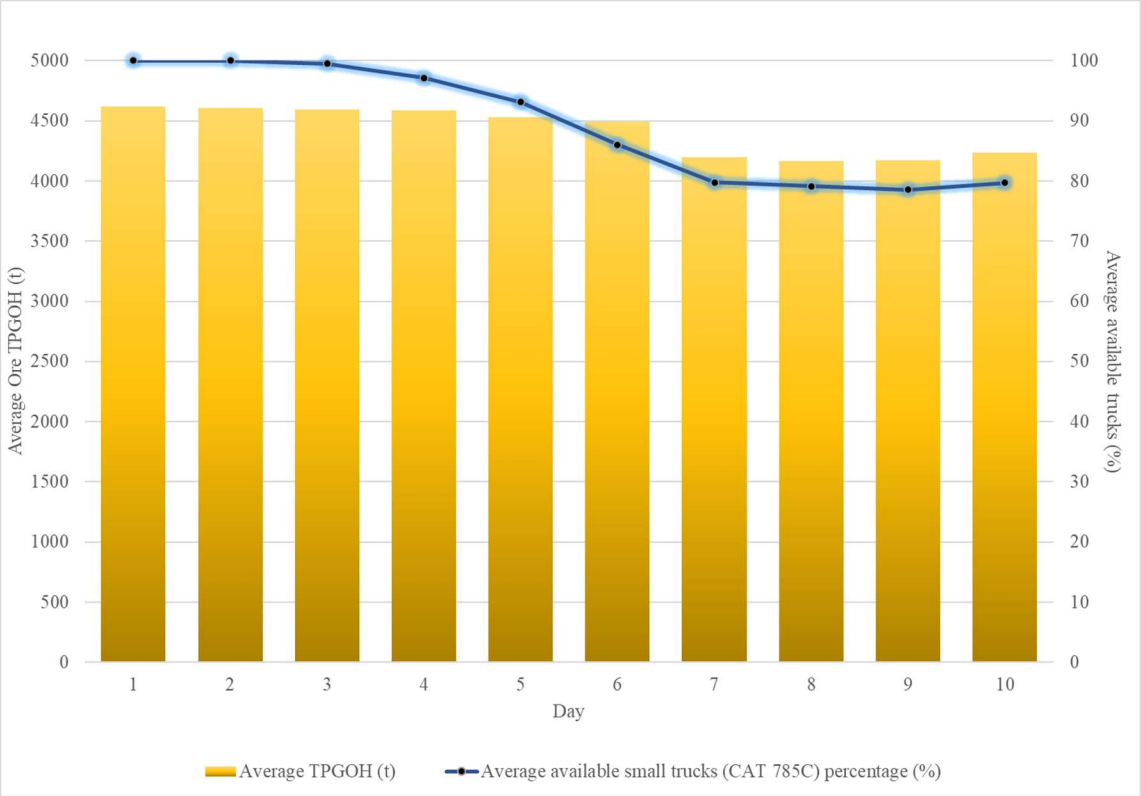


Figure 8, and Figure 9 illustrate that the daily average TPGOH for scenario 6 and scenario 24, respectively, is significantly impacted by the daily average number of active trucks available in the system. This underscores that a decrease in the active truck count can result in a corresponding reduction in the TPGOH and consequently, total ore production.

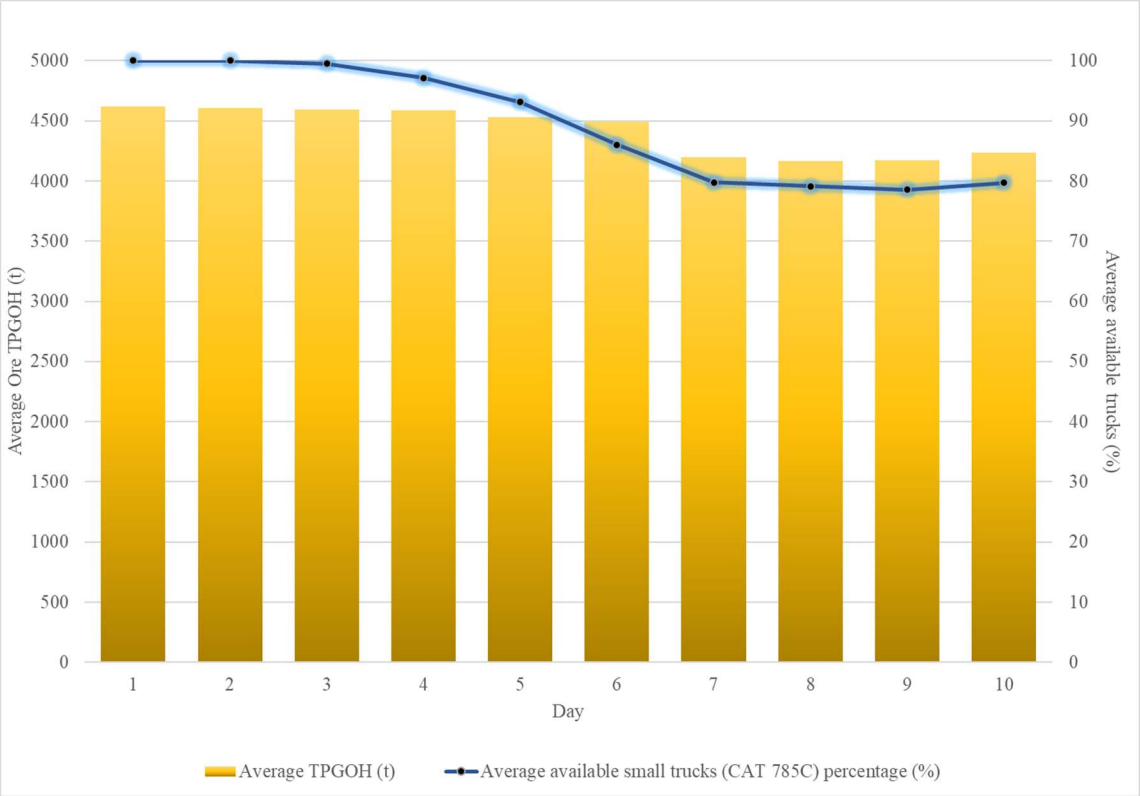


Figure 8. Scenario 6 (Homogeneous fleet - 30 small trucks) - impact of truck failures on average TPGOH.

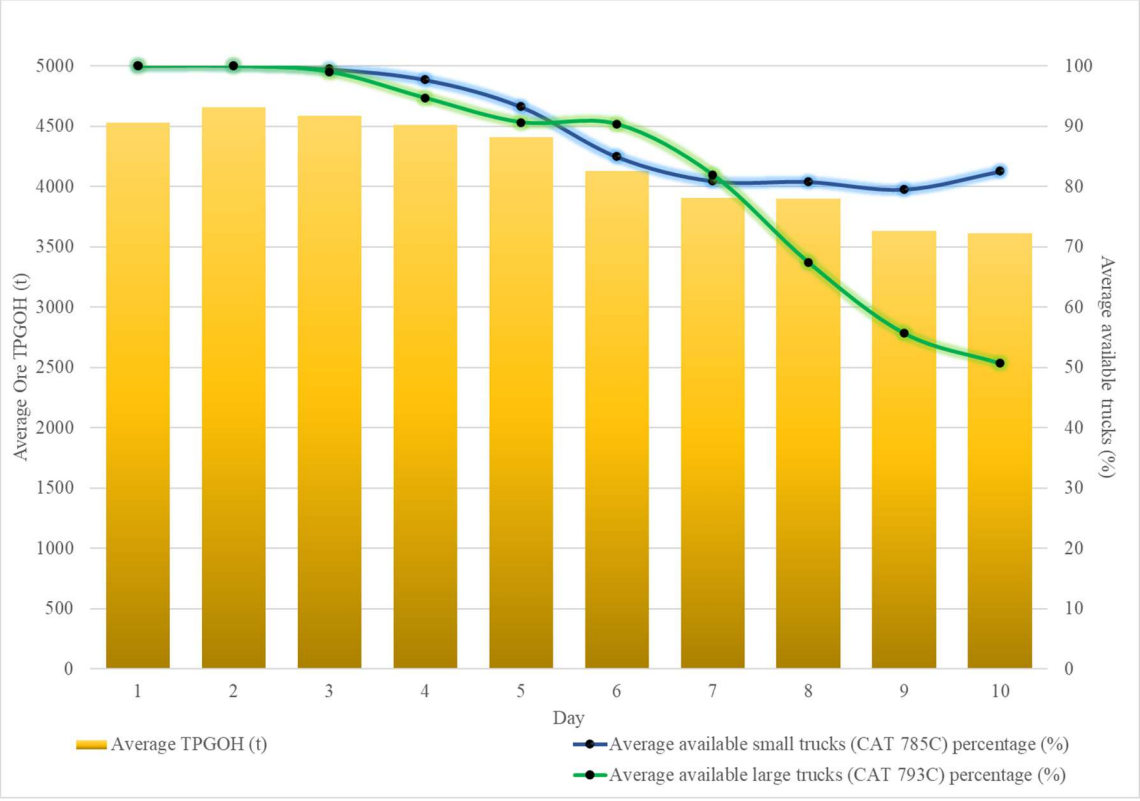


Figure 9. Scenario 24 (Heterogenous fleet - 25 Small and 5 large trucks) - impact of truck failures on average TPGOH.

5. Conclusions

The study primarily focused on determining the optimal quantity and types of trucks required within the system, utilizing a developed truck dispatching optimization model. model's primary objective was to minimize deviations in path flow rates, shovel idle time, truck wait time, and truck fuel consumption. An important contribution of this research was the incorporation of fuel consumption and GHG emissions as criteria for truck fleet selection and sizing. Furthermore, the study enhanced the model's practicality and reliability by considering truck uptime and downtime.

The number and types of trucks within a mining fleet exerted a substantial impact on operational efficiency, productivity, and cost-effectiveness. Apart from an efficient dispatching system, optimizing the selection and quantity of available trucks played a pivotal role in establishing a sustainable and productive haulage system for open-pit mines. Among the various scenarios explored, scenario 24, a mix of 20 CAT 785C and 5 CAT 793C trucks in a heterogeneous fleet, displayed optimal performance in meeting production targets and minimizing fuel consumption. This configuration effectively balanced high productivity with the imperative to reduce fuel consumption and environmental impact, aligning well with the study's sustainability goals. Scenario 6, consisting of 30 CAT 785C trucks, exhibited a 5.83% higher fuel consumption ratio and 5.45% higher fuel consumption per tonne of production. The CAT 793C trucks transported more waste material per truck due to their higher capacity. Notably, while dumping in the waste disposal area had no hourly capacity restriction, the processing plants had specific hourly hopper capacities. Trucks with lower capacities offered enhanced flexibility in transferring ore materials and were better suited for assignment to ore shovels.

In scenarios accounting for truck failures, a fleet with a higher number of smaller trucks proved advantageous in maintaining the hourly ore production rate due to increased flexibility, despite the smaller average capacity per truck. Additionally, smaller trucks had lower average downtimes compared to larger counterparts, contributing to their superior performance in the context of truck failures. When prioritizing fuel consumption per tonne of production, scenario 6 with a homogeneous fleet of 30 small trucks, along with scenarios 20 (comprising 22 small and 4 large trucks) and 24 (comprising 20 small and 5 large trucks) with heterogeneous fleets, emerged as the most reliable and efficient choices. However, scenario 6 stood out due to its higher production rate and dispatching flexibility, making it the optimal selection when accounting for unforeseen failures in the model. In conclusion, considering truck failures, fuel consumption, and production rates, scenario 6 with a homogeneous fleet of 30 CAT 785C trucks demonstrated favorable performance. Nonetheless, introducing one or more stockpiles into the system and having a slightly higher number of trucks of both types could potentially lead to a heterogeneous fleet outperforming homogeneous ones. It is important to note that stockpiling wasn't a part of this study's framework. These considerations ensured steady material flow, mitigated truck failure effects, and optimized overall production efficiency in mining operations.

Future research should consider aspects such as truck age, shovel failure impact, and stockpile integration to improve the modeling approach's reliability, realism, and comprehensiveness. Incorporating these factors could lead to more accurate predictions, refined optimization strategies, and ultimately, greater efficiency and sustainability in mining operations.

6. References

[1] A. Krause, A., Musingwini, C., 2007. Modelling open pit shovel-truck systems using the Machine Repair Model. J. South. African Inst. Min. Metall. 107, 469–476.

[2] Ataeepour, N., Baafi, E.Y., 1999. ARENA simulation model for truck-shovel operation in despatching and non-despatching modes. Int. J. Surf. Mining, Reclam. Environ. 13, 125–129. https://doi.org/10.1080/09208119908944228

[3] Baafi, E.Y., Ataeepour, M., 1998. Using ARENA® to simulate truck-shovel operation. Miner. Resour. Eng. 7, 253–266.

[4] Bandopadhyay, S., Venkatasubramanian, P., 1987. Expert systems as decision aid in surface mine equipment selection. Int. J. Surf. Mining, Reclam. Environ. 1, 159–165.

[5] Bazzazi, A.A., Osanloo, M., Karimi, B., 2011. Deriving preference order of open pit mines equipment through MADM methods: Application of modified VIKOR method. Expert Syst. Appl. 38, 2550–2556.

[6] Bozorgebrahimi, E., Hall, R.A., Blackwell, G.H., 2003. Sizing equipment for open pit mining–a review of critical parameters. Min. Technol. 112, 171–179.

[7] Burt, C.N., Caccetta, L., 2018. Equipment selection for mining: with case studies. Springer.

[8] Burt, C.N., Caccetta, L., 2014. Equipment selection for surface mining: a review. Interfaces (Providence). 44, 143–162.

[9] Burt, C.N., Caccetta, L., 2007. Match factor for heterogeneous truck and loader fleets. Int. J. Mining, Reclam. Environ. 21, 262–270. https://doi.org/10.1080/17480930701388606

[10] Caterpillar Performance Handbook Edition 29, 1999.

[11] Chaowasakoo, P., Seppälä, H., Koivo, H., Zhou, Q., 2017. Improving fleet management in mines: The benefit of heterogeneous match factor. Eur. J. Oper. Res. 261, 1052–1065. https://doi.org/10.1016/j.ejor.2017.02.039

[12] Dindarloo, S.R., Siami-Irdemoosa, E., 2016. Determinants of fuel consumption in mining trucks. Energy 112, 232–240. https://doi.org/10.1016/j.energy.2016.06.085

[13] Douglas, J., 1964. Prediction Shovel-Truck Production: A Reconciliation Of Computer And Conventional Estimates.

[14] Edwards, D.J., Malekzadeh, H., Yisa, S.B., 2001. A linear programming decision tool for selecting the optimum excavator. Struct. Surv. 19, 113–120.

[15] Ercelebi, S.G., Bascetin, A., 2009. Optimization of shovel-truck system for surface mining. J. South. African Inst. Min. Metall. 109, 433–439.

[16] Knights, P.F., Bonates, E.J.L., 1999. Applications of discrete mine simulation modeling in South America. Int. J. Surf. Mining, Reclam. Environ. 13, 69–72. https://doi.org/10.1080/09208119908944211

[17] Kolonja, B., Mutmansky, J.M., 1994. Analysis of truck dispatching strategies for surface mining operations using SIMAN. Trans. Min. Metall. Explor. Inc. 296, 1845–1851.

[18] Li, X., Song, X., 2009. Application of genetic algorithm to optimize the equipment of coal mine, in: 2009 International Conference on Computational Intelligence and Software Engineering. IEEE, pp. 1–3.

[19] Manríquez, F., Morales, N., Pinilla, G., Piñeyro, I., 2019. Discrete event simulation to design open-pit mine production policy in the event of snowfall. Int. J. Mining, Reclam. Environ. 33, 572–588. https://doi.org/10.1080/17480930.2018.1514963

[20] Maran, J., Topuz, E., 1988. Simulation of truck haulage systems in surface mines. Int. J. Surf. Mining, Reclam. Environ. 2, 43–49. https://doi.org/10.1080/09208118808944136

[21] Markeset, T., Kumar, U., 2000. Application of LCC techniques in selection of mining equipment and technology, in: Mine Planning and Equipment Selection 2000. Routledge, pp. 635–640.

[22] Marzouk, M., Moselhi, O., 2004. Multiobjective optimization of earthmoving operations. J.

Constr. Eng. Manag. 130, 105–113.

[23] Mirzaei-Nasirabad, H., Mohtasham, M., Askari-Nasab, H., Alizadeh, B., 2023. An optimization model for the real-time truck dispatching problem in open-pit mining operations. Optim. Eng. 1–25.

[24] Mohtasham, M., Mirzaei-Nasirabad, H., Askari-Nasab, H., Alizadeh, B., 2021. Truck fleet size selection in open-pit mines based on the match factor using a MINLP model. Min. Technol. 130, 159–175.

[25] Moradi-Afrapoli, A., Askari-Nasab, H., 2020. A stochastic integrated simulation and mixed integer linear programming optimisation framework for truck dispatching problem in surface mines. Int. J. Min. Miner. Eng. 11, 257–284.

[26] Moradi-Afrapoli, A., Upadhyay, S., Askari-Nasab, H., 2021. Truck dispatching in surface mines-Application of fuzzy linear programming. J. South. African Inst. Min. Metall. 121, 505–512.

[27] Moradi Afrapoli, A., 2018. A hybrid simulation and optimization approach towards truck dispatching problem in surface mines (Unpublished doctoral dissertation). University of Alberta.

[28] Moradi Afrapoli, A., Tabesh, M., Askari-Nasab, H., 2019. A stochastic hybrid simulation-optimization approach towards haul fleet sizing in surface mines. Min. Technol. 128, 9–20.

[29] Moradi Afrapoli, A., Upadhyay, S.P., Askari-Nasab, H., 2022. A nested multiple-objective optimization algorithm for managing production fleets in surface mines. Eng. Optim. 1–14.

[30] Nobahar, P., Pourrahimian, Y., Mollaei Koshki, F., 2022. Optimum fleet selection using machine learning algorithms—Case study: Zenouz Kaolin mine. Mining 2, 528–541.

[31] Que, S., Anani, A., Awuah-Offei, K., 2016. Effect of ignoring input correlation on truck–shovel simulation. Int. J. Mining, Reclam. Environ. 30, 405–421. https://doi.org/10.1080/17480930.2015.1099188

[32] Rist, K., 1961. The solution of a transportation problem by use of a Monte Carlo technique. Appl. Comput. Oper. Res. Miner. Ind. (APCOM), Tucson, US.

[33] Rockwell Automation, 2019. Arena, Version 19.

[34] Salhi, S., Rand, G.K., 1993. Incorporating vehicle routing into the vehicle fleet composition problem. Eur. J. Oper. Res. 66, 313–330. https://doi.org/10.1016/0377-2217(93)90220-H

[35] Samanta, B., Sarkar, B., Mukherjee, S.K., 2002. Selection of opencast mining equipment by a multi-criteria decision-making process. Min. Technol. 111, 136–142.

[36] Ta, C.H., Ingolfsson, A., Doucette, J., 2013. A linear model for surface mining haul truck allocation incorporating shovel idle probabilities. Eur. J. Oper. Res. 231, 770–778. https://doi.org/10.1016/j.ejor.2013.06.016

[37] Upadhyay, S.P., Tabesh, M., Badiozamani, M.M., Moradi Afrapoli, A., Askari-Nasab, H., 2021. A simulation-based algorithm for solving surface mines' equipment selection and sizing problem under uncertainty. CIM J. 12, 36–46.

[38] Yeganejou, M., Badiozamani, M., Moradi-Afrapoli, A., Askari-Nasab, H., 2022. Integration of simulation and dispatch modelling to predict fleet productivity: an open-pit mining case. Min. Technol. 131, 67–79.

[39] Yuriy, G., Vayenas, N., 2008. Discrete-event simulation of mine equipment systems combined with a reliability assessment model based on genetic algorithms. Int. J. Mining, Reclam. Environ. 22, 70–83.

[40] Zeng, W., Baafi, E., Walker, D., 2019. A simulation model to study bunching effect of a truck-shovel system. Int. J. Mining, Reclam. Environ. 33, 102–117.

[41] Zhang, Y., Zhao, Z., Bi, L., Wang, L., Gu, Q., 2022. Determination of truck–shovel configuration of open-pit mine: a simulation method based on mathematical model. Sustainability 14, 12338.

7. Appendix

List of abbreviations:

CAT	Caterpillar
HIT	Hitachi
TPGOH	Tonne Per Gross Operating Hours
OTPGOH	Ore Tonne Per Gross Operating Hours
SR	Stripping Ratio
Q	Queue
SIT	Shovel Idle Time
TWT	Truck Wait Time
PD	Production Deviation
FC	Fuel Consumption
min	Minutes
hrs	Hours
t / kt	Tonnes / Kilo Tonnes
l / kl	Liters / Kilo Liters
tph	Tonne Per Hour

Table A. 1. KPIs for Various Types of Trucks and Number of Trucks.

Scenario	Number of trucks 785C	Number of trucks 793C	Utilization Ore (%)	Utilization Waste (%)	Average Q time (mins)	Total Q time (hrs)	FC (kl)	Ore Tonnage (kt)	Total Tonnage (kt)	Ore TPGOH (t)	SR
1	22	0	67.84	47.55	2.72	373.29	298.31	461.50	1080.23	3845.87	1.34
2	24	0	74.92	50.84	2.82	416.18	324.12	508.44	1166.06	4237.02	1.29
3	26	0	79.40	54.31	3.12	488.36	346.97	541.50	1241.02	4512.54	1.29
4	28	0	80.20	54.98	3.51	555.85	378.91	545.41	1253.44	4545.11	1.30
5	29	0	80.60	56.15	3.67	591.81	392.78	548.64	1272.59	4572.02	1.32
6*	30	0	81.16	56.22	3.85	622.29	410.04	552.39	1277.51	4603.23	1.31
7	32	0	81.29	58.40	4.16	686.96	440.67	552.36	1304.78	4603.02	1.36
8	34	0	81.18	59.44	4.61	770.65	470.49	552.26	1317.77	4602.15	1.39
9*	36	0	81.19	60.14	4.92	825.31	506.12	552.32	1324.50	4602.65	1.40
10	0	15	68.85	43.14	2.13	175.38	369.04	529.10	1196.37	4409.20	1.26
11	0	16	70.85	45.66	2.28	195.68	393.42	544.77	1248.65	4539.73	1.29
12	0	17	70.96	46.96	2.40	213.87	421.65	545.57	1270.10	4546.44	1.33
13*	0	18	71.60	48.20	2.63	229.66	454.54	550.06	1295.28	4583.85	1.35
14	0	19	71.73	49.06	2.66	239.92	485.36	551.08	1312.29	4592.29	1.38
15*	0	20	71.95	48.64	2.84	254.45	517.51	552.31	1305.70	4602.59	1.36
16	0	21	71.94	50.61	3.00	274.56	545.11	552.14	1333.44	4601.17	1.42
17	0	22	72.07	52.89	3.18	299.42	572.12	552.27	1372.42	4602.28	1.49
18	25	3	80.05	53.94	3.75	552.06	418.24	552.21	1263.46	4601.73	1.29
19	26	3	80.15	55.59	3.83	577.76	433.62	552.23	1285.20	4601.89	1.33
20*	22	4	79.39	54.70	3.59	521.00	388.72	551.17	1277.53	4593.06	1.32
21	23	4	79.70	55.45	3.70	543.67	405.79	551.96	1289.60	4599.71	1.34
22	24	4	79.55	54.89	3.77	549.45	429.54	551.29	1281.59	4594.05	1.32
23	19	5	76.77	53.48	3.14	432.65	376.35	538.51	1258.84	4487.59	1.34

24*	20	5	78.71	53.89	3.45	483.93	387.44	551.52	1276.65	4596.02	1.31
25	21	5	79.12	55.32	3.67	522.96	400.03	551.37	1292.61	4594.76	1.34
26	22	5	79.12	56.31	3.75	543.72	417.23	552.27	1306.81	4602.26	1.37
27	18	6	76.15	54.49	3.17	431.62	388.18	536.69	1279.36	4472.42	1.38
28	19	6	78.55	54.92	3.46	481.03	398.40	551.41	1298.85	4595.12	1.36
29	20	6	78.62	55.95	3.68	518.31	412.42	552.12	1309.17	4601.03	1.37
30	21	6	78.71	56.96	3.82	545.51	428.61	552.37	1322.11	4603.12	1.39
31	24	6	79.14	57.73	4.29	623.72	481.38	552.35	1334.03	4602.92	1.42
32	17	7	76.28	54.88	3.32	445.52	397.33	540.61	1298.82	4505.10	1.40
33	19	7	78.32	56.42	3.70	512.38	424.99	552.04	1322.56	4600.33	1.40
34	20	7	78.52	57.61	3.85	543.51	440.50	552.04	1341.86	4600.34	1.43
35	16	8	76.08	55.82	3.35	442.32	409.77	540.87	1321.28	4507.23	1.44
36	18	8	77.87	57.77	3.80	522.46	433.74	551.64	1351.33	4597.04	1.45
37	14	10	75.36	58.24	3.51	455.19	428.78	541.39	1375.32	4511.56	1.54
38	12	12	74.47	59.72	3.67	462.28	449.87	540.02	1413.49	4500.14	1.62
39	10	14	74.22	60.61	3.78	461.28	472.90	542.37	1449.22	4519.73	1.67
40	8	15	73.56	58.48	3.80	437.64	470.42	541.60	1423.36	4513.37	1.63

Oil Sand Operation Simulation Using HAULSIM-Practical Guide

Yaa Serwaa Karikari and Hooman Askari-Nasab
Mining Optimization Laboratory (MOL)
University of Alberta, Edmonton, Canada

ABSTRACT

Many sectors around the world want to optimize their operations to give the best and most effective ways of extraction. This is difficult to attain since experimenting on the grounds would be expensive. With the introduction of Industry 4.0, many mining companies are entering into an era of using software and digitization to make processes cost-effective and cheaper. The introduction of simulation software has made it easier for researchers to create scenarios to enable them to select the best scenario for the operation. This paper will focus on the use of HaulSIM, a mining simulation software that will be used for creating simulations of different scenarios. This paper will describe how discrete event simulation software HaulSIM is used to create a haulage network model. Discrete event simulation software is one of the few products that is recommended for developing real-time simulation models.

1. Introduction

Oil sands operations are one of the most popular operations in the North of Alberta. Oil sand is a combination of loose sands or partially consolidated sandstone containing a naturally occurring mixture of sand, clay, and water, soaked with bitumen, a dense and extremely viscous form of petroleum (Pierre-René, 2006). The extraction of oil is very expensive, so most oil sands companies want to find ways and means to mine oil sands without incurring any loss and efficiently optimize their equipment and processes. The use of simulation software such as HAULlSIM is a practical way that is used for simulating mining operations. Noriega and Pourrahimian (2022) have reviewed the applications of artificial intelligence and data-driven approaches in strategic open pit mining. Some of the instances of using simulation technique in mining optimization include the following; Afrapoli and Askari-Nasab (2020) have developed an integrated simulation-optimization framework truck dispatching in surface mining, Ben-Awuah et. al. have used discrete event simulation for hierarchical mine production scheduling. HAULlSIM is a mining simulation software that was developed by RPM Global. It uses discrete event simulation since it can capture everything around the environment. It quantifies the impact of changes in a haulage system and helps the user to test for "why" and "what-if" scenarios. This will enable the mine to select the most optimum and efficient method or process thereby improving safety and reducing costs. The features of HAULSIM include; Discrete Event Simulation, Electric vehicle, hydrogen, and hybrid simulation, Industry's largest public equipment library, Intuitive use, 3-D user interface, Trusted travel time calculations, and smart haulage decisions. We are going to give a brief guide on the use of HAULSIM for haulage networks in the oil sands operation. The most important thing to consider in modeling haulage systems in Oil Sands mines is to first receive accurate data from the surroundings of the area. The data should be accurate to prevent errors when simulating the model to give accurate results.

ISBN: 978-1-55195-503-2

In modeling an oil sands operation, one needs to first understand the haulage system in the oil sands operation. The material is mined with a shovel and dumped in haul trucks and hauled to the destination. In model development, HAULSIM is the software that will be used in the development of the simulation model. HAULSIM connects fleet assets, mining operational plans, and people to build a 'digital twin' of any mining operation - open pit or underground - to deliver an accurate representation of any mine site's haulage operations (RPM Global). The features of this software as listed above make it one of the most effective software for simulating mining operations. For this reason, HAULSIM will be the effective software for modeling this operation

2. Methodology

The data was obtained from the shell productivity database in which the EFH productivity table was used for the analysis. The model was therefore built from this data. The data included the following parameters; Year, Month, Day, Shift, Crew, DumpUnit, DumpLoc, EqmtUnit, EqmtType, Truck, Area, TruckOperName, Material, Tonnage, MeasuredTonnage, EmptyHaul, QueueTime, SpotTime, WaitToSpot], LoadingTime, FullHaul, DumpIdle, DumpingTime, CycleReady, CycleDelay, CycleSpare, CycleDown Speed, DistEH, LiftEH, LiftDistEH, DropEH, DropDistEH, DistFH, LiftFH, LiftDistFH and many more that is not listed. These parameters were used to build the model and analyze the data. The model was built with the HaulSIM software and will be analyzed with the PowerBI software. The following data will be analyzed and the future work will be proposed.

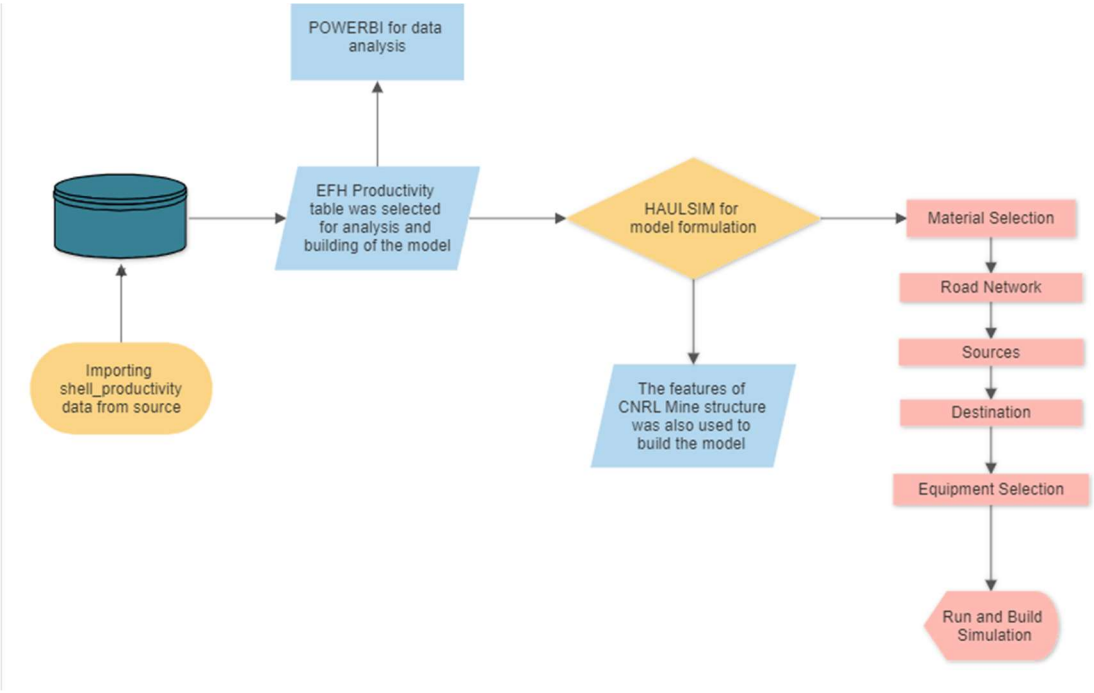


Figure 1 Flowchart of the model formulation.

2.1 Material Selection

The type of material that is hauled is really important in the analysis and simulation of the model. There are typically different types of material according to the data. But the material that is of most interest is the ore and waste. Since it is oil sands the material is loose sand and the material attributes such as the in-situ bank density, excavatability, swell factors and loose density, loader bucket fill factor, and load and haul or Load Carry Times should be considered. The values of the attributes of the material will be inputted by right-clicking on the material tab on the navigation pane, configuring it, and making the following changes to material attributes on the material pop-up pane. You click on add material and select earth-dry material and then review the information on the material pop-

up menu. This information will give you the various attributes of the material such as the swell factor, in-situ density, the struck and the heaped capacity. You close the window and save the project.

2.2 Road Network

The road network of the mine is necessary for the modeling process. The importance of the road network is to determine the speed at which the equipment moves around. When you import a CSV file, it must contain the String ID (which represents the grouping of nodes that belong to the same road), as well as the coordinates of each X, Y, and Z node. Each node is shown on its own line in the file. The road network has various indications; Grey represents the waypoints; blue represents the intersection and yellow represents termination points. Understanding the signs can help you with route analysis when simulating equipment on the road. On the navigation panel; left click on the road network and import the file for the road network and then save it. You can also show the grades on the road network using the legend button on the toolbar. Configure cutting planes by changing the elevation on the Build toolbar and selecting Configure. This helps you understand the dimensions of the road from top to bottom.

2.3 Sources

In simulation modeling of the haulage operation, the material is moved from the source which is the Load and Carry and Load and Haul and hauled to the destination which can be the dump, stockpile, crusher, Haul Load point, and Ore Pass In. In this case, the material is hauled from the digging location and stockpiles to the destination. The material is hauled from the Load and Haul unit and either sent to the dump or stockpile in the oil sand Mine. To import the source file, you click on the location on the navigation pane, select sources, open the file, and import. The next step is to configure and make changes to the methodology to single or double-sided and save the file. The next step is to navigate around the grids. To do this you need to click on the navigation pane, expand the location tab and select source, right-click on the source tab, and choose to configure. Click on the filter icon to select and filter the preferred source. Close the pop-up window and then save the project.

2.4 Destination

Destination in HAULSIM is where the truck will dump the material from the source. It is the end route of the road network. These are the following destinations according to the data; dump, crusher, and stockpile. The destination file is imported or manually added just like the source file. In this model, we will be dealing with three destinations: dump, stockpile, and crusher.

To import the destination file, you click on the location on the navigation pane, select the location and then destination, click on import, and then select the file and import. The information on the file will appear on the import destination pop-up window, you click on next and import. The next step is to configure and make changes to the destination pop-up window which will give the user the liberty to make changes to the layout, crush rate, initial quantity, material, and capacity of the following three destinations listed above, and then save the project.

2.5 Equipment Selection

Finally, after configuring the material, road, sources, and destination. We need to be able to simulate the equipment thoroughly to better understand the effectiveness of the model. Adding equipment to the model is one of the closest steps to completing the model. There is various equipment such as loading units, load and haul units, load and carry units, ancillary units, conveyors, and feeders. The shovel is assigned at the source of the location, the shovel fills the haul units which are the dump truck. The dump truck hauls the unit to the destination which is either the dump, stockpile, or plant. The ancillary equipment is the equipment that is not involved in the material movement but makes hauling and loading easier. The grader is for creating an even surface on the road to prevent bumps on the road, and the dozer is for pushing the material into a heap for the loader to easily dig the

material. The ancillary equipment such as the loader and the grader are added to the model to give it a more realistic scenario.

2.6 Run and Build Simulation

When the model is finally built, you can then run and build the simulation, you can select the start time and date and the duration of the haulage. You can also view the simulation in a 3D view and view the functionalities while the simulation is running. These are the following functionalities, yellow triangle- Loading; purple triangle- Travel loaded, green triangle- Travel empty, pink diamond- Waiting and Red Square-Blocked. The dashboard after the simulation has been run is used to view and track material movement, tasks, states, performance, and costs.

To run the simulation, you need to first click on the run tab, click and drag and type any value and then click run. Click the Task tab, click on the productivity tab and the material movement tab, and then save the project.

3. Data Analysis

We obtained data from CNRL, this data contained the various destinations, dig locations, equipment, cycle time, and material types that are found in the mine. With this data, we designed a simple model of the mine taking into consideration the following factors above.

With the data analysis, we will explore the data of the CNRL Data and analyze the given data. The data was stored in a structured form in a database form. From the database, 1000 rows of data were selected to be exported and analyzed. The data was exported to SQL Server and the data was analyzed using the PowerBI software.

3.1 Location of Sources and Destination with Measured Tonnage

This graph below shows the Measured payload among the destinations in the mine. The Measured payload is the difference between the Gross vehicle weight with the load in it and the actual weight of the vehicle without the load. The difference is the actual weight that the truck is hauling. From the bar graph, it can be deduced that the digging location has the most material. The least amount of material is in the stockpile, the crusher, and the in-transit material have almost the same amount of material, followed by the dump. From the data, it can be inferred that the digging location has the most material because that is where the material is taken from. Also, from the graph, the material taken to the crusher is a little higher than the dump.

At 66,195,224.73, Crusher had the highest Sum of Measured Tonnage and was 192,695.07% higher than In-Transit, which had the lowest Sum of Measured Tonnage at 34,334.50. Crusher accounted for 65.33% of Sum of Measured Tonnage. Across all 5 Dump Unit, Sum of Measured Tonnage ranged from 34,334.50 to 66,195,224.73.

From the second graph, the measured tonnage was plotted against the digging location in the mine. At 94,095,286.30, DigLoc had the highest Sum of Measured Tonnage and was 55,743,552.01% higher than Dump, which had the lowest Sum of Measured Tonnage at 168.80. DigLoc had the highest Sum of Measured Tonnage at 94,095,286.30, followed by Stockpile at 7,231,189.46 and Dump at 168.80. DigLoc accounted for 92.86% of Sum of Measured Tonnage. DigLoc had 94,095,286.30 Sum of Measured Tonnage, Stockpile had 7,231,189.46, and Dump had 168.80.

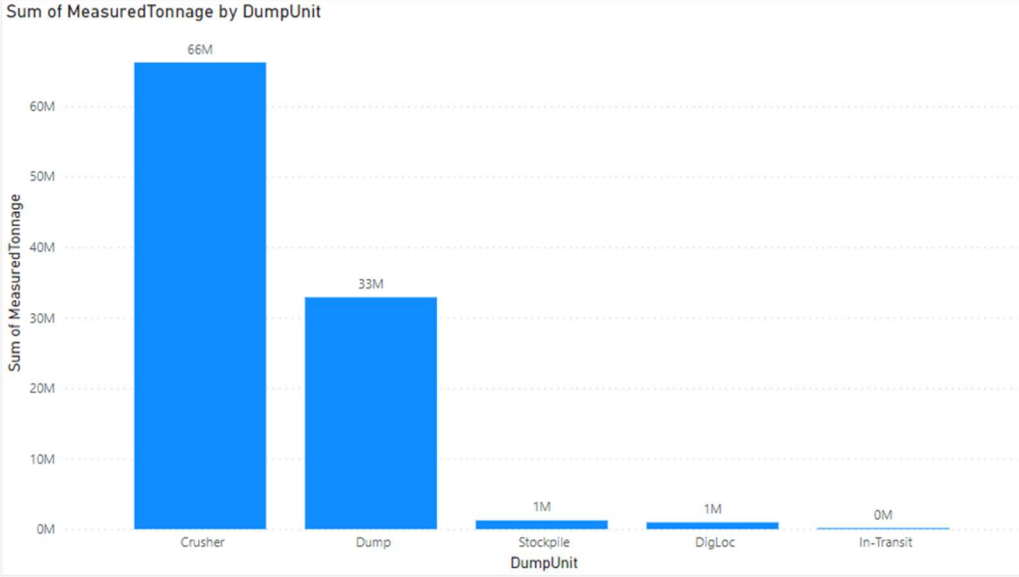


Figure 2. Graph showing Measured tonnage against dump unit.

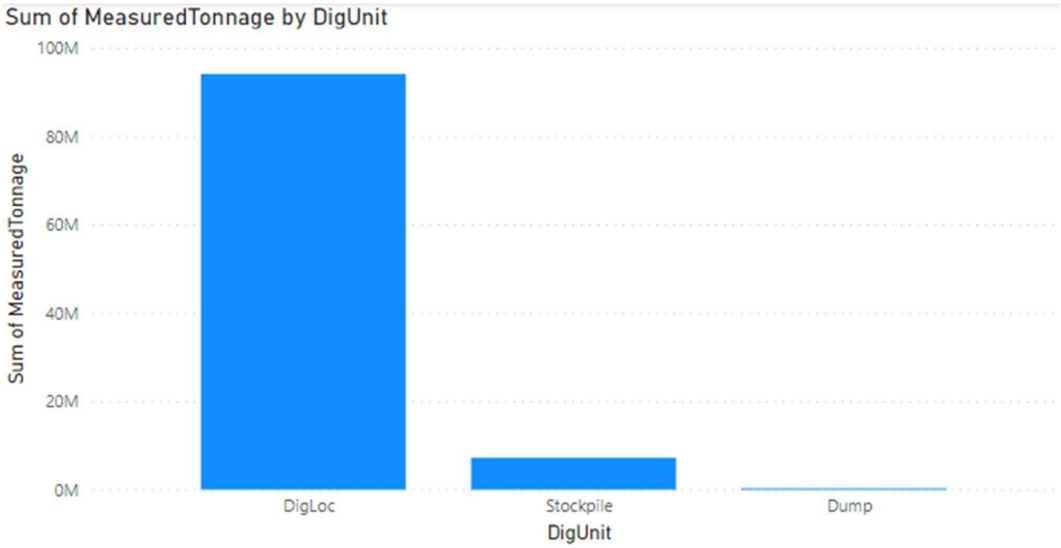


Figure 3. Graph showing Measured tonnage against dump unit.

3.2 Measured Tonnage with Truck and Shovel Types

Just from the last graph that showed the different types of trucks and their capacity, this graph also shows the different types of shovels and their measured tonnage. The BE 495B2 loads the most material, looking at the graph. The MISC loads the least material in the mine. From this graph, the mine can select the type of shovel in any case of a future purchase or replacement. They might purchase the machine with the most productivity or further assign those shovels to dig locations where the material is crucial to be moved that week. At 56,534,182.83, BE 495B2 had the highest Sum of Measured Tonnage and was 1,614,562.62% higher than Cat 330CL, which had the lowest Sum of Measured Tonnage at 3,501.30. BE 495B2 accounted for 55.79% of Sum of Measured Tonnage. Across all 9 tblDataShovelType, Sum of Measured Tonnage ranged from 3,501.30 to 56,534,182.83.

From the second graph, the various types of trucks were plotted against the measured payload. The types of trucks and their payload amount. The CAT 797B and the CAT797 have the most amount of

material, compared to the CAT785. It can be inferred the most of the material is hauled by the CAT 797 compared to the CAT 785. Sum of Measured Tonnage for Cat 797B (90,749,247.90) was higher than Cat 785 (10,577,396.67). Cat 797B accounted for 89.56% of Sum of Measured Tonnage. Cat 797B had 90,749,247.90 Sum of Measured Tonnage and Cat 785 had 10,577,396.67.

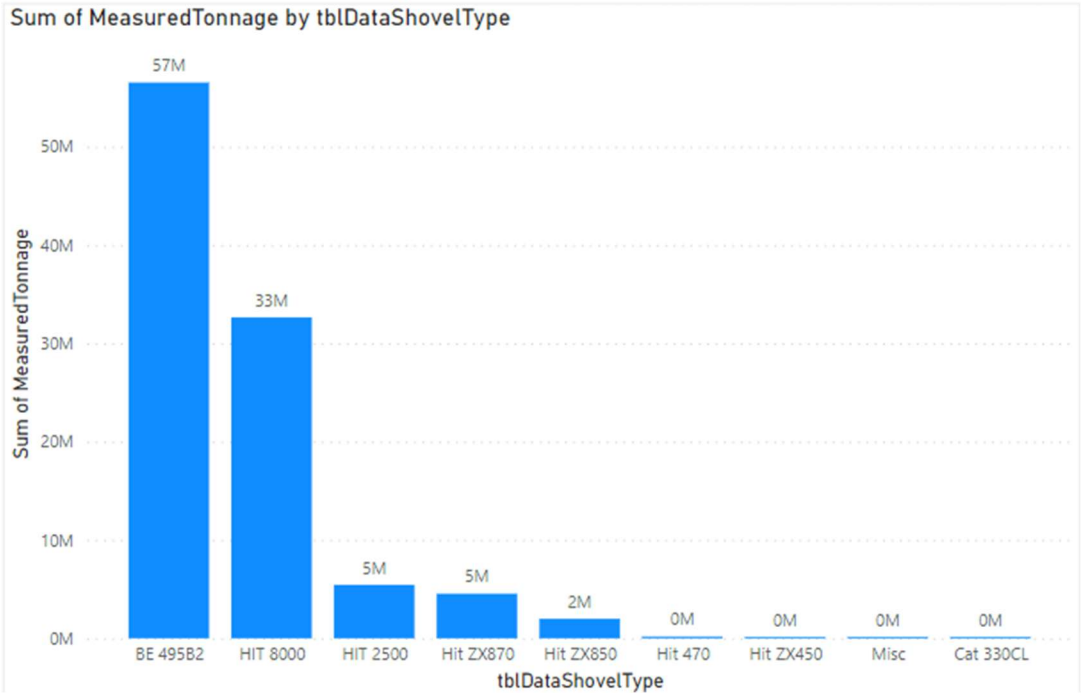


Figure 4. Graph showing Measured tonnage against shovel type.

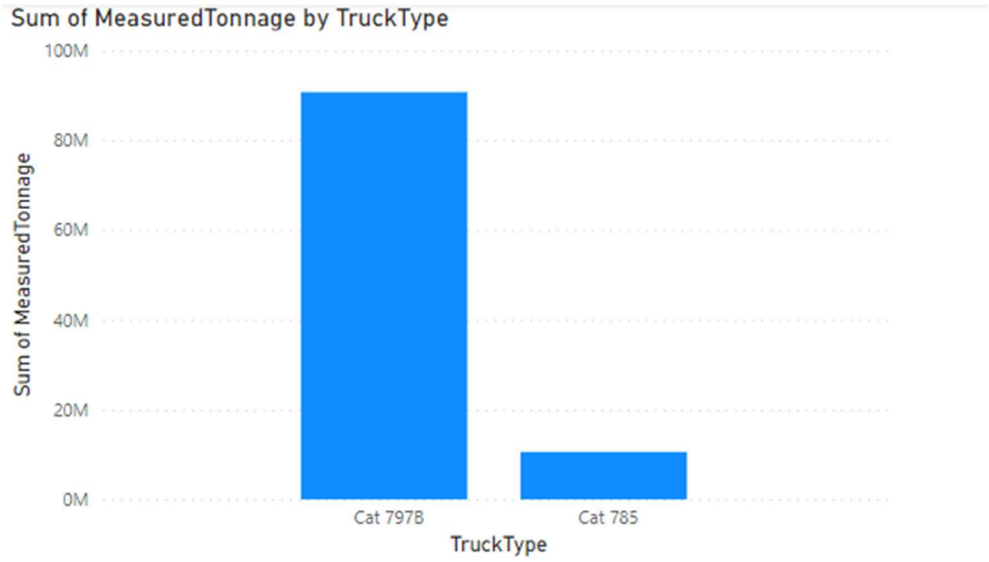


Figure 5. Graph showing Measured tonnage against truck type.

3.3 Measured Tonnage with Material Types

The measured tonnage was plotted against the material found in the mine. Of the various types of material and the measured tonnage, the most amount of material is the type 1 material which is the in-transit material, followed by the ore and the least amount of material is the type 6 material. The second most moved material is the ore which is good but other more material which is not profitable

to the mine is also moved. The mine must find a way to move less material that is unprofitable to the mine. At 61,712,616.30, Ore had the highest Sum of Measured Tonnage and was 56,409,968.96% higher than Reclaim, which had the lowest Sum of Measured Tonnage at 109.40. Ore accounted for 60.90% of Sum of Measured Tonnage. Across all 25 Material, Sum of Measured Tonnage ranged from 109.40 to 61,712,616.30.

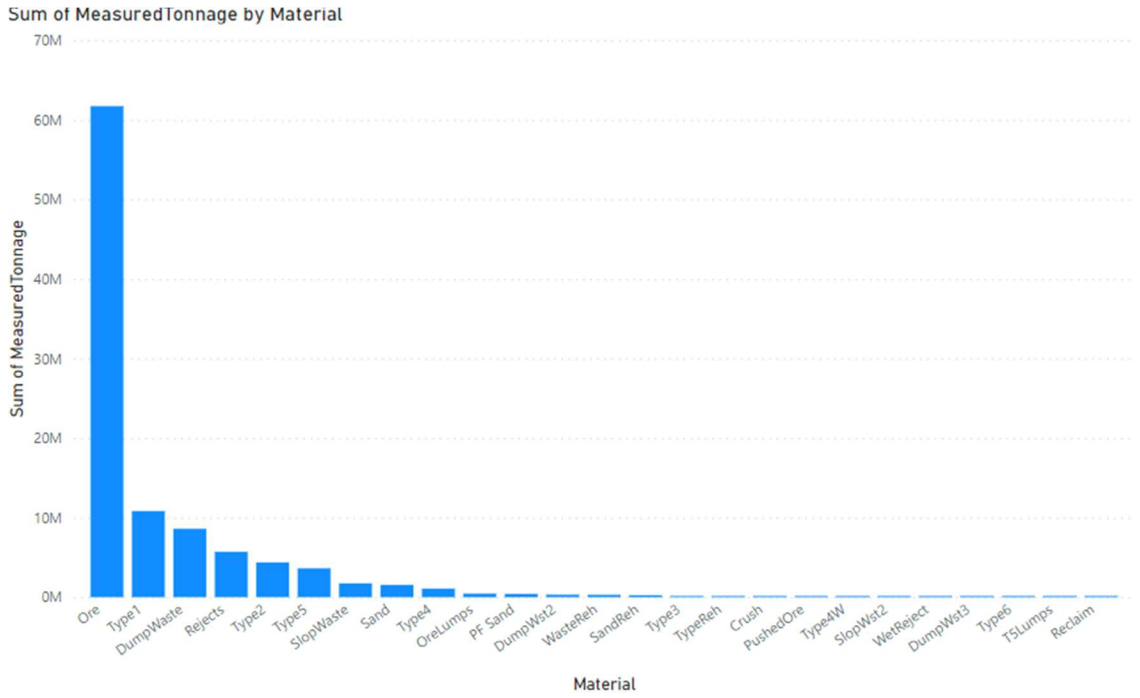


Figure 6. Graph showing Measured tonnage against Material type.

3.4 Cycle Time for Trucks

The cycle times for both trucks were recorded as part of their data. The graph of the loading and queuing times was shown and from the chart, it can be seen that the loading times for the CAT 797B and CAT 797 were shorter than the CAT 785. From the queuing time, you can see that the CAT 797B and the CAT 797 have longer queued times than the CAT 785. This is because of its fast loading it tends to queue faster than the CAT 785. Due to the higher queuing time, it tends to have a higher overall cycle time as shown above. Even with its shorter loading times due to its long queue times, the overall cycle time tends to be higher. At 4.40, Cat 785 had the highest Average of Loading Time and was 45.58% higher than Cat 797B, which had the lowest Average of Loading Time at 3.02 minutes. Cat 785 had the highest Average of Loading Time at 4.40, followed by Cat 797 at 3.26 and Cat 797B at 3.02 minutes. Cat 797B had 3.02 Average of Loading Time, Cat 797 had 3.26 minutes, and Cat 785 had 4.40 minutes. At 1.53 minutes, Cat 797B had the highest Average of Queue Time and was 18.74% higher than Cat 785, which had the lowest Average of Queue Time at 1.29 minutes. Cat 797B had the highest Average of Queue Time at 1.53 minutes, followed by Cat 797 at 1.32 minutes and Cat 785 at 1.29 minutes. Cat 797B had 1.53 minutes of average Queue Time, Cat 797 had 1.32 minutes, and Cat 785 had 1.29 minutes. At 26.39 minutes, Cat 797 had the highest Average of Cycle Ready and was 6.82% higher than Cat 785, which had the lowest Average of Cycle Ready at 24.70 minutes. Cat 797 had the highest Average of Cycle Ready at 26.39, followed by Cat 797B at 26.02 minutes and Cat 785 at 24.70 minutes. Cat 797B had 26.02 minutes Average of Cycle Ready, Cat 797 had 26.39 minutes, and Cat 785 had 24.70 minutes. The cycle times for both trucks were recorded as part of their data. The graph of the loading and queuing times was shown and from the chart, it can be seen that the loading times for the CAT 797B and CAT 797 were shorter than the CAT 785. From the queuing time, you can see that the CAT 797B and the CAT 797 have longer queued times than the CAT 785. This is because of its fast loading it tends to queue faster than the

CAT 785. Due to the higher queuing time, it tends to have a higher overall cycle time as shown above. Even with its shorter loading times due to its long queue times, the overall cycle time tends to be higher.

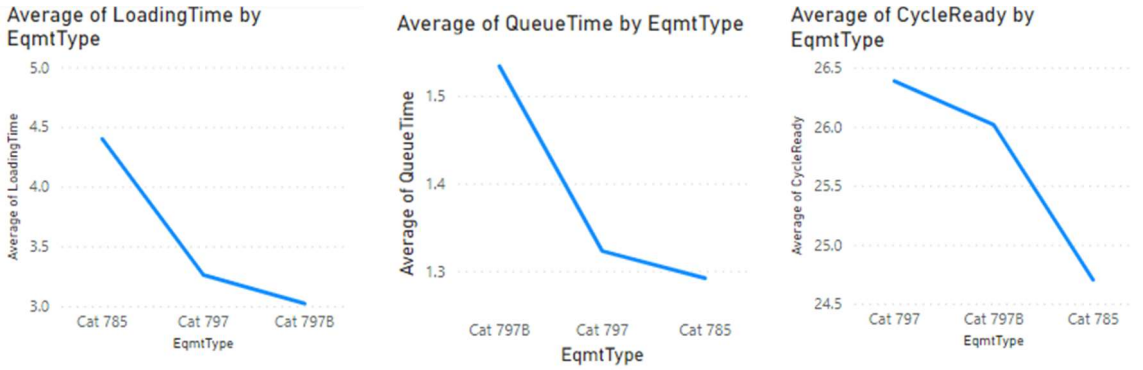


Figure 7 Loading time, Queue time and Full cycle time for each truck type.

4. Future Work

The development of discrete event simulation is revolutionizing the effectiveness of managing data and predictions in fleet management systems. The goal of this study is to comprehend the state of the CNRL sand operations and analyze the data. There are a lot of studies into fleet management and its applications. This kind of work will be applied to the real-life scenarios in mining operations where several scenarios are simulated and the one with the best results is selected. Mine operations can also be simulated to give the most optimal performance that the industry must take. The advent of discrete event simulation will decrease cost, increase profit and boost the effectiveness of the operation thereby removing any lagging situation that may compromise the operation.

5. Conclusion

The CNRL data was given and a simple model using the HAULSIM discrete event simulation was used to create a model of the fleet system. The data was analyzed using graphs created by the PowerBI software. Discrete event simulation is very important in simulating real-life scenarios since it captures everything. The collection of data is important for analysis and future prediction in the mine. Creating scenarios and analyzing the data collected will help the mine in the future to make predictions that will help them in a cost-effective way and optimize processes. From the analysis, it can be inferred that the production or material movement of the mine is not bad, but the productivity of the mine is not bad comparing the volume of the material and the cycle times of the machines. Also from the data, more non-production material is moved out of the mine than production material. The mine should therefore find a way of optimizing the processes, to reduce non-production material and increase more production material. From the analysis of the cycle time, there is a lot of queuing for the CAT 797 B and CAT 797 thereby making the cycle time very long for both trucks. The mine should effectively assign trucks to dig locations to minimize the queuing or eradicate it. Eradicating the queuing in the trucks will help improve the productivity of the mine.

This is the analysis of the data I have made so far with the data. I strongly believe all mining companies should incorporate Industry 4.0 in their processes. The use of simulations and other digital technologies is going to save mining companies from loss and underproduction. Making future predictions is going to help the mine make more profit, improve safety and optimize its operations and processes. Since the world is moving into the digitization age it's very important that the mine moves in that direction from its exploration to its closure stage.

6. References

[1] Pierre-René Bauquis (2006). What the future for extra heavy oil and bitumen: the Orinoco case. World Energy Council.

[2] RPM Global. "Mining Software, Consulting & Training Solutions." *RPMGlobal*, 25 Jan. 2023, rpmglobal.com/.

[3] Noriega, R. and Pourrahimian, Y. (2022). A systematic review of artificial intelligence and data-driven approaches in strategic open-pit mine planning. Resources Policy, 77, p.1027-27.

[4] Afrapoli, A.M. and Nasab, H.A. (2020). A stochastic integrated simulation and mixed integer linear programming optimisation framework for truck dispatching problem in surface mines. International Journal of Mining and Mineral Engineering, 11(4), p.257.

[5] Ben-Awuah, E., Kalantari, S., Pourrahimian, Y. and Nasab, H.A. (2010). Hierarchical mine production scheduling using discrete-event simulation. International Journal of Mining and Mineral Engineering, 2(2), p.137.

Numerical Simulation of Blast-Induced Fracturing of Jointed Rock Masses Based on a Case Study[1]

Magreth S. Dotto and Yashar Pourrahimian
Mining Optimization Laboratory (MOL)
University of Alberta, Edmonton, Canada

ABSTRACT

Fragmentation by blasting is a critical process in hard rock mining. The interaction between the rock mass and blast energy influences the outcomes, specifically on the rock mass response to higher stresses and loading rates and the influence of structures. Each rock mass is unique, but some features affect the blast energy similarly, leading to similar outcomes. Having analyzed these features and their influence on blast outcomes, they can be addressed during the blast design to achieve better results. In this study, the Riedel-Hiermaier-Thoma (RHT) material model in L-S DYNA is used to model the nonlinear dynamic fracturing of the rock to understand the effects of rock mass properties on the blast outcomes. In a case study, rock mass properties, explosive properties, and design parameters are used as input parameters to the model, and the blast outcomes are used to validate simulation results. The results show that several factors influence the fracturing process by blasting. The formation of damage zones around the charge among others depends on the rock mass strength and structural properties which control energy distribution and crack propagation. Furthermore, the simulation results indicate that when the model parameters are calibrated from the existing data, they can be used to simulate the fragmentation process in a more simplified and controlled environment and therefore provide insight into blast design.

1. Introduction

Blasting is a commonly used method of rock fragmentation in mining and civil engineering constructions. Although it is the most efficient way of breaking the rock, it is a complicated process mainly due to the complex nature of the rock mass, the non-ideal detonation of commercial explosives, the interaction between the rock mass and explosive energy, and the interaction with the neighboring charges. The efficiency of the blasting process is measured by how loose and well-fragmented the rock is while managing the overall production costs and limiting the impacts on the surrounding structures. To achieve blast efficiency, understanding the physical and mechanical properties of the rock mass and blasting mechanisms is essential.

Several approaches have been developed to describe blast-induced fragmentation and thus estimate damage zones ranging from analytical [1], experimental [2] to numerical modeling [3-6]. The analytical approach uses parameters such as peak particle velocity (PPV) [7, 8] or borehole pressure [9] to estimate the damage zones. Numerical modeling uses algorithms such as the Discrete Element Method (DEM), Finite Element Method (FEM), etc., to analyze stress fields around the charge and estimate the damage zones. These approaches have come up with valuable insights into the

[1] A version of this paper is submitted to the International Journal of Mining, Reclamation, and Environment.

ISBN: 978-1-55195-503-2

interaction between explosive energy and rock mass; they still are not exhaustive, especially when considering heterogeneous, anisotropic, and discontinuous rock mass.

In the rock mass, discontinuities such as fractures, joints, and faults are common. The knowledge of their geometric and structural attributes is vital in earth science studies, particularly stress wave propagation[10-12]. These discontinuities are known to alter rock mass fracture patterns in quasi-static loading and affect the propagation of stress waves, and the formation and propagation of cracks in dynamic loading. Several studies have been conducted to study wave propagation in the rock mass and the effects of rock joints through site monitoring and numerical simulations [13-20]. These studies concluded that the intensity of the stress wave at any point around the charge depends on the size of the charge, rock mass properties, and the distance from the blast hole. The stress wave attenuates faster near the charge and slower with increased distance from the blast hole. The presence of joints in the rock mass influences the attenuation and distribution of explosive energy depending on the properties of the joints and their orientation to the direction of the wave front.

This study presents the results of the numerical simulation of blasts using the LS-DYNA [21] for the intact and jointed rock mass, considering various joint parameters and structural properties. The simulation model is first calibrated from the rock mechanical properties, joint parameters, and explosive properties of an existing mine. Empty joints (with air as filling material) and joints filled with soft rock material (clay) are modeled to evaluate the effect of filling material on the distribution of wave energy and rock fracturing. Further analysis is conducted on different joint parameters, such as thickness, orientation, spacing, and joint set orientation when soft rock is the filling material. This analysis aims to investigate their influence on stress wave propagation and the creation of damage zones around the blast hole. The results are compared with post-blast field measurements from a similar setup through fragmentation analysis. The study is essential in understanding the interaction of explosive energy with the rock mass to predict the blast outcomes and aid blast design.

2. Numerical Modeling

Numerical modeling, both finite element modeling (FEM) [22, 23] and discrete element modeling (DEM) [5, 6] have been used as the most economical and effective techniques to simulate the blasting process and optimize blast fragmentation. In DEM, the rock mass is represented as an assembly of bonded elements with specified tensile or shear strength. Failure is achieved when the stress exceeds this value [5]. This approach can successfully track crack evolution and fracture patterns, but without some modifications and assumptions, it falls short in tracking explosive gas dispersion, as noted by Yoon and Jeon [5]. In FEM, the damage mechanics is due to the growth and nucleation of cracks in the brittle rock mass defined by the appropriate damage evolution law [24].

Most blast-induced fragmentation studies are based on two dimensions (2D) analysis. Although they simplify the computation process and provide a significant understanding of the fragmentation process and the influence of discontinuities, they do not capture the spatial stress distribution and blast damage in the three-dimensional (3D) setup. This study investigates 2D and 3D numerical simulation models for a single blast hole in various applications. In both cases, the reference model is an intact rock whose outcomes are compared with jointed rock mass to analyze the effects of various joint parameters.

LS-DYNA, a nonlinear transient finite element code with an explicit integration scheme capable of implementing dynamic problems, is used for blasting modeling. LS-DYNA can successfully model the interaction between the solid material and fluid and gas flow using the Lagrangian algorithm and Arbitrary Lagrangian-Eulerian (ALE). LS-DYNA can incorporate coupling between the Lagrangian and ALE interface when required. Boundary conditions to restrict elements' movements can also be applied as needed. Two main damage models commonly used to simulate the damage evolution of rock mass under blasting loads in LS-DYNA are the Holomquist–Johnson–Cook (HJC) model [25] and the Riedel–Hiermaier–Thoma (RHT) model [26]. From the study conducted by Wang [27], the

RHT model is observed to define damage distribution in rock well and describe the formation of the crushed zone and propagation of radial tensile cracks, while the latter could not be captured in the HJC model

2.1. The RHT material model

The rock is modeled with the Riedel-Hiermaier-Thoma (RHT) material model, an advanced brittle plasticity model for impulsive and dynamic loadings. The RHT model has been used extensively to model blast-induced fragmentation [27-29] since the rock has numerous randomly distributed pores and micro-cracks and behaves nonlinearly under compression. The RHT material strength model is coupled with a polynomial Equation of State (EOS) that accounts for porous compaction as expressed in Equation (1); where Bo and B1 are constants for polynomial EOS, αo is the initial porosity, ρo is the rock density, e is the internal energy per unit mass, μ is the volumetric strain and A1, A2, and A3 are Hugoniot polynomial coefficients.

$$P_{EOS} = \frac{1}{\alpha}\left(\left(B_o + B_1\mu\right)\alpha_o\rho_o e + A_1\mu + A_2\mu^2 + A_3\mu^3\right) \quad (1)$$

Figure 1 describes the p-α compaction model. Pore crush pressure (P_{crush}) and compaction pressure (P_{comp}) define failure modes in the model. Below the P_{crush}, the model is elastic. Beyond P_{crush}, with pressure increase, porous compaction occurs accompanied by a reduction in the effective bulk modulus of the material and volumetric stiffness. When the pressure reaches the P_{comp}, the material is fully compacted, and the conventional equation of the state model governs the damage evolution [30].

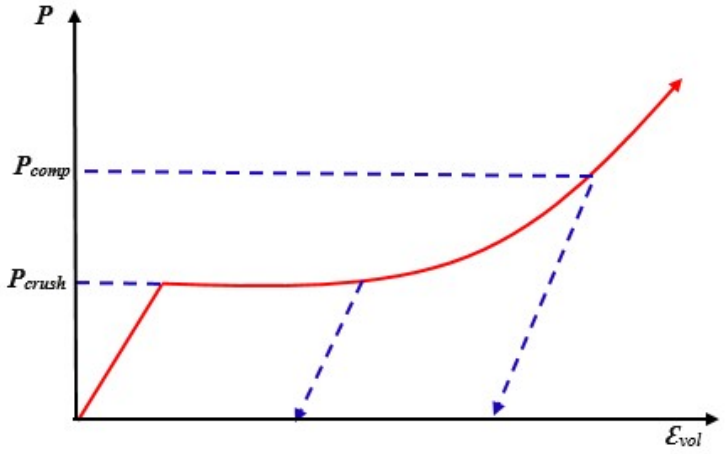


Figure 1. P-Q equation of state [30].

Three limit surfaces define the RHT strength model; the initial elastic yield surface, residual friction surface, and failure surface, which depend on the hydrostatic pressure. The damaged surfaces represent the reduction in material strength in different meridians and the effect of strain rate. Surface material failure is achieved when its ultimate compressive, shear, or tensile strength is reached. Figure 2 illustrates an example of static compressive meridian surfaces. Figure 2 shows that the model is elastic until it reaches the initial yield surface, beyond which plastic strain prevails. The elastic-plastic yield surface in compression is defined by compressive strength, regularized yield function, which describes pressure dependence on principal stress conditions, and William-Warnke function, representing reduced strength on shear and tensile meridian presented in Equation (2).

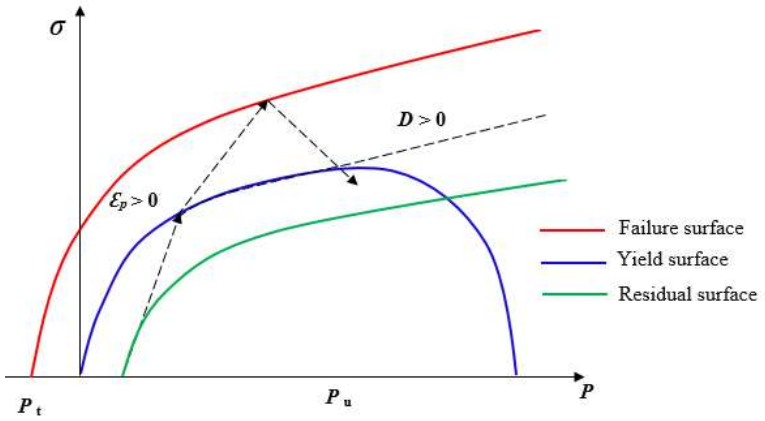


Figure 2. Stress limit surfaces and loading scenario [30].

$$\sigma_y \left(P_o^*,\ \varepsilon_p^{\bullet},\ \varepsilon_p^*\right) = f_c \sigma_y^* \left(P_o,\ F_r\left(\varepsilon_p^{\bullet}\right),\ \varepsilon_p^*\right) R_3\left(\theta_l,\ P_o^*\right) \tag{2}$$

Where σ_y^* is the normalized yield function $\left(\sigma_y^* = \sigma_y / f_c\right)$, f_c is uniaxial compressive strength, P_o^* is the normalized pressure $\left(P_o^* = P_o / f_c\right)$, P_o is hydrostatic pressure, F_r is the dynamic strain rate increase factor, $\varepsilon_p^{\bullet}$ is the strain rate, ε_p^* is the effective plastic strain, R_3 is William Warnke function, and θ_l is lode angle. The strain rate affects the strength of the rock. Equation (3) defines the rate dependency.

$$F_r(\varepsilon_p)\begin{cases}\left(\dfrac{\varepsilon_p^{\bullet}}{\varepsilon_o^{\bullet c}}\right)^{\beta_c} & P \geq f_c/3 \\ \dfrac{P+f_t/3}{f_c/3+f_t/3}\left(\dfrac{\varepsilon_p^{\bullet}}{\varepsilon_o^{\bullet t}}\right)^{\beta_c} - \dfrac{P-f_c/3}{f_c/3+f_t/3}\left(\dfrac{\varepsilon_p^{\bullet}}{\varepsilon_o^{\bullet c}}\right)^{\beta_t} & -f_t/3 < P < f_c/3 \\ \left(\dfrac{\varepsilon_p^{\bullet}}{\varepsilon_o^{\bullet t}}\right)^{\beta_c} & P \leq -f_t/3\end{cases} \tag{3}$$

Where $\varepsilon_o^{\bullet c}$ is the reference strain rate in compression = 3×10^{-5} s^{-1} and $\varepsilon_o^{\bullet t}$ is the reference strain rate in tension = 3×10^{-6} s^{-1}, f_t is tensile strength and β_c and β_t are material constants in compression and tension, respectively [30]. The failure surface is given by Equation (4).

$$\sigma_f^* \left(P_o^*,\ F_r\right) = A_1 \left(P_o - F_r/3 + \left(A_1/F_r\right)^{-1/N_1}\right)^{N_1} \qquad 3P_o^* \geq F_r \tag{4}$$

Where σ_f^* is normalized strength and N_1 and A_1 are failure surface parameters. Under blast loads, reduction in material strength is governed by relative pressure;

$$Q\left(P_o^*\right) = Q_o + BP_o^* \tag{5}$$

Where Q_o is the ratio between tensile and compressive radii meridians and B is the lode angle dependency factor. When stress reaches the failure surface, damage strain accumulation governs damage evolution. The damage variable of the RHT model (D) is calculated using Equation (6).

$$D = \sum \frac{\Delta \varepsilon_m^P}{\varepsilon_f^P} \tag{6}$$

Where ε_m^P is the accumulated plastic strain and ε_f^P the plastic strain failure. *D* takes a value between 0 and 1 where $D = 0$ is the un-damaged material state and $D = 1$ is the damaged material. Wang, Wang (27) defined the damage pattern from blasting as the elements with a damage level above 0.7. The plastic strain at failure is calculated using Equation (7).

$$\varepsilon_f^P \begin{cases} D_1 \left(P_o^* - (1 - D) P_t^* \right)^{D_2} & P_o^* \geq (1 - D) P_t^* + \left(\varepsilon_m^P / D_1 \right)^{\frac{1}{D_2}} \\ \varepsilon_m^P & P_o^* < (1 - D) P_t^* + \left(\varepsilon_m^P / D_1 \right)^{\frac{1}{D_2}} \end{cases} \quad (7)$$

Where P_t^* is failure cut-off pressure, D_r is the RHT model's damage variable, and D_1, D_2 are damage constants. More references on the RHT model can be found in Livermore Software Technology Corporation [21] and Borrvall and Riedel [30].

3. Rock Properties and Blast Design Parameters for the Case Study

This study uses the blast design, rock mass, and explosive properties of Geita Gold Mine (GGM), Nyankanga Pit in Tanzania, for modeling. Nyankanga Geology comprises a banded iron formation (BIF) and diorite as host rocks. Mineralization is controlled by tectonic structures within fault zones passing through the host rock. The banded iron formation is of sedimentary origin, consisting of cyclic deposition of iron-rich sediments and chert. The diorite is igneous with variable mineral composition and grain size, defining the Nyankanga Intrusive Complex. The principal composition of the Nyankanga diorite is plagioclase-rich diorite (DPH) and hornblende-rich diorite (DHP). Porphyry intrusions within the fault zones are the youngest Nyankanga geology. The intrusions are mainly feldspar porphyry (FP) and Quartz feldspar porphyry (QFP) dykes.

Nyankanga rock mass is categorized as a good rock made up of hard rock with uniaxial compressive strength (UCS) between 78 and 129 MPa, slightly rough joints spaced 0.2 to 0.42 m with joints apertures mostly less than 5 mm filled with calcite and clay material. The groundwater condition is generally moist, with water dripping in a few areas. Table 1 presents the physical and mechanical properties of the two prominent rock types in the Nyankanga Pit. Nyankanga Pit is mined by benches 10 m high on both ore and waste. The blast design on the main shot is described in Table 2.

Table 1. Nyankanga Rock Properties.

Rock type	Brazilian Tensile strength (MPa)	UCS (MPa)	Young's modulus (GPa)	Poisson's ratio	Mean sonic speed (m/s)	Rock density (t/m^3)
BIF	14.2	126	90.8	0.24	4,369	2.67
DHP/DPH	15.2	110	78.2	0.25	4,683	2.62

DPH – Plagioclase rich diorite, DHP – hornblende rich diorite, BIF – banded iron formation,

Table 2. Blast design parameters.

Parameter	Unit	Symbol	Value
Hole diameter	Mm	D	203
Burden	M	B	5.5
Spacing	M	S	6.5
Bench Height	M	H	10
Sub-drilling	M	Sd	1.5
Stemming height	M	Sl	4.5

Explosive density	kg/m3	ρe	1,180
Maximum instantaneous charge	Kg	W	267
Powder factor	kg/m3	PF	0.75

The blast holes are drilled vertically in a staggered pattern and charged with a specially manufactured emulsion by ORICA; Fortis extra with properties summarized in

Table 3 [31]. The velocity of detonation (VOD) measurements were conducted during a blast using MREL's MicroTrap Data Recorder from four blast holes. The characteristics of each hole and results are presented in Table 4.

Table 3. Explosive properties.

Explosive property	Unit	Value
Density, ρ_e	kg/m^3	1,100 – 1,250
Minimum charge diameter	Mm	64
VOD	m/s	4,100 – 6,700
Bulk Energy	MJ/kg	3.47 – 4.35 (at 1180 kg/m^3)

Table 4. VOD measurements.

Pit/Lavel/Shot	Hole ID	Rock properties	Hole depth (m)	Initial density (kg/m^3)	Final density (kg/m^3)	VOD (m/s)
Nyankanga 8/910/ 6	KO2	Hard, less fractured	12.8	1250	1180	4401.5
Nyamulilima 1/1460/3&4	EC1	Soft rock	10	1265	1217	4694
Nyamulilima 1/1460/3&4	EC2	Transitional rock	9.8	1265	1217	5334
Nyamulilima 1/1460/3&4	EC3	Soft rock	9.4	1265	1217	4727

4. Modeling a Case Study in LS-DYNA

The numerical models were created and executed using LS-DYNA Version: smp s R11.1 on a Dell Precision7810 with two Intel(R) Xeon(R) eight-core CPUs running at 2.40 GHz and equipped with 32GB RAM. Figure 3 illustrates the full-size single blast hole model established for the intact rock. The model dimensions follow the size of the blast pattern in Table 2, where the burden is 5.5 m, and the spacing is 6.5 m. The bench height is 11.5 m with a charge column of 7 m and a stemming height of 4.5 m. The radius of the blast hole is 101.5 mm, and a coupled charge is adopted where the diameter of the charge is the same as that of the blast hole. The detonation takes place 1.5 m from the bottom of the blast hole. Two free boundaries are introduced on top of the bench and along the burden, in which case the stress wave is reflected to the rock mass. Non-reflecting boundary conditions are set on the remaining sides, allowing the stress wave to transmit. The mesh size near the charge is 3 cm, and the average mesh size is 8 cm.

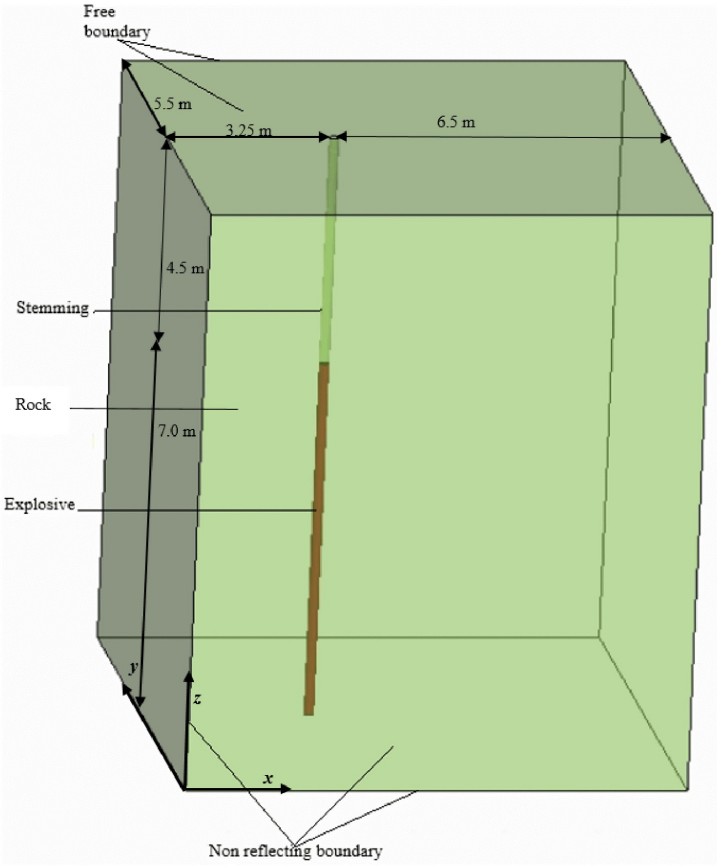


Figure 3. Numerical model of an intact rock.

For the numerical modeling, the rock mechanical properties of the Banded Iron Formation in Table 1 were calibrated to be used for analysis in the RHT model. Table 5 summarizes the calibrated properties.

Table 5. RHT model parameters for BIF.

Density (kg/m^3)	Elastic shear modulus (GPa)	Unit conversion factor	Eroding plastic strain	Pore crush, B_0	Pore crush, B_1	Bulk Modulus (GPa)	
2670	27.03	0	2	1.22	1.22	47.06	
Failure surface constant, A	Failure surface constant, N	Compressive strength (MPa)	Relative shear strength	Relative tensile strength	Lode angle, Q0	Lode angle, *+ B	Parameter for polynomial EOS, T_2 (GPa)
1.6	0.6	126	0.18	0.11	0.68	0.1015	0
Ref. compressive strain rate (s^{-1})	Ref. Tensile strain rate (s^{-1})	Break compressive strain rate (s^{-1})	Break tensile strain rate (s^{-1})	Compressive strain rate exponent, β_c	Tensile strain rate exponent, β_t	Pressure influence on plastic flow	
0.00003	0.000003	3E+25	3E+25	0.026	0.007	0.001	
Compressive yield surface parameter	Compressive yield surface parameter,	Shear modulus reduction factor	Damage parameter, D_1	Damage parameter, D_2	Minimum damage residual strain	Residual surface parameter, AF	Residual surface parameter, NF
0.53	0.7	0.5	0.04	1	0.015	0.61	1.6
Gruneisen gamma	A_1 (GPa)	A_2 (GPa)	A_3 (GPa)	P_{crush} (MPa)	P_{comp} (GPa)	Porosity exponent	Initial porosity
0	32.5	37.8	9.5	125	6	3	1

The explosive column was modeled using an Eulerian grid. The high explosive burn material and Jones-Wilkins-Lee (JWL) EOS are used to model explosive charge detonation. The JWL equation of state is a high-energy combustion model that can reliably predict higher explosion pressures. The model defines the pressure of detonation products P_{cj} using equation (8) [32].

$$P_{cj} = A\left(1-\frac{\omega}{R_1 v}\right)e^{-R_1 v} + B\left(1-\frac{\omega}{R_2 v}\right)e^{-R_2 v} + \frac{\omega E}{v} \quad (8)$$

Where A, B, R_1, and R_2 and ω are material constants, E is detonation energy per unit volume, and v is the relative specific volume of detonation products. The input parameters for the JWL Model for Fortis Extra properties are adapted from the similar emulsion explosive E682 calibrated by Hansson [33] in Table 6.

Table 6. E682 explosive parameters.

Explosive Type	Density (kg/m^3)	VOD (m/s)	P_{cj} (GPa)	A (GPa)	B (GPa)	R_1	R_2	ω	E_o (GPa)	v_o
E682	1,180	5,211	9.53	276.2	8.44	5.2	2.1	0.5	3.87	0

Rock masses are made up of intact rock and discontinuities such as joints, faults, and bedding planes. Such discontinuities, usually weaker than the intact rock, affect rock masses' response to blast loadings. The joint parameters such as the joint width, infill material, orientation, persistence, spacing, and distribution pattern significantly impact the propagation of blast waves and hence rock mass fracturing. The numerical model analyzed two types of joints to determine the impact of parameters: joints without filling material and joints filled with soft rock. Air in the empty joint was modeled as NULL material and ALE part with properties described in Table 7, while soft rock infill was modeled using the plastic kinematic material model as a Lagrangian part with properties defined in Table 8.

Table 7. Parameters for Air

Density (kg/m^3)	C4	C5	C6	Eo (MPa)	Vo
1.29	0.4	0.4	0	0.5	1

Table 8: Soft rock parameters

Density (kg/m^3)	Young's Modulus (GPa)	Poisson's ratio	Yield stress, (MPa)	Tangent Modulus, (GPa)	Hardening parameter	Failure strain, FS
1,160	5	0.35	0.4	4	0	0.5

5. Results and Discussion of Simulation Results

5.1 Damage Zones Estimation on the Intact Rock

The theory of rock fracture and fragmentation due to blasting suggests an overall combined damage mechanism. The intensity, propagation, and interaction of shock waves (stress waves) are responsible for initially fracturing the rock (conditioning), and the ensuing gas pressure predominantly affects fragmentation breakage and displacement beyond the immediate blast hole region. The detonation pressure from the commercial explosives, usually higher than 10 GPa, induces high shock waves on the blast hole wall way ahead of expanding gases (the gas pressure), causing the borehole's initial pulverized zone. The shock wave quickly decays into a high amplitude stress wave traveling at longitudinal wave speed in the rock mass, forming the fractured and incipient cracked zones. When encountering a free surface, these waves are reflected, causing spalling if its intensity exceeds the rock's tensile strength. Further extension and propagation of cracks are caused by penetrating gases. From the study conducted by Hustrulid [34] using ANFO in medium-strength rock, the crushed zone can extend up to 6 times the hole diameter, the fracture zone up to 20, and the influenced zone up to 60 times the hole diameter.

The blasting process was modeled for a 3D intact rock described in Section 4. The estimate of damage zones is based on the damage contours on the x-y plane 2 m from the bottom of the bench, where the crushed zone is represented by the circular red contour around the charge; the fractured zone is represented by the cracks propagating from the crushed zone. Spalling occurs at the free face propagating inwards towards the blast hole, causing further fracturing, as seen in Figure 4. The blast hole expands due to gas expansion from a radius of 101.5 mm to 163.2 cm. The rock around the blast hole is completely pulverized, forming a crushed zone of 250 mm at 0.8 ms, which is 2.5 times the blast hole radius. The damage decreases with increased distance, with the pattern crossing near the blast hole and extending radially away from the blast hole, forming a fractured zone extending to 5 m in all directions at 2.5 ms.

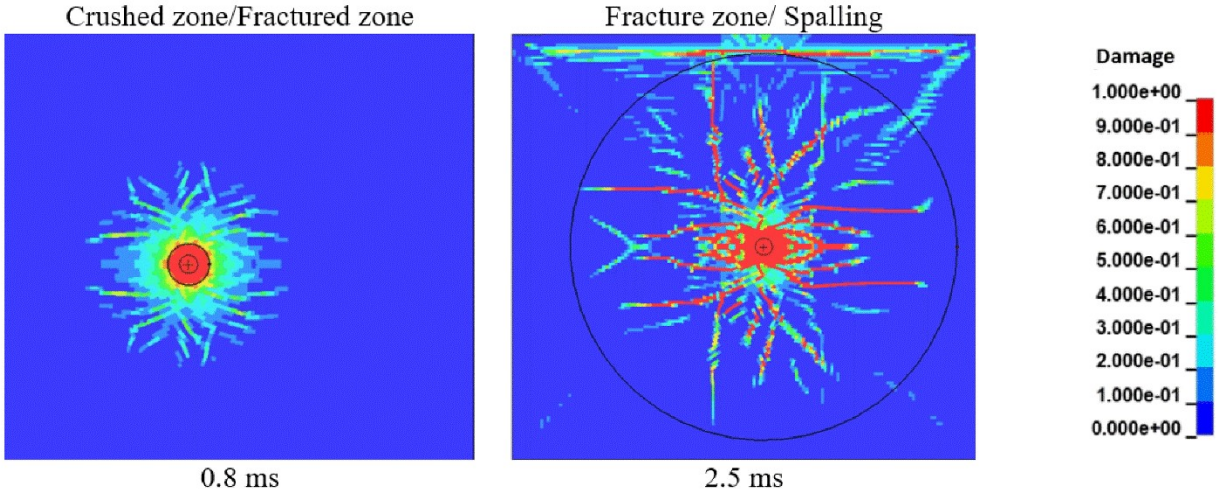


Figure 4. Damage zones around the blast hole.

The pressure at the end of the crushed zone is 949 MPa, and the PPV is 124 m/s. Dotto et al. [35] conducted a study to estimate the damage zones around the charge from the same case study, and they compared several approaches. Table 9 summarizes the result of their study. From the numerical model, the pressure at 161 mm is 1330 MPa, close to the predicted value of 1488 MPa; the PPV at 161 mm is 180 m/s. The numerical model results suggest that the wave still has the crushing capacity until it reaches 949 MPa, which is close to the pressure estimated using the Hugoniot elastic limit approach in Dotto et al. [35] study. In the previous study by Dotto et al. [35], the fractured zone was obtained to extend to 5.4 m at 1.21 m/s PPV. From the numerical model, the fractured zone at 2.5 ms has extended to 5 m, where the maximum PPV and the peak pressure are 6.2 m/s and 48 MPa, respectively. At 5.4 m, the maximum pressure is 40.8 MPa, and the PPV is 1.2 m/s, the same value obtained in the previous study.

Table 9. Crushed zone parameters [35].

Approach	Crushed zone radius (rc; mm)	Pressure at the limit of the crushed zone (Pe; MPa)	PPV at the limit of the crushed zone (m/s)
Study approach	161	1,488.13	77.9
Shock wave transfer	185	1,683.94	105.25
Hugoniot elastic limit	164	912.15	80.47
Far-field monitoring	161	510.79	54.32

5.2 The Influence of Joints Parameters

The influence of joint properties and parameters on blast-induced fragmentation has been studied by several researchers for various applications [18, 19, 36-38]. Each study concluded that the presence of joints affects blast outcomes and is worth investigating for effective blast design. In this study, several properties are investigated with their influence on blast energy distribution and crack propagation.

5.2.1. Joint Filling Material

When a stress wave encounters a joint, partial to complete wave reflection may occur depending on the joint properties. The effects of joints infill material were analyzed through simulations of empty joints and joints filled with soft rock. Table 6 and Table 7 define material properties utilized for this purpose. The intact rock is used as the base case. Three horizontal joints were modeled 1.8 m from the bottom of the bench; each joint is 3 cm wide and spaced 0.42 m. The simulation models were run for 2 ms. Figure 5 shows the pressure (a-1, a-2, and a-3) and the damage contours (b-1, b-2, and b-3). During the simulation, the pressure was monitored 1 m away from the blast hole at four locations marked A, B, C, and D. Figure 5(a) shows the locations.

Figure 5(a-1, a-2, and a-3) illustrates that the stress wave energy is affected by the presence of joints, and the effect depends on the joint filling material. In this case, the effect is more pronounced on empty joints than on the joints filled with soft rock. The resulting damage is presented in Figure 5 (b-1, b-2, and b-3) for the three cases where a clear distinction of damage progression in regions separated by the joints is observed. With the stress wave reflected on each joint, an upper section has a narrower damage zone compared with the preceding section with a clear boundary at the rock/joint interface, in this case, the empty joints have more variable damage zones.

Figure 6 (a, b, and c) shows the peak pressure variations at the four locations (A, B, C, and D). In the intact rock, the peak pressure in all locations is relatively uniform. In the jointed rock mass, the peak pressure increases significantly between the joints, with a hig her effect between empty joints. In the soft rock, the pressure increase is consistent after every joint due to partial wave reflection at the joint and the increase in the joint's stiffness increasing its transmission capacity. The highest pressure between joints is observed with empty joints at locations B and C, where more energy is reflected at the joints. The damage at such locations, however, is less than what is observed in the intact rock and soft rock joints due to higher confinement which requires way higher energy for the fracture to occur. At location D, where no more joints are encountered, the peak pressure is almost the same as the intact rock.

Figure 7 shows that beyond the joints nearly 2 m away, for the jointed rock mass, the peak pressure drops to the average of 150 MPa, close to the peak pressure encountered by the intact rock. For the four monitoring points, the peak pressures in the intact rock are achieved between 0.28 and 0.44 ms; for the joints with soft rock filling, the peak pressure happens between 0.28 and 0.48 ms, and with empty joints between 0.28 and 0.52 ms demonstrating that with variable joint infills, the stress wave speed varies too.

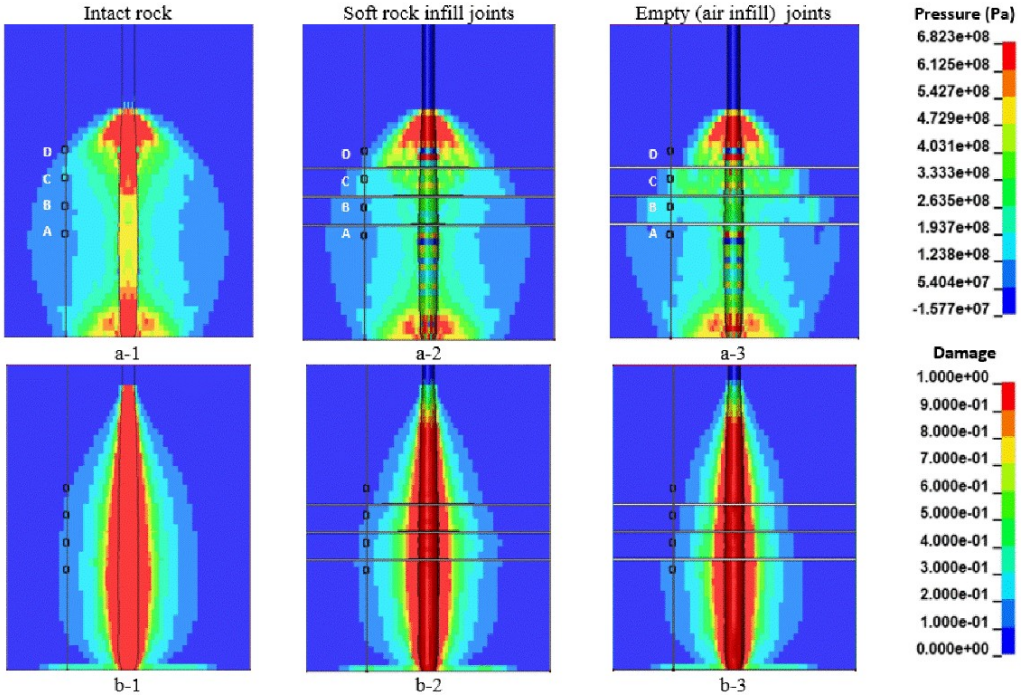


Figure 5. Stress wave propagation and damage in variable joint properties.

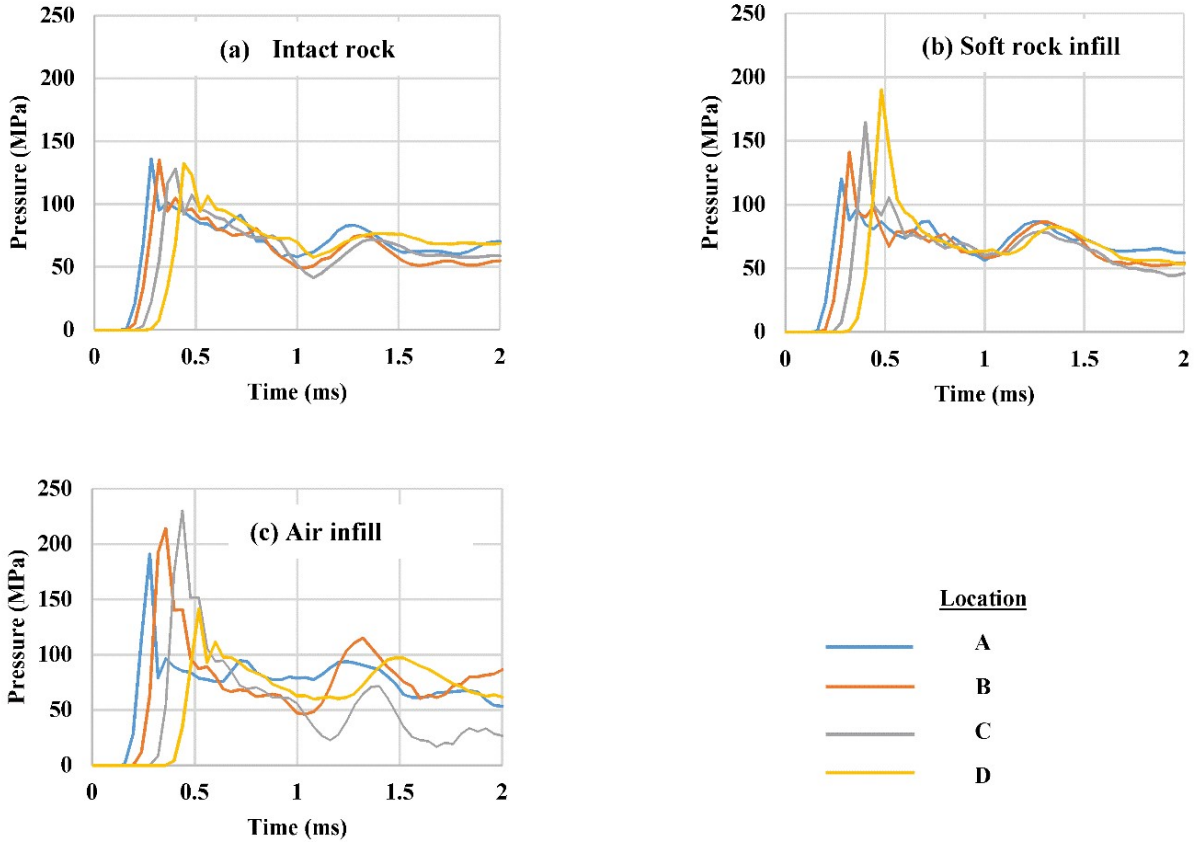


Figure 6. Pressure plots for horizontal joints.

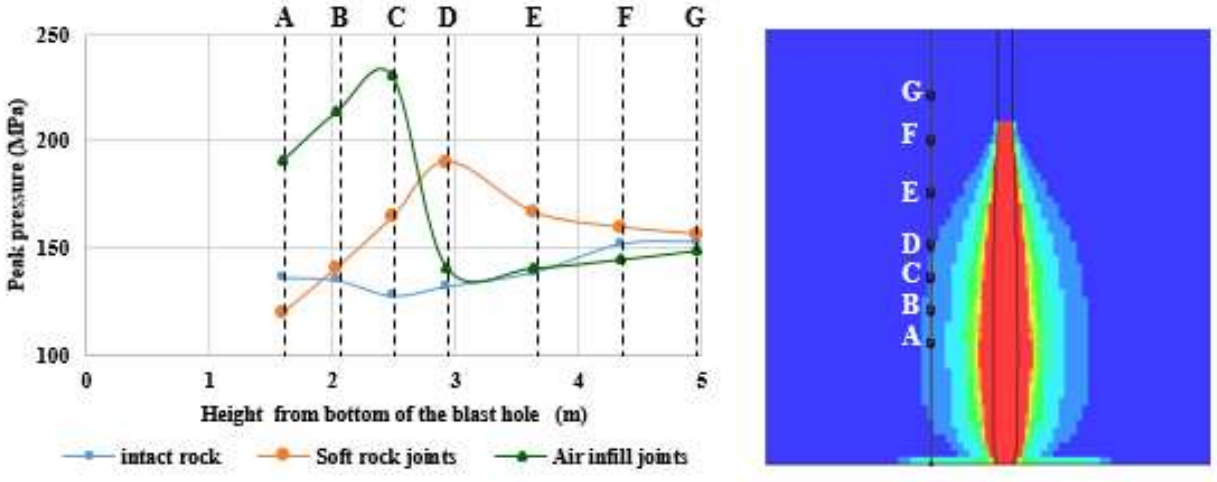


Figure 7. Peak pressure variation with distance from the bottom of the blast hole.

When similar joints, 10 cm wide, were placed 0.5 m from the blast hole, reflection at the joint/rock boundary is observed with more effect on air-infill joints, as shown by pressure contours at 0.7 ms in Figure 8. Such occurrence leads to a bigger crushed zone forming around the charge on the incident side of an empty joint and less fracturing beyond, as illustrated by Figure 9. For the air-infill joints, a pressure-neutral part is also observed between the joint and blast hole due to collision between the reflected wave and the wave front. The peak pressure was monitored at 0.5 m intervals from the blast hole. Figure 10 illustrates the relationship between pressure and distance for the two joint filling materials. With an empty joint, higher pressure near the blast hole (at 0.5 m distance) is from wave

reflection and higher compressibility at the joint. The pressure drops drastically and falls below the pressure through soft rock at a 1.5 m distance from the blast hole.

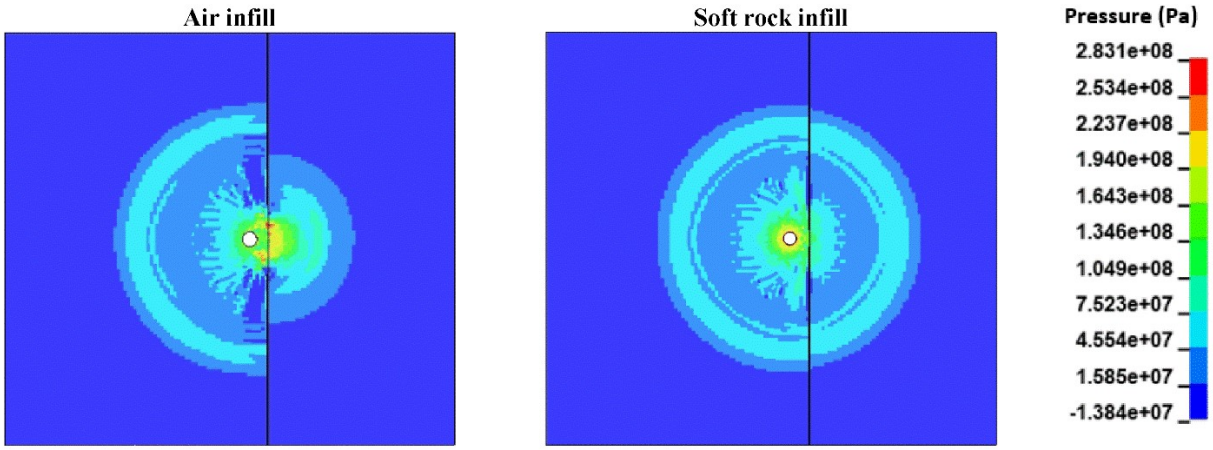


Figure 8. Pressure attenuation along different joints infill properties at 0.7 ms.

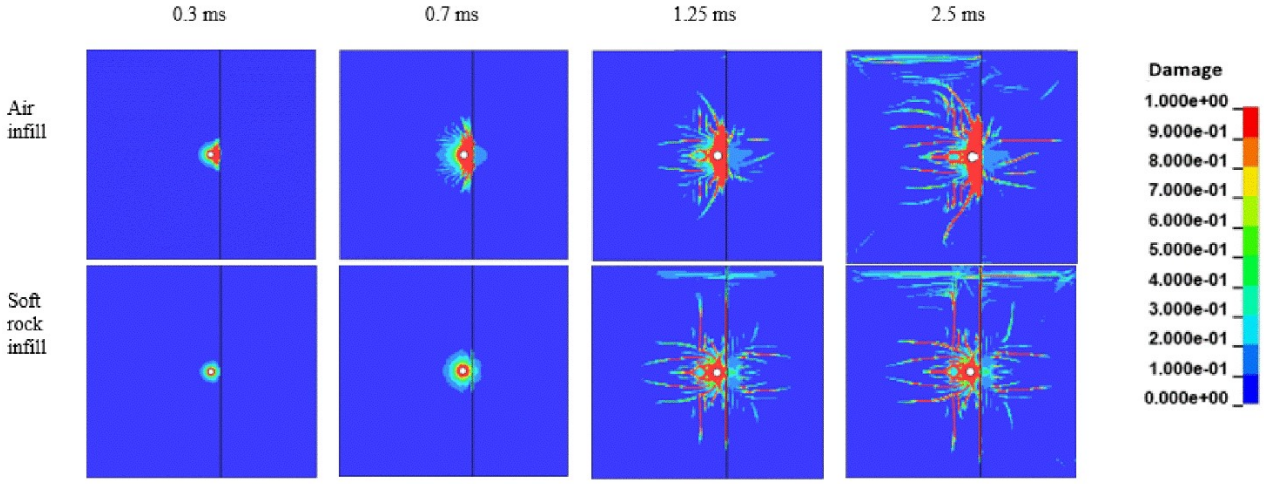


Figure 9. Damage beyond different joints′ material.

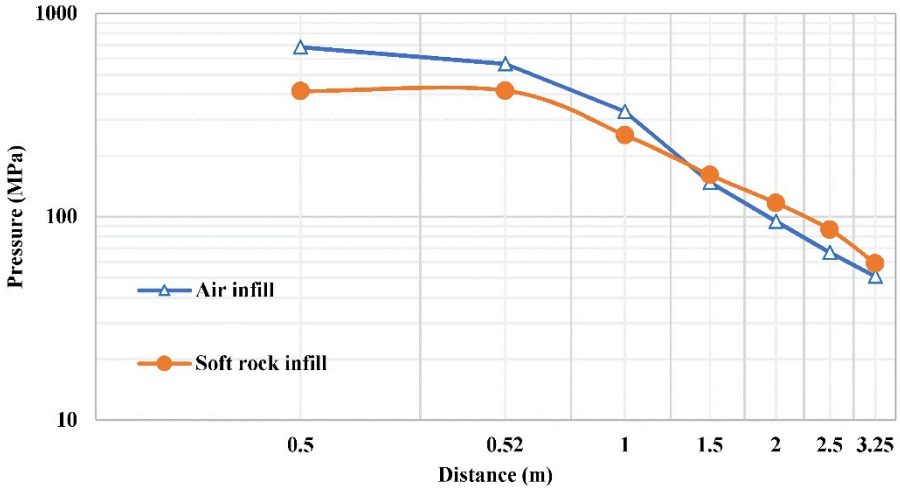


Figure 10. Pressure propagation in different joint materials.

5.2.2. Joint Width

Two scenarios analyzed the effects of joint size in blast wave propagation with joints 3 cm and 10 cm wide on a 2D model. In both cases, the joints are perpendicular to the burden and are placed 1 m from the charge. Figure 11 shows the influence of the joint width on crack propagation captured at 2.5 ms. With a wider joint, the extent of damage indicates that the rock on the opposite side of the joint is experiencing less fracturing. When the stress wave reaches the joint interface, the stiffness of the joint increases at a rate that depends on the thickness of the joint and the normal stress. For the same infill material and normal stress, smaller joints have higher specific stiffness growth than wider joints. An increase in joint stiffness increases the joint's transmission coefficient. Figure 12 describes the pressure history for both cases from the rock/joint interface before and after and within the joint. The two peak values are observed on the pressure plots before the joint from the wave front and the reflection at the joint. The pressure in the joint is higher than the incident pressure in both cases, a higher peak is observed in the narrow joint. The transmitted stress wave on a wider joint is lower due to filling material deformation under the stress wave, which is also seen at the rock/joint interface in Figure 11, causing energy absorption and a decrease in the energy transfer capacity of the joint.

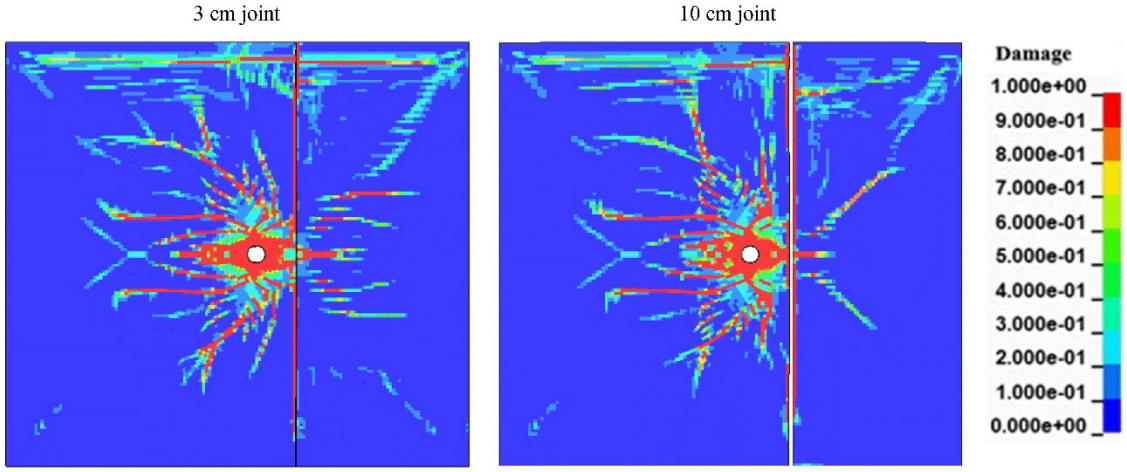


Figure 11. Joint width effects on crack propagation.

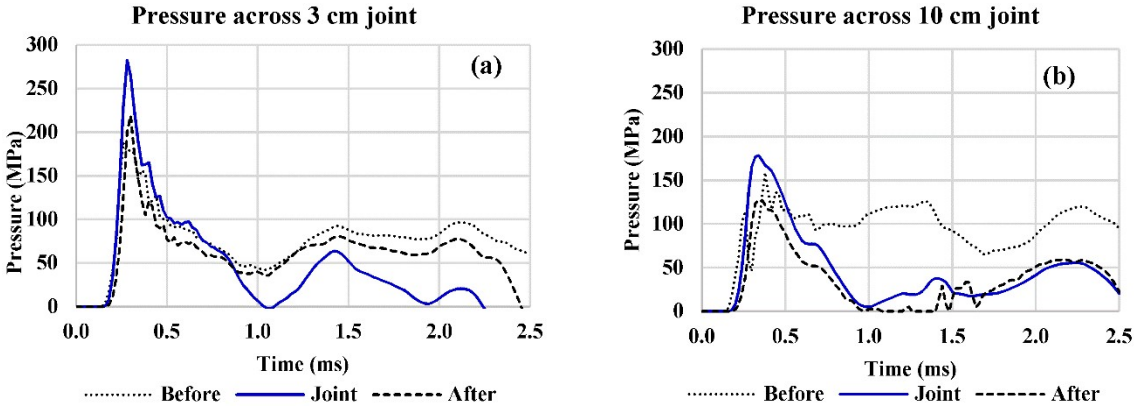


Figure 12. Pressure across joint width.

5.2.3. Joint Distance from the Blast Hole

Four scenarios with the joint placed at 0.5 m, 1 m, 2 m, and 3.25 m from the blast hole were analyzed for the effect of joint distance on stress wave and crack propagation from a 2D model. The joint infill

material is a soft rock. The results are summarized in Figure 13. Crack propagation beyond the joint increases as the joint distance from the blast hole increases, except for the last scenario, where the joint is 3.25 m from the blast hole. As demonstrated in Figure 14, the stress wave initially propagates outwards until it reaches the joint where it is partially blocked and reflected as a tensile wave causing more cracking/crushing on the incident side. Pressure build-up occurs inside the joint due to an increase in the joint's stiffness. Since the infill material is weak, deformation occurs inside the joint absorbing some of the stress wave energy. Such deformation transmits to the rock around the joint as seen in Figure 13. This effect decreases with the increase in the joint distance. Wave transmission through the joint depends on the wave strength and the extent of deformation within the joint.

At 0.5 m joint distance, most of the wave energy is reflected and used up on joint deformation, causing less fracturing on the other side. Wave energy reflection and joint deformation decrease with distance increase hence better wave transmission across the joint and increasing crack propagation on the opposite side as seen in 1 m and 2 m joint distance scenarios. At 3.25 m, the stress wave has attenuated a lot, way less deformation occurs in and around the joint, less stress wave is transmitted across the joint, and therefore less cracking on the opposite side of the joint.

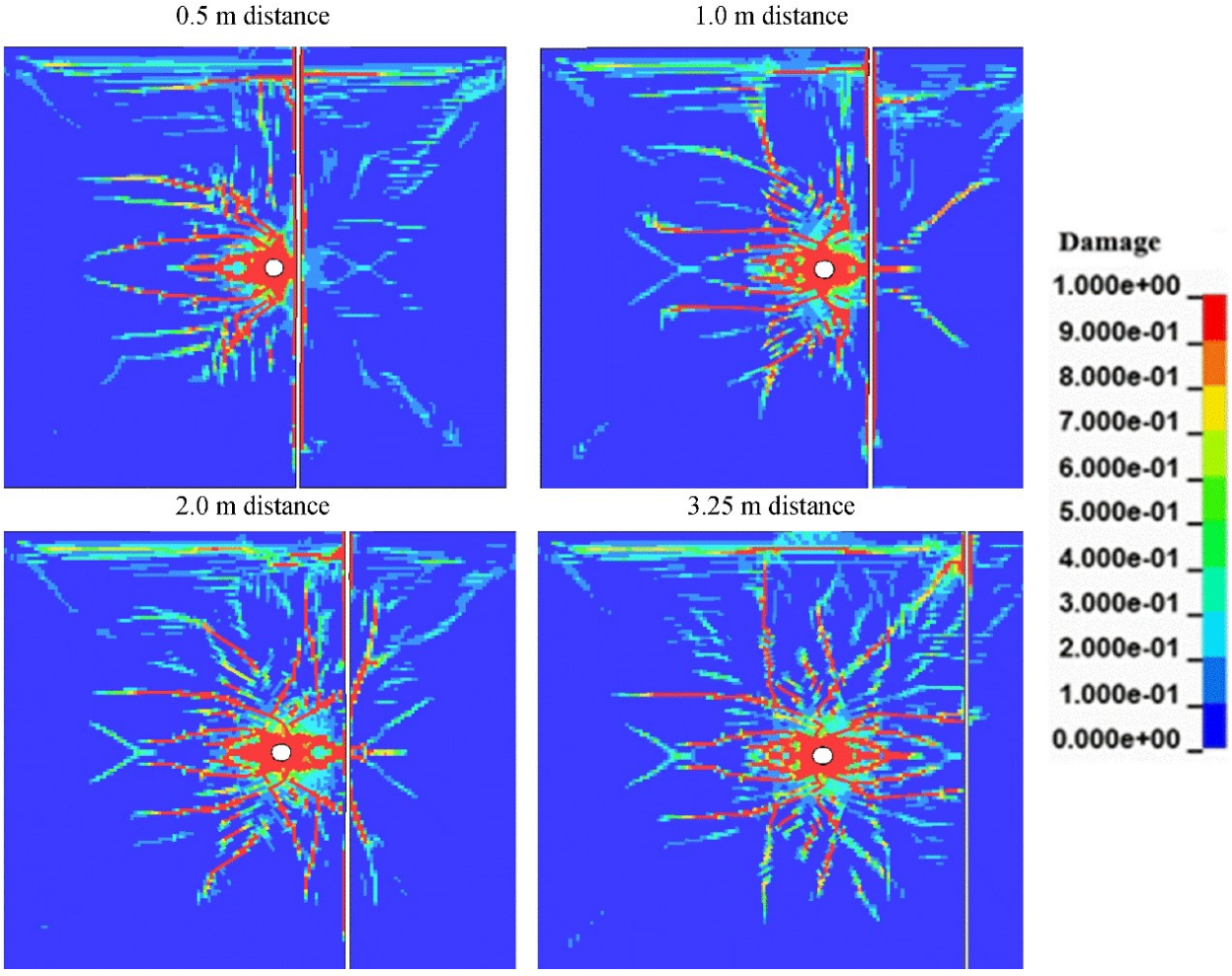


Figure 13. Damage distribution in variable joints distance.

5.2.4. Joints Spacing

Three scenarios were investigated for variable joint frequency, which are 2, 3, and 4 joints per meter. The simulation results show that the increase in joints frequency reduces the burden cracking

significantly. Figure 15 illustrates the effect of joint frequency on wave and crack propagation. With an increase in joint frequency, the wave goes through multiple partial reflections and transmissions, weakening the wave strength. Similarly, joint deformation consumes some wave energy, and with the increase in joint frequency, this occurs multiple times contributing to weakening the stress wave. This results in less fractures on the opposite side of the joints.

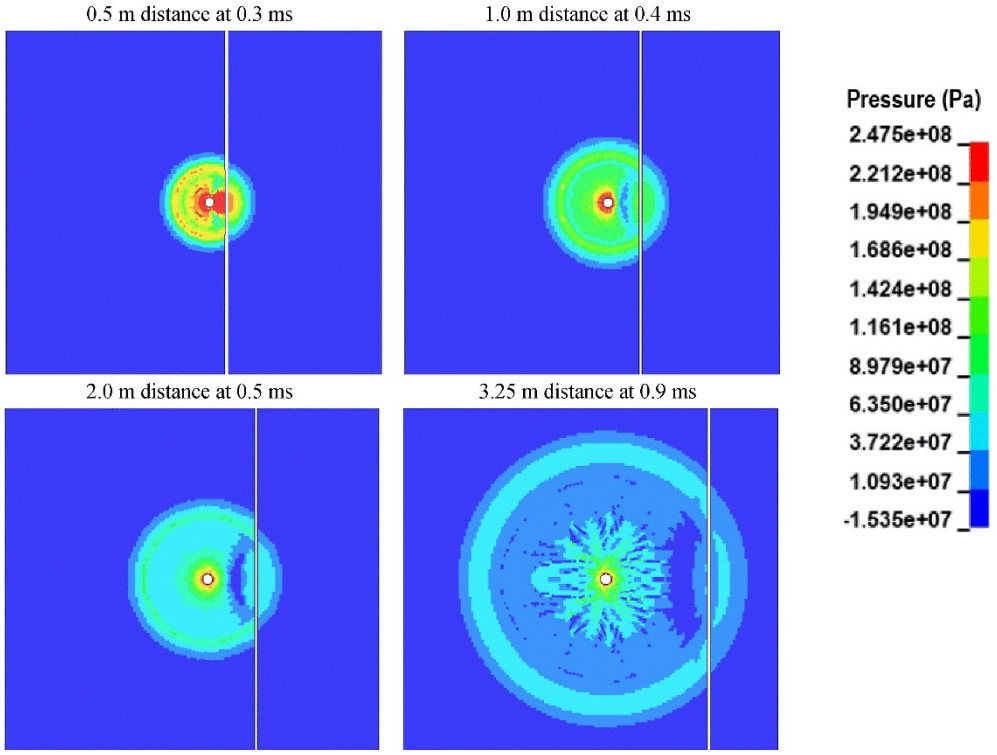


Figure 14. Stress propagation in variable joint distances.

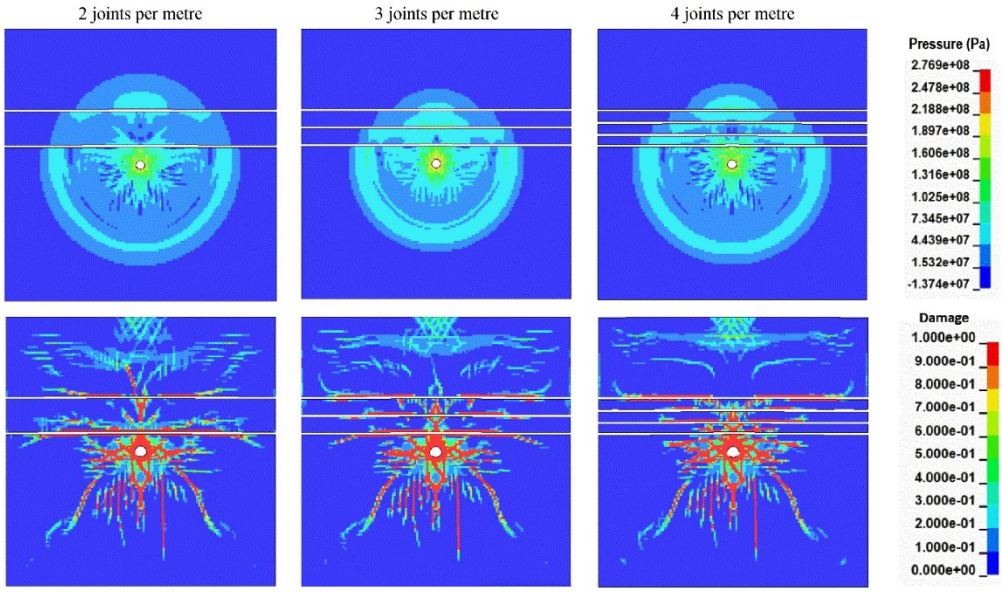


Figure 15. Joints frequency.

5.2.5. Joints Orientation

Five models of different joint orientations, including joints at 15, 30, 45, 60, and 90 to the free face, were analyzed to investigate the effects of joint orientation on blast wave propagation and rock mass fragmentation. The joints are 3 cm wide, with soft rock as the infill material. The general view of the models and the damage distribution at 2.5 ms for variable joint orientations and the intact rock as a baseline is illustrated in Figure 16. The orientation of the joints influences the direction and propagation of cracks. Cracks propagation beyond the joint depends on the angle at which the stress wave hits the joints. Compared with the intact rock, near horizontal angles, i.e., 15 and 30 degrees, the joints are hit perpendicular to the joint, energy gets transmitted, and cracks propagate beyond the joint. Transmission decreases with the increase in the joint orientation, as seen with 60- and 90-degree joints. Since the joints' orientations do not favor further cracking from wave reflection at the free face, the burden cracking is reduced significantly.

5.2.6. Parallel Versus Random Joint Sets

A model with a free face on the top of the bench and the two opposite sides of the blast hole was used to analyze the effect of joint sets' orientations on the blast wave propagation and rock fracturing for parallel and random joints. On the opposite sides, free faces were used to ensure the two scenarios' fair comparison. In both scenarios, three (3) joints are placed within 2 to 4 m of the blast hole. When the wave encounters a joint set, multiple reflections and partial transmissions occur at the joints' interfaces. With intersected/random joints, the direction of transmitted and reflected waves is changed, adding to the attenuations caused by the joints' properties. Figure 17 (a) describes the pressure contours at 1 ms, and Figure 17 (b) the damage at 2.5 ms for parallel and random joint orientations. The burden breakage is better with parallel joints case due to less attenuation across the joints as shown in Figure 18.

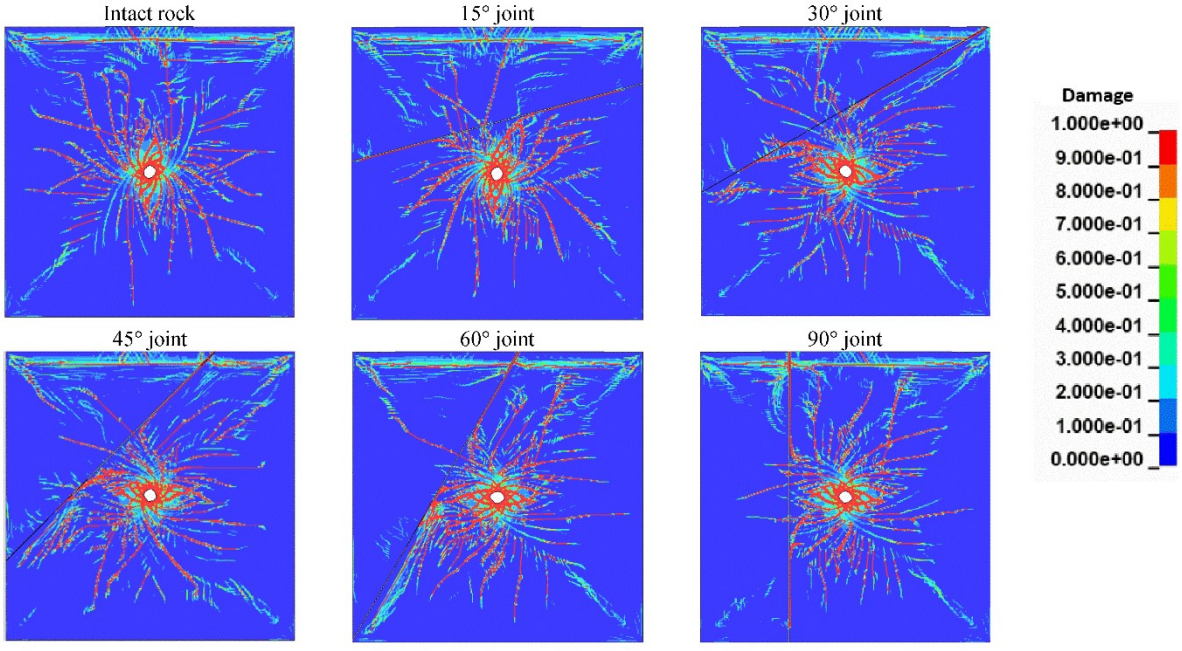
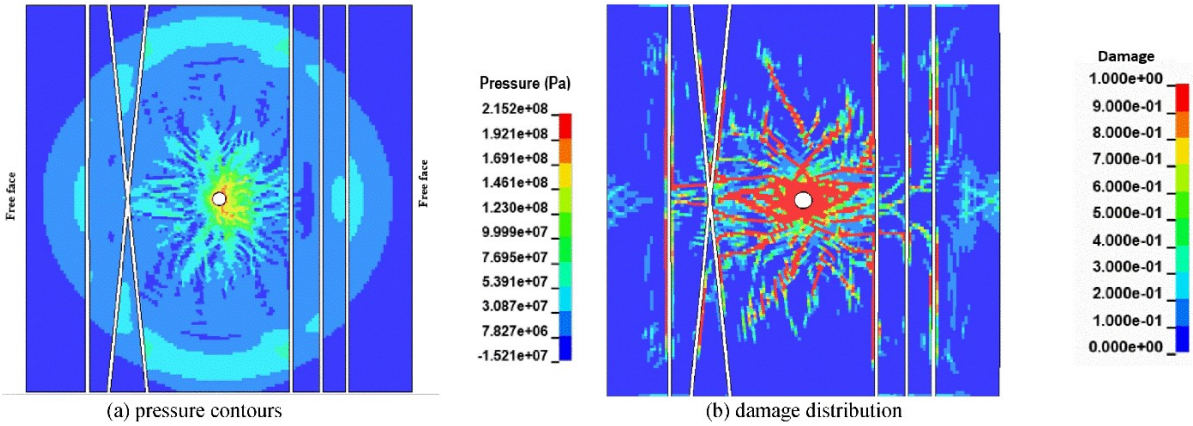


Figure 16. Damage distribution from joints orientation.



(a) pressure contours (b) damage distribution

Figure 17. Random joint sets analysis.

5.3 Initiation Delay

The stress wave intensity and the interaction from neighboring charges control rock fragmentation around the blast hole. The effect of initiation timing is investigated from two blast holes with one joint 1.5 m from the first blast hole. Two scenarios are run, the first being both charges detonated at the same time and the second with a 1 ms delay on the second blast hole. The simulation is run for 2 ms from the detonation of the second blast hole; therefore 2 ms and 3 ms for the first and the second scenarios, respectively. The results in Figure 19 reveal that the delay is important in enhancing fragmentation by allowing enough time for the cracks to grow especially beyond the joint. It is important to determine the optimum delay, which is the function of the rise and duration of the stress pulse, the stress wave speed, and crack propagation in the rock mass, [39].

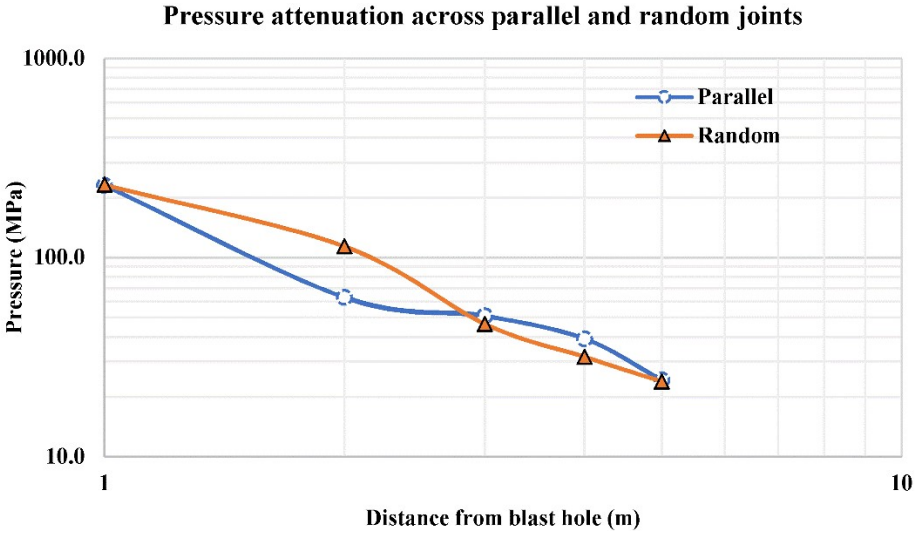


Figure 18. Pressure attenuation across joint sets.

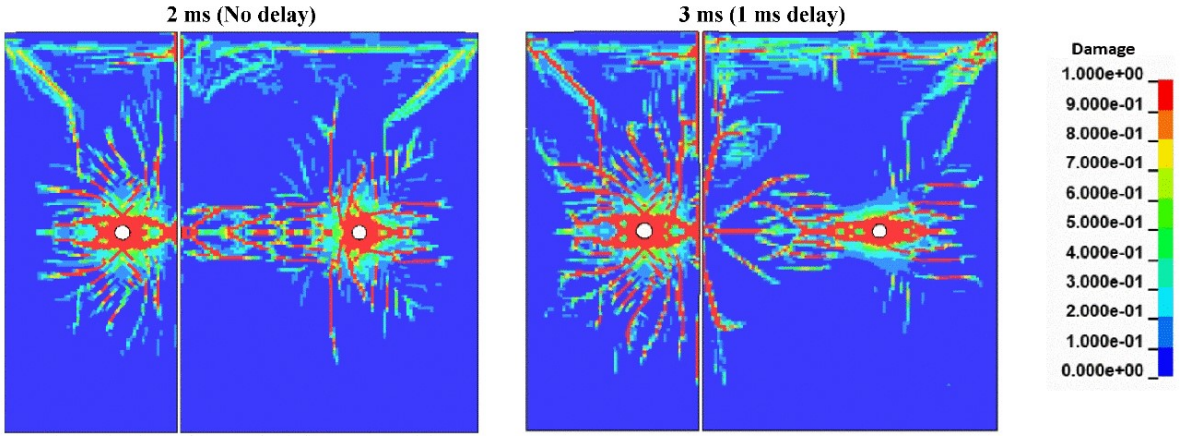


Figure 19. Blast-induced damage from detonation timing.

5.4 Rock Properties

During the blasting process, wave propagation and crack propagation are greatly influenced by the rock's physical and mechanical properties. Two models are investigated for the effects of rock strength on the propagation of stress waves and the formation of damage zones around the charge. hard rock.

Table 10 shows the properties of the weaker rock. Figure 20(a) shows that the stress waves propagate faster in the hard rock than in the soft rock. Damage zones in Figure 20(b) are clearly defined on the hard rock; on the soft rock, on the other hand, due to less resistance offered by the rock strength, the crushed zone is not formed around the charge nor the distinctive cracks around the charge, instead the damage is defined by the separation between individual elements of the model. Figure 21 illustrates that pressure attenuates faster in soft rock than in hard rock.

Table 10. Soft rock properties.

Density (kg/m^3)	Compressive strength (MPa)	Tensile strength (MPa)	Young's modulus (GPa)	Poisson ratio	Elastic shear modulus (GPa)
1600	10	1	25	0.3	9.8

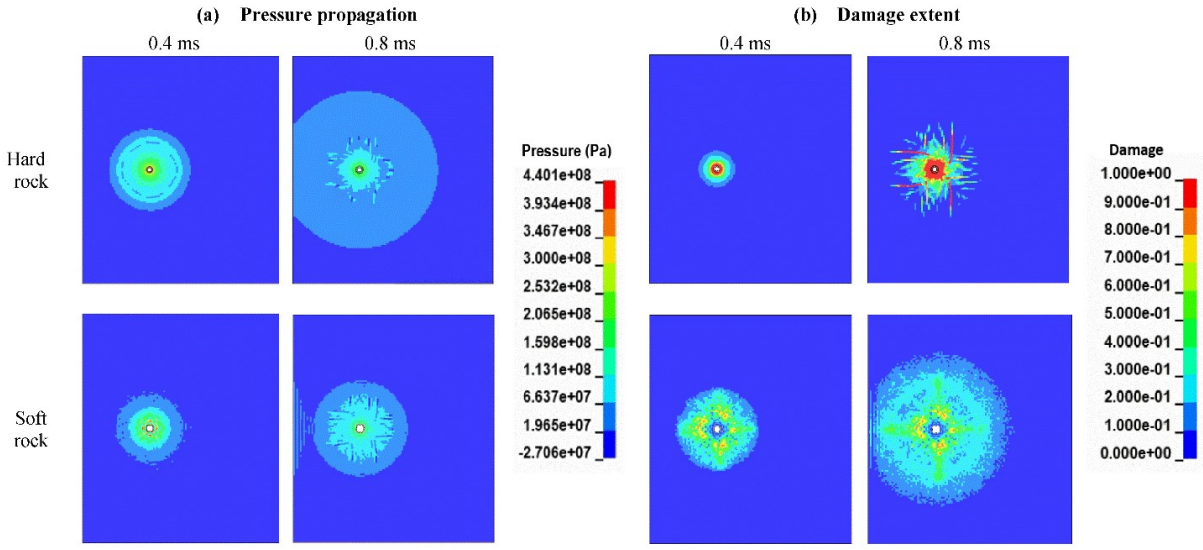


Figure 20. Pressure and damage propagation in hard and soft rock.

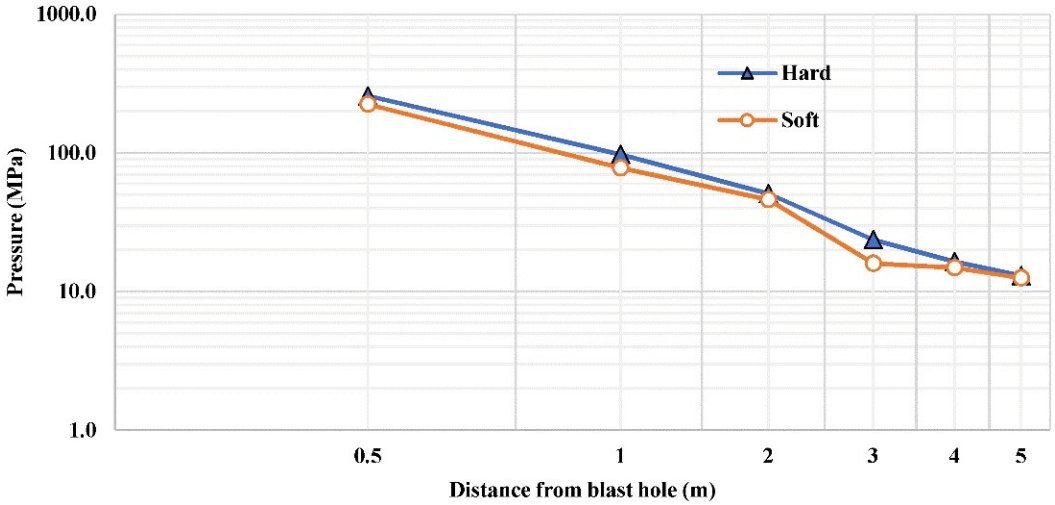


Figure 21. Pressure attenuation in hard and soft rock.

6. Field Blast Fragmentation

This section presents the outcomes of the filed blast for the same data used in the simulation. Data for rock mass properties, blast design, and explosive properties for the case study are discussed in Section 2. Figure 22 shows the lithologies and joint orientations mapped on the pit wall on locations P1, P3, P5, P7, P9, P11, and P13 and projected into the bench. Blast monitoring and fragmentation analysis for the blast shot was performed using Wip-frag software [40] from the images taken on top of the blasted muckpile at locations P2, P4, P6, P8, P10, P12, and P14 (Figure 22). Please refer to Dotto et al. [35] for a complete analysis of the results. Figure 23 shows the relationship between the fragmentation size (P50) and the distance between the blast hole to the monitoring point.

In the case of isotropic and homogeneous rock mass, the fragmentation size increases with the increase in distance from the blast hole. Based on the analysis of fragmentation, P8 has the smallest fragmentation size and is the closest to the blast hole. Although multiple random joints are crossing the burden, the monitoring location is very close to the blast hole (within 0.8 m), within the high-intensity stress wave zone, resulting in good fragmentation. P6 is the furthest from the blast hole and has several random joints crossing the burden, leading to oversize fragmentation. P10 and P12 are almost a quarter burden from the blast hole with no joint between the blast hole and the monitoring point. A medium size fragmentation is observed in both cases since they are within the fractured zone. Although P10, which is closer to the blast hole has a bigger fragmentation (103.97mm) than P12 (87.98 mm), it has a higher size reduction factor (22) as compared to P12 (16), which is the ratio of the average intact block size to the average fragmentation size.

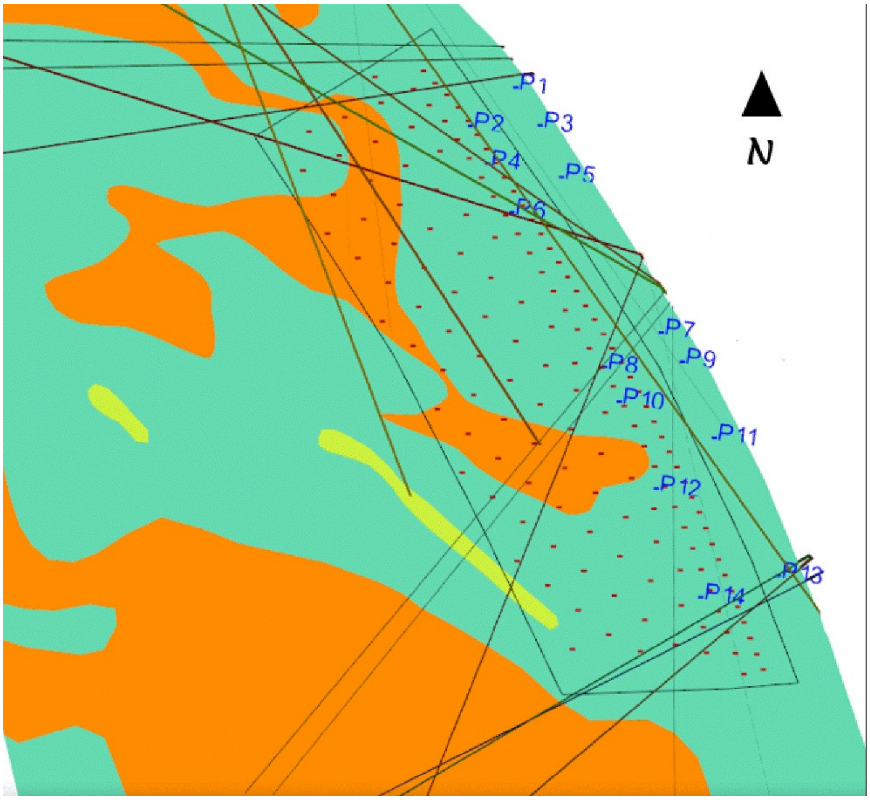


Figure 22. Mapped structures on the pit wall.

Muckpile Point	Distance from blast hole (m)	Intact block size (mm)	Frag. size P_{50} (mm)
P8	0.8	670	73.67
P6	2.8	2,380	267.09
P10	1.27	2,260	103.97
P12	1.65	1,420	87.98
P14	1.99	1,300	184.40

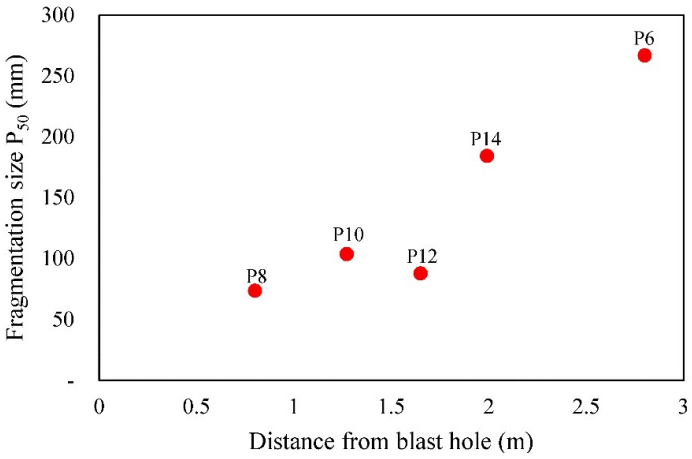


Figure 23. Fragmentation along the burden.

7. Discussion

The simulation results show that several factors influence the fracturing process by blasting. The formation of damage zones around the charge depends on explosive strength and detonation efficiency which determine the energy output, and the rock mass strength and structural properties which control fracturing and energy transmission. In soft rock, distinct damage zones are not formed due to less confinement from a weaker material. Instead, damage occurs through the separation of individual elements in the model. This has also been observed in the study conducted by Cui et al. [41]. For the hard rock, the analytical models using the field data underestimate the size of the crushed zone. For the same rock strength, the simulation results show that the wave still has a

crushing capacity at 1488 MPa until it reaches 949 MPa. Both field results and simulation results show that the fracture zone for the intact rock can extend to 5.4 m where the pressure is 40 MPa, and the PPV is 1.2 m/s. Beyond that, the damage caused is not significant in rock fragmentation.

Joint parameters such as filling material, joint width, joint distance from the charge, fracture frequency, and joints/joint sets orientations affect the distribution of blast energy and therefore impact the blast-induced fragmentation. Results from the simulation model are similar to the field blast, both indicating that, for the same amount of blast energy, the burden fracturing depends on the distance from the blast hole, the structures present, and their properties.

Interaction between charges plays a major role in blast outcomes. Simultaneous detonation hinders crack propagation by increasing confinement between the charges. Initiation delay between adjacent holes is important in minimizing the interference of the stress wave and allowing time for cracks to form. Delays are also important in pre-conditioning the rock at a distance from the charge with micro-cracks that can be extended by the gas pressure or the next charge, improving fragmentation.

Generally, efficient fracturing in jointed rock mass requires understanding the rock mass's physical and mechanical properties, the influence of joint parameters, and the design modifications necessary to improve the outcomes. Design modifications can include burden and spacing adjustments, changes in the type of explosive to ensure fracturing efficiency depending on the encountered rock mass, or techniques to vary explosive quantity per volume blasted to ensure effective distribution of explosive energy.

8. Conclusion and Future Work

Variable rock mass properties impact the distribution of explosive energy and blast outcomes. Several methodologies have been used to understand the interaction between the rock mass and explosive energy and predict the blast outcomes. This study used finite element numerical modeling using the RHT model in LS-DYNA to simulate the effect of rock properties, joint parameters, and initiation delay on the distribution of explosive energy and the fracturing process.

The simulation outcomes were compared to the results obtained from the field blast. Joint parameters such as the filling material, joint width, joint distance from the charge, fracture frequency, and individual joints and joint sets orientations were modeled, and outcomes were compared with the field blasts. The results showed that when the RHT model parameters are calibrated based on real data, they can be used to simulate the fragmentation process, as confirmed by the similarities between the simulation's damage plots and the distribution measured in the field.

The three-dimensional simulation of blast-induced damage on intact rock showed that the damage begins with forming a crushed zone around the charge, which propagates outwards, preferably towards the free surface. The reflection of the stress wave from the free surface causes spalling at the free face progressing towards the blast hole if the stress wave exceeds the rock's tensile strength. Less fracturing is evident on non-reflecting boundaries. In the case of jointed rock mass, the formation and shape of damage zones vary significantly depending on the properties of discontinuities.

This work can be extended by coupling LS-DYNA with other software to measure and estimate the fragmentation size from the damage plots to be able to compare with the field-blasted muckpile fragmentation. One of the major focuses in mining blasts is to attain the pit design. This study can be extended to assess the impact of the rock mass properties on the final pit wall and pit floor and check for over-breaks and under-breaks.

9. References

[1] Liu Q, Katsabanis PD. A Theoretical Approach to the Stress Waves Around a Borehole and Their Effect on Rock Crushing. Proceedings of the Fourth International Symposium on Rock Fragmentation by Blasting-Fragblast-4; Vienna, Austria1993. p. 9-16.

[2] Esen S, Onederra I, Bilgin HA. (2003). Modelling the size of the crushed zone around a blasthole. *International Journal of Rock Mechanics and Mining Sciences, 40*(4), 485-95. doi:https://doi.org/10.1016/S1365-1609(03)00018-2

[3] Grady DE, Kipp ME. (1980). Continuum modelling of explosive fracture in oil shale. *International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts, 17*(3), 147-57. doi:https://doi.org/10.1016/0148-9062(80)91361-3

[4] Zhu Z, Mohanty B, Xie H. (2007). Numerical investigation of blasting-induced crack initiation and propagation in rocks. *International Journal of Rock Mechanics and Mining Sciences, 44*(3), 412-24. doi:https://doi.org/10.1016/j.ijrmms.2006.09.002

[5] Yoon J, Jeon S, editors. Use of a modified particle-based method in simulating blast-induced rock fracture. Proceedings of the 9th International Symposium on Rock Fragmentation by Blasting, Fragblast; 2010.

[6] Onederra IA, Furtney JK, Sellers E, Iverson S. (2013). Modelling blast induced damage from a fully coupled explosive charge. *International Journal of Rock Mechanics and Mining Sciences, 58*, 73-84. doi:https://doi.org/10.1016/j.ijrmms.2012.10.004

[7] Fleetwood K, Villaescusa E, Li J, editors. Limitations of using PPV damage models to predict rock mass damage. Thirty-Fifth Annual Conference on Explosives and Blasting Technique; 2009; Denver, CO, USA: International Society of Explosives Engineers.

[8] Persson PA, Holmberg R, Lee J. Rock blasting and explosives engineering: CRC Press; 1994.

[9] Sun C. Damage zone prediction for rock blasting. Salt Lake City, UT, USA: University of Utah; 2013.

[10] Junkin W, Ben-Awuah E. (2023). Determining characteristic fractured volumes in DFN models using fracture intensity variability analysis. *GEM - International Journal on Geomathematics, 14*(1), 17. doi:10.1007/s13137-023-00226-9

[11] Zhang ZX. Rock Fracture and Blasting: Theory and Applications Amsterdam: Elsevier; 2016.

[12] Azadmehr A, Jalali SME, Pourrahimian Y. (2019). An Application of Rock Engineering System for Assessment of the Rock Mass Fragmentation: A Hybrid Approach and Case Study. *Rock Mechanics and Rock Engineering, 52*(11), 4403-19. doi:10.1007/s00603-019-01848-y

[13] Lizotte Y, Scoble M. (1994). Geological control over blast fragmentation. *CIM Bulletin, 87*(983), 57-71.

[14] Yang RL, Rocque P, Katsabanis P, Bawden WF. (1994). Measurement and analysis of near-field blast vibration and damage. *Geotechnical & Geological Engineering, 12*(3), 169-82. doi:10.1007/BF00426985

[15] Bhandari S. Changes in fragmentation processes with blasting conditions. Fragmentation by blasting. Fragblast 5. Quebec, Canada: A. A. Balkema; 1996. p. 301-9.

[16] Mortazavi A, Paventi M, Brummer RK, Mohanty B. Modelling of blast-induced stress wave propagation and fracturing in hard rock material. Canadian Institute of Mining (CIM)-Annual Conference; May, 2002; Vancouver, BC, Canada2002.

[17] Wang ZL, Konietzky H. (2009). Modelling of blast-induced fractures in jointed rock masses. *Engineering Fracture Mechanics, 76*(12), 1945-55. doi:https://doi.org/10.1016/j.engfracmech.2009.05.004

[18] Wang Z, Huang Y, Xiong F. (2019). Three-Dimensional Numerical Analysis of Blast-Induced Damage Characteristics of the Intact and Jointed Rockmass. *Computers, Materials \& Continua, 60*(3), 1189 -206.

[19] Jiang X, Xue Y, Kong F, Gong H, Fu Y, Zhang W. (2023). Dynamic responses and damage mechanism of rock with discontinuity subjected to confining stresses and blasting loads. *International Journal of Impact Engineering, 172*, 104404. doi:https://doi.org/10.1016/j.ijimpeng.2022.104404

[20] Zhang F, Yang L, Hu H, Huang C, Chen S. (2023). Study on the crack propagation behaviour of eccentric uncoupled blasting in a deep-level rock mass. *International Journal of Mining, Reclamation and Environment, 37*(6), 419-40. doi:10.1080/17480930.2023.2213546

[21] Livermore Software Technology Corporation L. LS-DYNA® Keyword User's Manual R11 Volume II Material Models2018.

[22] Ma GW, An XM. (2008). Numerical simulation of blasting-induced rock fractures. *International Journal of Rock Mechanics and Mining Sciences, 45*(6), 966-75. doi:https://doi.org/10.1016/j.ijrmms.2007.12.002

[23] Dehghan Banadaki MM, Mohanty B. (2012). Numerical simulation of stress wave induced fractures in rock. *International Journal of Impact Engineering, 40-41*, 16-25. doi:https://doi.org/10.1016/j.ijimpeng.2011.08.010

[24] Wang J, Yin Y, Esmaieli K. (2018). Numerical simulations of rock blasting damage based on laboratory-scale experiments. *Journal of Geophysics and Engineering, 15*(6), 2399-417. doi:10.1088/1742-2140/aacf17

[25] Holmquist TJ, Johnson GR, Cook WH, editors. A Computational Constitutive Model for Concrete Subjected to Large Strains, High Strain Rates and High Pressures. 14th International symposium, Vol 2; Warhead mechanisms, terminal ballistics; 1993; Arlington, Quebec; Canada: ADPA;.

[26] Riedel W, Thoma K, Hiermaier S, Schmolinske E, editors. Penetration of Reinforced Concrete by BETA-B-500 Numerical Analysis using a New Macroscopic Concrete Model for Hydrocodes. 9th international symposiumon interaction of the effects of munitions with structures; 1999; Berlin, Germany.

[27] Wang Z, Wang H, Wang J, Tian N. (2021). Finite element analyses of constitutive models performance in the simulation of blast-induced rock cracks. *Computers and Geotechnics, 135*, 104172. doi:https://doi.org/10.1016/j.compgeo.2021.104172

[28] Xie LX, Lu WB, Zhang QB, Jiang QH, Chen M, Zhao J. (2017). Analysis of damage mechanisms and optimization of cut blasting design under high in-situ stresses. *Tunnelling and Underground Space Technology, 66*, 19-33. doi:https://doi.org/10.1016/j.tust.2017.03.009

[29] Yi C, Sjöberg J, Johansson D. (2017). Numerical modelling for blast-induced fragmentation in sublevel caving mines. *Tunnelling and Underground Space Technology, 68*, 167-73. doi:https://doi.org/10.1016/j.tust.2017.05.030

[30] Borrvall T, Riedel W, editors. The RHT concrete model in LS-DYNA. 8th European LS-DYNA users conference; 2011; Strasbourg, Austria.

[31] ORICA. (2018). Technical data sheet - Fortis Extra System - Africa.

[32] Lee EL, Hornig HC, Kury JW. Adiabatic Expansion Of High Explosive Detonation Products. United States; 1968. Contract No.: UCRL-50422.

[33] Hansson H. Determination of properties for emulsion explosives using cylinder expansion tests and numerical simulation. Swebrec - Swedish Blasting Research Centre; 2009. Report No.: ISSN 1653-5006.

[34] Hustrulid WA. Blasting Principles for Open Pit Mining: CRC Press; 1999.

[35] Dotto MS, Pourrahimian Y, Joseph T, Apel D. (2022). Assessment of blast energy usage and induced rock damage in hard rock surface mines. *CIM Journal, 13*(4), 166-80. doi:10.1080/19236026.2022.2126924

[36] Chen SG, Zhao J. (1998). A study of UDEC modelling for blast wave propagation in jointed rock masses. *International Journal of Rock Mechanics and Mining Sciences, 35*(1), 93-9. doi:https://doi.org/10.1016/S0148-9062(97)00322-7

[37] Ismail MA, Gozon JS. (1987). Effects of discontinuities on fragmentation by blasting. *International Journal of Surface Mining, Reclamation and Environment, 1*(1), 21-5. doi:10.1080/09208118708944098

[38] Yang R, Ding C, Yang L, Chen C. (2018). Model experiment on dynamic behavior of jointed rock mass under blasting at high-stress conditions. *Tunnelling and Underground Space Technology, 74*, 145-52. doi:https://doi.org/10.1016/j.tust.2018.01.017

[39] Saadatmand Hashemi A, Katsabanis P. (2020). The Effect of Stress Wave Interaction and Delay Timing on Blast-Induced Rock Damage and Fragmentation. *Rock Mechanics and Rock Engineering, 53*(5), 2327-46. doi:10.1007/s00603-019-02043-9

[40] WipWare. Sampling and Analysis Guide2021.

[41] Cui J, Xie L, Qiao W, Qiu L, Hu Z, Wu L. (2022). Study on blasting characteristics of rock mass with weak interlayer based on energy field. *Scientific Reports, 12*(1), 12698. doi:10.1038/s41598-022-17028-y

Review of Recent Developments in Short-Term Mine Planning and IPCC with a Research Agenda[1]

Nasib Al Habib[a], Eugene Ben-Awuah[b] and Hooman Askari-Nasab[a],
Mining Optimization Laboratory (MOL)
[a] University of Alberta, Edmonton, Canada
[b] Laurentian University, Sadbury, Canada

ABSTRACT

Equipment allocation is an integral part of short-term planning. In the past few decades, In-Pit Crushing and Conveying (IPCC) has gained much momentum to replace trucks partially or fully in large open pit mines because of the increasing fuel and labour cost of the shovel-truck system, low operating cost and less greenhouse gas emissions of conveyor systems. This article aims to review the work done on short-term mine planning and IPCC in open pit mines to find research gaps and future research opportunities in short-term planning with IPCC as the prime means of material handling. The most recent literature since 2010 on short-term planning, based on different formulation and solution approaches, and IPCC, based on primary objectives such as optimum crusher location, economic/environmental comparison etc., have been reviewed. The review reveals that hardly any short-term planning model can generate mine extraction sequences with IPCC integration. The authors propose a theoretical problem formulation to explore this research gap as a future research direction. One of the key contributions of this article is to point out the fact that developing a short-term planning methodology considering the IPCC system would be a pioneering step in the mine planning literature.

***Key words**: Short-term mine planning and scheduling, simulation-optimisation, IPCC*

1. Introduction

This article is intended to do a review of short-term mine planning and IPCC to provide an idea about the prospects that IPCC may have on short-term planning of open pit mines. The review reveals that short-term planning with IPCC has hardly been explored yet by any researcher. Hence, a theoretical short-term planning methodology by IPCC integration is proposed as a future research opportunity. The appendix section of the paper contains the tabular summary of the reviewed short-term planning and IPCC related paper, their key features, missing attributes, constraints etc.

Open pit mining is a highly capital-intensive operation. Studies such as, Moradi Afrapoli and Askari-Nasab (2017), Osanloo and Paricheh (2020), Rodovalho, et al. (2016), Bozorgebrahimi, et al. (2003) etc. have indicated that about 50% of the operating costs in surface mining is allocated to truck-shovel operation. Therefore, hauling has the highest operating cost among all the material handling operations in open-pit mines. Short-term planning is concerned with meeting production with proper head grade requirements at the mill and minimising ore-waste misclassification. These objectives can be achieved by operational activities such as maximising the production rate, equipment availability, utilisation, minimising grade deviation from plant target by grade blending, minimising equipment movement and cost of ore extraction etc. In-pit crushing and conveying (IPCC) has gained much momentum in the past few decades because of

[1] This paper has been published in Mining Technology journal in June 2023.

ISBN: 978-1-55195-503-2

the high fuel cost, labour cost and low operating cost of conveyors (McCarthy 2011). Many mines have been employing IPCC in recent years with a comparatively smaller fleet of trucks. S11D, the largest iron ore mine in Brazil, valued at $14.3 billion, started its operation in 2017 with a truck less IPCC operation. The total length of the conveyor belts operating in the mine and the plant is an astounding 68 km (Topf 2017). A list of all mines from 1956 to 2014 with in-pit crushing and conveying has been summarised by Ritter (2016). Researchers are now looking to integrate IPCC systems in mine planning and scheduling. Mine planning can be divided into long-term and short-term planning based on the planning time-horizon and the objectives being optimised. The next section briefly describes the purposes of short-term mine planning.

1.1. Short-Term Planning

The primary objective of any mining project is to maximise the net present value (NPV) by minimising the cost. While the long-term plan is created at the management level to maximise the net present value (NPV) throughout the life of mine, the short-term planning aims at optimizing the operational activities like shovel allocation, grade blending, truck requirement etc. to help achieve the ultimate long-term schedule. The time horizon of short-term planning can be monthly, weekly or even daily. The output of short-term planning is used as a basis for day-to-day mine operations, and adjustments are made as needed to respond to changing conditions or unexpected events. Effective short-term mine planning is crucial for ensuring the profitability and sustainability of a mining operation.

1.2. In-Pit Crushing and Conveying (IPCC)

In-pit crushing and conveying is not a new concept in mining. It has been in use since 1956 (Osanloo and Paricheh 2020) in mines to partially or fully replace trucks in mining operation. IPCC can be divided into three categories: fully mobile, semi-mobile and fixed. Fully mobile IPCC can be loaded directly from shovels, which completely eradicates the need for off-highway trucks. However, it is the least flexible and not quite suitable for deep metalliferous mines (Dean, et al. 2015). Semi-mobile IPCC (SMIPCC) systems are the most flexible. They retain a small haulage fleet for transferring material from the shovel to the crusher, which makes them the most suitable option for mines that have been being actively extracted for years (McCarthy 2011). These crushers are relocated once every one to ten years and have the highest potential for being the most popular IPCC system in large mines in coming years because of its increasing capacity and flexibility (Osanloo and Paricheh 2020). Fixed-type in-pit crushers are placed inside the pit and are not relocated at least for a period of 15 years or more. They are also typically installed in a concrete structure and fed by trucks. Up until 2014, 209 fully-mobile, 213 semi-mobile and 25 fixed in-pit crushers were in use around the world (Osanloo and Paricheh 2020).

1.3. Why IPCC is Thriving in Open Pit Mines

McCarthy (2011) explained the advantages, disadvantages and the reasons of using IPCC in open pit mines. We will review some of these reasons for the readers' ease and to shed light on IPCC integration to existing and new mines:

- ✓ Mines are becoming deeper resulting in increasing haulage distance and the grade of existing reserves becoming smaller.
- ✓ Increasing diesel price; 10% increase from 2005 to 2018 (2018) and 67% increase from 2019 to 2022 (2022a).
- ✓ Availability of equipment, i.e., long lead time for purchasing trucks.
- ✓ Tyre shortages and high tyre costs resulting in inability to adequately utilize truck fleet.
- ✓ Personnel shortages for trucking operations. IPCC systems require fewer operating personnel.
- ✓ Environmental considerations: IPCC offers 60 million litres per year reduction in diesel consumption which is equivalent to 130,000 tonnes per year reduction in CO2 emissions and lesser noise pollution (Nehring, et al. 2018).

- ✓ Less operational risk due to fewer mobile vehicles and simpler maintenance.
- ✓ Lower operating cost in most applications because of lower personnel requirement and higher energy efficiency; 81% of the consumed energy is used to transport material compared to 39% by trucks (Nehring, et al. 2018).

1.4. When to Use IPCC

- ✓ Large mine life of at least ten years because IPCC is capital intensive and short mine life cannot make up for the capital investment by lower operating cost. The initial investment for an IPCC system is about $220M compared to $5M for a 360-ton truck (Osanloo and Paricheh 2020). Therefore, the capital requirement for one IPCC system is equivalent to the capital requirement for a fleet size of forty trucks as shown in Figure 1 .
- ✓ Large quantity of material movement is required to justify the use of IPCC; four to ten Million ton per year (McCarthy 2011).
- ✓ The differential between diesel and electricity cost should be 25% or more (Nehring, et al. 2018).

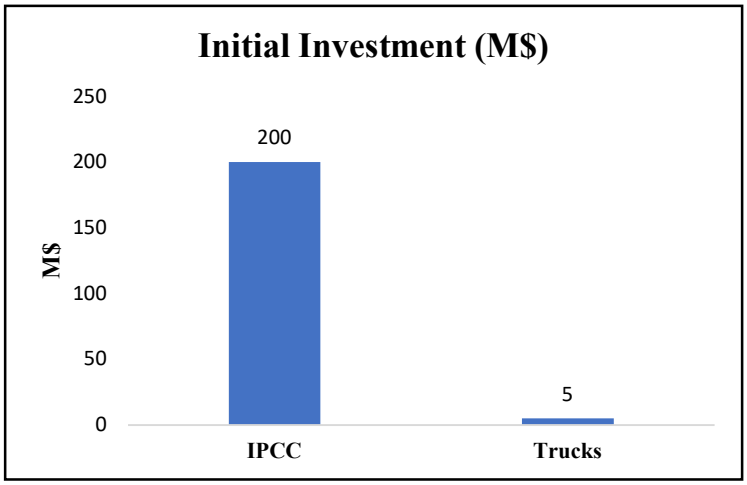


Figure 1. Initial investment for truck vs IPCC.

1.5. Risks Associated with IPCC

- ✓ IPCC installation results in higher stripping ratio to accommodate the crusher and conveyor belts.
- ✓ Skilled labour is required to operate IPCC systems, especially the fully mobile IPCC. Training employees to learn IPCC operation might be a challenge as people are habitually averse to accepting new technologies (McCarthy 2011).
- ✓ IPCC system reduces overall flexibility of mining operation because unlike trucks, IPCC cannot be scaled to increase or decrease production as required (Osanloo and Paricheh 2020).
- ✓ The conveyor system of IPCC is complex and the parts of the conveyor are dependent on each other. Failure of one conveyor part might shut the complete operation because of the interdependency of the parts.

1.6. Impact of Carbon Tax on IPCC

Environmental sustainability is getting more and more importance for every industry including mining. Traditional mining haulage by trucks is not environment friendly because of trucks' dependency on fossil fuel (Nehring, et al. 2018). Canada recently announced that it plans to increase its carbon tax rate to $170 per tonne of greenhouse gas emissions by 2030, up from the current rate of $40 per tonne (2023b). The new carbon tax rule can impact in-pit crushing and conveying (IPCC) in mines in several ways.

Firstly, IPCC can reduce greenhouse gas (GHG) emissions associated with truck haulage and therefore, reduce the carbon footprint of mining operations (Norgate and Haque 2013). As such, IPCC systems may become more economically viable due to the carbon tax incentives to reduce GHG emissions.

Secondly, the cost of implementing and operating IPCC systems may increase due to the additional costs associated with complying with the new carbon tax rule. For example, there may be additional costs for the installation and operation of emissions control systems, monitoring equipment, and carbon credits. These additional costs may impact the feasibility of IPCC systems for some mining operations.

Thirdly, the new carbon tax rule may lead to changes in mine planning and operations to reduce GHG emissions. Mining companies may be incentivized to reduce energy consumption, improve efficiency, and incorporate renewable energy sources to reduce their carbon footprint. This may lead to changes in mine design and planning to incorporate IPCC and other low-carbon technologies.

Overall, the new carbon tax rule can impact IPCC in mines in both positive and negative ways. While the reduction of GHG emissions is desirable, the additional costs associated with compliance may impact the feasibility of IPCC systems for some mining operations. However, the incentives to reduce GHG emissions may also lead to innovation and new opportunities for low-carbon mining technologies like IPCC.

1.7. Importance of IPCC in Short-term Mine Planning

Haulage is one of the largest sources of expense in any open pit mine. Traditional truck haulage is expensive and environmentally harmful because of the dependency on fossil fuel. IPCC has the potential to reduce this cost and provide a more environmentally sustainable haulage option. Hence it is crucial to explore the effects of IPCC on short-term planning of open pit mines. Several key decisions regarding IPCC, such as optimum location, relocation time, conveyor design and length etc., are made in the strategic level of mine planning. Therefore, it is important to investigate the changes that will occur in short-term mining sequences because of housing and moving a crusher inside the pit over time. It is also important to verify if the operational plans can sync with the long-term plan to deliver the desired NPV of the mine in presence of IPCC.

1.8. Research Question and Motivation

As discussed before, equipment operations comprise more than half of the operational cost in mining. Various algorithms have been proposed to optimise mine plan and schedule over the past few decades to deal with this cost. Blom, et al. (2018) summarised the range of techniques developed and used for generating short-term plans, capturing both mathematical programming-based methods and heuristic approaches. Moradi Afrapoli and Askari-Nasab (2017) reviewed mining fleet management algorithms used in both academic and industrial purposes. Osanloo and Paricheh (2020) reviewed the development in IPCC literature. The research questions that this review article poses are:

Is there existing methodologies that can generate short-term mine plan with IPCC? How does IPCC affect mine plan on the operational level?

In order to answer the research questions, a comprehensive review of short-term planning and IPCC literature, mainly post 2010 has been performed. Table 1 summarises the number of different types of short-term planning and IPCC papers based on some key features. The detailed summary of the papers in a tabular format is available in Table 2 and Table 3 of the Appendix.

Table 1. Count of different types of Short-term planning and IPCC papers post 2010 based on decisive features.

Category	Key attributes	Number of papers
	Strictly Deterministic	14

Short-term planning	Stochastic	15
	Designed for Truck Haulage	29
	Designed for IPCC	0
IPCC	Crusher location/relocation time optimization	14
	Economic or environmental comparison	14
	Integration with long-term plan	4
	Integration with short-term plan	0

IPCC is assumed to be the future of open pit mines, but a glaring research gap that exists in mine planning is the integration of IPCC to short-term mine planning. Our review reveals that there is hardly any short-term planning model that can generate mining extraction sequence with IPCC as a haulage option. This paper provides a brief research proposal in the form of a theoretical framework for short-term planning with IPCC integration to fill in the research gap. The framework upon implementation will be a pioneering work in short-term mine planning which will provide a tool for mine planners to select a better haulage option, in terms of cost saving, between trucks and IPCC for open pit mines for a specific year of mine life.

2. Review of Short-Term Mine Planning

Researchers have used several methodologies, such as, linear programming, mixed integer programming, simulation, stochastic programming etc. to optimise short-term schedules. The most recent short-term planning articles are reviewed in this section based on the methodologies used.

3. Mixed Integer Programming (MIP) Based Models

Most of the modern short-term planning models are MIP based with explicit precedence constraints applied. Smith (1998), was the first to use the precedence constraints in mine planning and scheduling. The authors used an MIP for constructing short-term schedules with explicit accessibility constraints, requiring the nine blocks above a block to be mined before that block can be accessed. The objective of this MIP is to minimise deviation between expected and produced grade.

Gholamnejad (2008) proposed a binary integer programming model to solve the short-term mine scheduling problem to decide which blocks of ore and waste to be mined in which period (shift, days, weeks or months) by satisfying several operational and geometrical constraints simultaneously. This model ensures that all the blocks have been opened and the material can be loaded and transported by shovels and trucks respectively.

Eivazy and Askari-Nasab (2012) proposed a short-term planning MIP model with varying mining directions and precedence constraints to minimize overall mining costs, including processing, haulage, rehandling, and rehabilitation costs. However, the model's use of aggregated mining blocks may result in suboptimal solutions as it ignores preferred ore type selectivity and actual hauling processes. Additionally, the model only prioritizes cost savings, disregarding profit. Therefore, considering profit when generating mining sequences is important, even for short-term planning.

L'Heureux, et al. (2013) developed a detailed math model for short-term planning (up to 3 months) that includes truck, shovel, drilling, and blasting operations to minimize operational costs. The model was solved for up to 5 shovels, 90 periods, and 132 faces. Kozan, et al. (2013) created a multi-resource, multi-stage scheduling problem to minimize makespan or the time between the start and end of a process by modelling drilling, blasting, mining of blocks, and allocating equipment. An initial schedule was generated using a hybrid shifting bottleneck approach, then re-optimized using tabu search metaheuristic algorithm, used particularly in combinatorial optimisation, until there was no improvement in makespan, which is the time required for a production process from start to end. The approach was compared to CPLEX

optimiser in an iron ore mine, showing significantly lower solution times and negligible optimality gap (<5%) for up to 10 jobs.

Later Kozan and Liu (2016) formulated another short-term planning model to maximise the throughput and minimise the total idle times of equipment at each stage of drilling, blasting and excavation. The optimisation was subject to equipment capacity, speed, read times and activity precedence constraints. The MIP model determines how and when the mining equipment will be allocated to the selected block units to perform the mining tasks at various operational stages. Variables in the MIP model assign pieces of equipment to each job, with binary sequencing variables indicating whether job 'i' just precedes job 'j' on a particular equipment. The resulting timetable generated for an Australian iron ore mine is confusing because the time units have not been clarified and the optimality gap of the model's results has not been disclosed.

The latest contribution of Liu and Kozan (2017) is a mine management system that integrates long-term, medium-term and operational level mathematical models to improve mining efficiency. The system includes long-term ultimate pit limit determination, medium-term block sequencing, and operational-level equipment planning with a job-shop scheduling model. The long- and medium-term models maximize net present value, while the operational-level model minimizes makespan and tardiness. The integrated model combines block sequencing and equipment scheduling while minimizing total weighted tardiness in job completion times, improving planning efficiency using mathematical modelling instead of manual methods.

Thomas, et al. (2013) formulated an integrated planning and scheduling problem for a coal supply chain with multiple independent mines where they have to share the limited transportation capacity available. The objectives are to minimise the total earliness, tardiness and operation cost constrained by due dates and transportation capacity. The proposed Lagrangian Relaxation-based solution approach performs better than traditional MILP models in terms of upper and lower bounds generation and the lower CPU time. Later, Thomas, et al. (2014) presented a column generation based solution approach for a similar case study.

Mousavi, et al. (2016a) proposed an MIP model to minimize stockpile rehandling costs by optimizing material flows while adhering to ore grade upper and lower bounds. The model uses three metaheuristics: simulated annealing, Tabu search, and a hybrid approach. Tabu search yields the best results when a pre-defined lower bound is used as a termination criterion. The hybrid approach performs better for large instances with an optimality gap of less than 4%. This model introduces the application of the three metaheuristics to the short-term block sequencing problem, making it a significant contribution. A similar study by Mousavi, et al. (2016b) presents a comprehensive mathematical formulation model for a short-term block sequencing problem constrained by precedence relationship, machine capacity, grade requirements and processing demands, which aims to minimise the total cost including rehandling, holding, misclassification and drop-cut costs. The authors presented a hybrid solution approach of branch and bound and simulated annealing which is able to yield solutions with less than 1% optimality gap compared to CPLEX solution, when large neighbourhood search is applied.

Blom, et al. (2014) and Blom, et al. (2016) propose a breakdown and MIP-based algorithm to optimise the short-term planning of a multi-mine, multi-port supply chain for iron ore. The algorithm is divided into two parts: mine optimisation and port blending. The mine optimisation model generates candidate blocks for extraction using MIPs, assuming normally distributed production grades. The port optimiser selects schedules and assigns trainloads of ore from mine to port, minimising deviation from desired composition targets. The algorithm maximises profit by maximising blended product production.

Later, Blom, et al. (2017) presented a rolling planning horizon-based MIP model to generate multiple short-term production schedules to optimise equipment use and shovel movement, constrained by precedence relationships, blending requirements, equipment availability and trucking hours considering multiple processing paths. Multiple schedules are generated using a split-and-branch approach where the optimiser makes several different choices on activities performed in period 't' and a new schedule is generated for each of these sets of choices. The model produces weekly extraction schedules for a three-month planning horizon.

Manriquez, et al. (2019) developed a short-term planning approach to optimize multiple hierarchical objectives in mining. Objectives include minimizing maximum deviation between ore tonnage and plant capacity, metal fines and expected metal fines, and shovel fleet movement cost. They used two goal programming techniques, weighed sum and hierarchical method (Grodzevich and Romanko 2006) and found both to produce plans with the same optimal values in a Copper mine case study. The model does not consider geological uncertainties and is deterministic. Another goal programming based short-term planning model by optimal shovel allocation over continuous time frame has been formulated by Upadhyay, et al. (2021). The objectives of the model are to maximize production, minimize mill grade deviation and shovel movement. The allocation of shovels on mining cuts over a continuous time frame makes the optimization more practical than their previous model (Upadhyay and Askari-Nasab 2017), where shovel allocation was done on a discrete time frame. However, the case study in an iron ore mine shows that the use of continuous time frame makes the model computationally expensive and the solution time increases exponentially with the number of faces.

Nelis and Morales (2022) presents an optimization model for defining mining cuts and scheduling for short-term open-pit planning, which maximizes profits while satisfying operational and scheduling constraints. The model was applied to a real Copper mine and evaluated based on operational considerations, production plans, and optimization runtime. Results show that the model successfully defined the mining cut configuration and production plan simultaneously, providing useful shapes for mining cuts and flexibility to handle different cases in the short-term. The model is computationally very efficient as it could generate representative mining cuts in less than fifteen minutes, which could take days to do it manually.

3.1. Drawbacks of MILP Models

While MILP models guarantee convergence to optimality, it has several shortcomings.

- One general shortcoming of the MIP models is that they are generally strictly deterministic except for the two-stage stochastic programming, which requires a higher level of mathematical understanding. The Mining operations have inherent uncertainties that cannot be captured by deterministic models.
- Non-linearity is beyond the limits of MIP formulations (Urbanucci 2018).
- Big MIP models are computationally very expensive if the planning horizon or solution space is large.

Some strategies that researchers use to overcome these difficulties are clustering, rolling planning horizon etc., that reduce the number of variables involved (Urbanucci 2018). Another approach that researchers frequently use is a combination of simulation with MIP models that enables the models to consider operational uncertainties (Fu 2015). The next section of this article reviews the simulation optimisation approaches used in short-term mine planning. A summary of the short-term planning models showing the key aspects, objectives and constraints, time horizon, tools used etc., has been presented in Table 3 in the Appendix.

4. Simulation-based Optimization Models

Simulation-based optimization is a computational approach that combines simulation modelling and mathematical optimization techniques to solve complex problems. In this approach, a simulation model is used to represent the system under study and to generate performance data for different sets of input parameters. These data are then used as inputs to a mathematical optimization model to find the best set of input parameters that optimize a given performance metric or objective function. Many researchers have focused on simulation-based optimisation for short-term mine planning.

Fioroni, et al. (2008) used simulation in conjunction with a MIP model to reduce mining costs by optimal production planning. The objective is to demonstrate how simulation and optimisation models can be combined, with simultaneous execution, in order to achieve a feasible, reliable and accurate solution.

Ben-Awuah, et al. (2010) developed a discrete event simulation model to minimise discrepancies between long and short-term planning in the context of a life-of-mine planning problem considering uncertainties associated with mining and processing capacities, crusher availability, stockpiling strategy and blending requirements. The simulation model could bridge the gap between the deterministic long-term plan and the dynamic short-term plan. Comparison of the simulated schedule and the expected behaviour allows the planners to analyse the short-term feasibility or robustness of a long-term schedule.

Bodon, et al. (2011) and Sandeman, et al. (2011) The authors proposed simulation-based optimization models to maximize tonnes mined and shipped while meeting blending requirements and minimizing deviation from assigned targets for mine and port stockpiles. The model was subject to constraints such as equipment and port capacity and precedence constraints for a pit-to-port supply chain. An LP determined the amount of ore to be extracted from each mining face and its destination. The model integrates optimization with simulation, providing a more accurate representation and better solution, albeit with a longer run time. It also shows how simulation models can assess trade-offs between capital expenditures and alternative operating practices, including maintenance options.

Shishvan and Benndorf (2014) and Shishvan and Benndorf (2016) proposed an approach to combine geostatistical and discrete event simulations for short-term production planning in complex continuous mining operations. They accounted for geological uncertainty by simulating twenty realizations of the block model and operational uncertainty by discrete event simulation. The objective function considered two key performance indicators: penalty due to deviation in production and equipment utilization. This approach can help predict critical situations affecting supply of material and system performance. However, the article does not provide detailed information about the simulation framework. The developed simulation model was applied in industrial case studies by the authors in Shishvan and Benndorf (2017).

Torkamani and Askari-Nasab (2015) developed and verified a discrete event simulation model to analyse the behavior of truck-shovel material handling and haulage systems in open pit mining. The authors developed an MIP model to deal with the optimum allocation of trucks and shovels in mining faces, and then linked the solutions to the simulation model.

Linear programming only focuses on a single linear objective function with linear constraints. Goal programming is an extension of linear programming that is capable of handling multiple and conflicting objectives. The objective function of the model, therefore, is usually a combination of multiple objectives. It does not get a single optimal solution, but it generates the so-called pareto optimal solutions, a set of points in a multi-dimensional space, where each point represents a solution that is optimal or efficient in terms of the multiple objectives. Upadhyay and Askari-Nasab (2016) and Upadhyay and Askari-Nasab (2017) used goal-programming for a simulation based short-term planning optimization model, to illustrate how proactive decisions can be made in dynamic environment of mining and operational plans and how they can be synced with long-term planning to reduce opportunity cost, maximise production and equipment utilisation.

Manríquez, et al. (2020) proposed a simulation-based optimization framework to increase short-term mining schedule adherence to execution. The framework generates an initial schedule using a MILP model embedded in UDESS, which is then simulated using any discrete event simulation (DES) software to estimate equipment utilization. The utilization of each iteration is fed as input to the next iteration, and the process continues until the material adherence index is less than 5%. The framework was tested in an underground bench and fill mine, showing increased schedule adherence with each iteration without compromising overall NPV (less than 1%). The simulation accounts for equipment uncertainty in an otherwise deterministic model and is applicable to open pit mines. However, the optimization model only considers maximizing extraction the value of each extraction without accounting for operational costs.

4.1. Limitations of Reviewed Simulation-based Optimisation Models

While simulation is a powerful tool to mimic operations and capture uncertainties, simulation-based optimisation models have their limitations.

- A truly representative simulation model is hard and time consuming to develop (Dellino, et al. 2014). Mining operations like dispatching, shovel movement are difficult and time consuming to model.
- Truck and shovel operation in mining is a continuous process. A continuous process should be modelled with continuous data type. The discrete event simulation models developed by Upadhyay and Askari-Nasab (2016), Upadhyay and Askari-Nasab (2017) and Manríquez, et al. (2020) model continuous events like shovel operation by discrete event simulation.
- A simulation model is just as good as the data fed to it. The selection of distribution for the random activities modelled is a major challenge in simulation modelling. The fit will be better if a lot of historical data is available on the activity being modelled. However, identifying and removing outliers, running statistical tests like Kolmogorov-Smirnov test, chi-square test to test the goodness of fit of available data to different distributions is time consuming.
- Due to the confidentiality requirements of the mining companies, it is often very difficult to extract and publish data from a real mining operation (Ritter 2016). If enough data is not available on the event being modelled, the distribution fit will hardly be representative of the real-life event. This is a prime reason why most of the simulation model discussed in this paper have been implemented in hypothetical mines.
- Most simulation models provide less user flexibility towards various stochastic parameters of the system, such as shovel bucket cycle time, truck spotting, hauling on various gradients, payload, dumping, and queuing etc. Truck haulage is a major part of the total production time. It involves a lot of uncertainties due to failure probability, road conditions etc., and needs more attention than what it has got so far in mine planning.
- The runtime for simulation optimisation models is generally higher than mathematical optimisation models. Short-term mine planning requires models to generate results quickly as any change in state, such as an equipment failure, a mined out face etc., calls for a re-optimisation on the schedule (Upadhyay and Askari-Nasab 2017).

Despite the limitations involved in simulation-based optimisation, it is a preferred method in mine scheduling to get the best of both worlds: dealing with uncertainties involved in equipment operation and haulage by simulation and the guarantee of convergence of mathematical models (Fu 2015). Refer to Table 3 of Appendix for a comparison among the reviewed short-term planning literature.

5. Stochastic Optimisation Models

Stochastic programming is a method for solving optimization problems when there is uncertainty in the environment. There are different types of stochastic optimization models, including stochastic optimization with recourse, robust optimization, and stochastic integer programming. Stochastic optimization with recourse involves making decisions at different points in time, with uncertain outcomes of previous decisions. The goal is to maximize the expected value of an objective function. Robust optimization considers uncertain parameters and seeks to find a solution that is optimal for all possible scenarios. Stochastic integer programming involves making decisions under uncertainty with integer-valued variables and is useful in many applications such as production planning and transportation planning. It is commonly used in short-term mine planning.

Dimitrakopoulos and Jewbali (2013) and Jewbali and Dimitrakopoulos (2018) proposed a multi-stage planning process that considers short-term variability in long-term planning. Short-term

schedules deviate from long-term plans due to a lack of grade control data. The proposed stochastic integer programming model maximizes NPV and minimizes deviation in planned production by generating possible future observations of grade control data based on mined material's grade. The model integrates these sets of potential observations into conditionally simulated realizations of the mine's orebody, with each realization forming a different scenario. Compliance between short- and long-term schedules is expected to increase the probability of meeting production targets and productivity. The approach generated substantially more ore and NPV when applied to a large gold mine.

Matamoros and Dimitrakopoulos (2016) formulated a stochastic integer programming model that simultaneously optimises fleet and production schedules by taking uncertainty in orebody metal quantity and quality, fleet parameters and equipment availability. They divided the objective function into eight components to minimise the cost of extraction, haulage time under uncertainty of trucks' availability, loss of shovel production and geological risks. The authors claim that this model improves the overall production performance and minimises the production scheduling changes required during operation, compared to the deterministic models because of their simultaneous optimisation approach by considering the uncertainties of the input parameters.

Quigley and Dimitrakopoulos (2019) proposed an improvement of Matamoros and Dimitrakopoulos (2016) model to generate short-term schedule to minimise cost of shovel movement and production deviation, deviation of tonnage and grade sent to plants and maximise truck hours of the allocated fleet, constrained by processing capacity, equipment availability, shovel performance and truck cycle time. The model considers uncertainty of geology by geostatistical simulation.

Paduraru and Dimitrakopoulos (2018) demonstrated how updated grade estimates can be integrated into short-term planning through adaptive policies for assigning destinations to mined blocks. These policies are state-dependent, with a state being a numerical vector describing the block's attributes. As new estimates become available, the policy reassigns a destination to the block that yields the largest immediate improvement in profit or cost. The use of state-dependent policies led to better cash flows and mill usage. The approach is expected to help mill operators decide when to close the mill for maintenance.

Both and Dimitrakopoulos (2020) developed an optimisation model for simultaneous optimisation of short-term extraction sequence and fleet management, in contrast to the traditional approach of optimizing production schedule first and then allocating the fleet. The objectives are to maximise total profit and production by minimising the risk of underproduction by shovels and trucks. The model is constrained by precedence relationships, production targets and number of trucks available over a 12-month planning horizon under geological and equipment performance uncertainty.

5.1. Drawbacks of the Reviewed Stochastic Short-term Planning Models

Stochastic programming is a powerful methodology to deal with the dynamic and uncertain environment of open pit mining. The stochastic models discussed here are stochastic integer programming models and some of them involve geostatistical simulation to account for grade uncertainty. Some of the limitations that the proposed stochastic integer programming has are:

- Stochastic integer programming is computationally expensive. The solution time can increase exponentially with problem size and number of scenarios. Short-term mine planning optimization usually involves thousands of variables for a large sized deposit. The dynamic environment of mining operation demands scheduling models that offer quick convergence. The solution times for the discussed model are substantially higher than deterministic mixed integer programming models.
- Solving stochastic integer programming problems can be challenging because the presence of integer variables often leads to a combinatorial structure that makes the problem non-convex. Moreover, the addition of uncertainty to the problem further complicates the optimization problem, potentially leading to multiple local optima (Can and Grossmann 2021).

- Most of the reviewed stochastic models involve geostatistical simulation of the ore body or block model to generate different realisations of the deposit. If the spatial correlation is poorly understood, the accuracy of the model may be compromised. Knowing the spatial correlation structure of the mining blocks for a real deposit with certainty is difficult (Chilès and Delfiner 2012). This is the reason why most of the reviewed models have been applied on hypothetical mines instead of a real mining data set.
- Generating a scenario tree that has a low error in practice requires high fidelity and accurate historical data, which is very difficult to attain and use in capital sensitive mining industry (Can and Grossmann 2021).

The above-mentioned shortcomings and difficulties are reasons why stochastic scheduling optimisation is still not very common in mine planning. Most of the available models are tested on hypothetical data sets under simplified assumptions. It is impossible to guarantee that a model tested on hypothetical data will verify in real life situations without validating it with real data. However, taking certain measures like ensuring resemblance of hypothetical data to real world event, testing the model on a diverse range of test data, monitoring the performance of the model over time etc., increase the likelihood that the model will perform well in real-world scenarios (Elkan C. and Noto 2008). Eventually, more research contributions and improvements in the existing models will make them applicable to real mining operations.

6. IPCC Review

In-pit crushing and conveying related research has increased in recent times as mines are looking into IPCC as a feasible alternative to traditional truck-shovel operations. The IPCC articles have been divided into the following categories depicted in Figure 2.

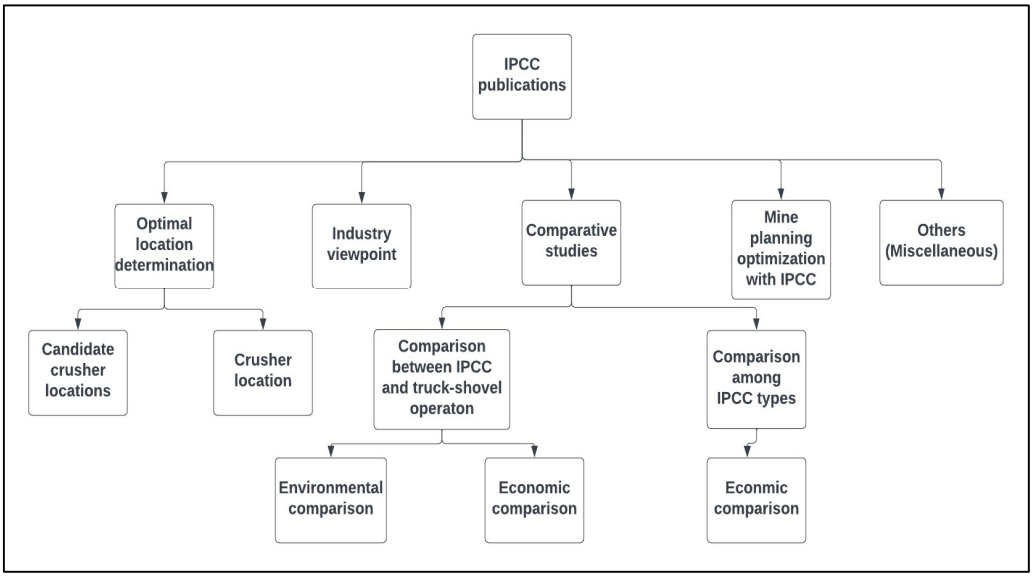


Figure 2. Categories of IPCC research.

The most recent publications will be discussed under the above-mentioned categories to find the progress and research opportunities in the field of IPCC. A summary of the IPCC models has been presented in Table 2 of the Appendix section.

7. Crusher Location Optimisation

Konak, et al. (2007) studied the selection of an optimal crusher location for an aggregate production plant in Turkey based on minimum haulage distance. They considered both stationary and semi-mobile crusher cases and developed an algorithm to calculate the average haulage distance to the crusher from the mine for all possible crusher locations, with up to three

relocations during the mine's lifetime. However, the model oversimplified the calculation by only considering haulage distance as the decision variable, and the cost savings shown by the model may be offset by the capital or relocation costs of the in-pit crusher.

A similar but comparatively simpler approach was used by Taheri, et al. (2009) to determine optimum crusher location in deep open pit mines. This approach is simpler than Konak, et al. (2007) because it only considers the case of a stationary in-pit crusher, which would remain in the same location throughout the life of the mine and thus substantially reduces the possible alternative routes. The model calculates the NPV of haulage and installation costs for three candidate locations and selects the one with the lowest cost. However, it does not account for uncertain costs due to crusher breakdown or shovel downtime and lacks a systematic approach to selecting candidate locations. Unlike Konak, et al. (2007), this model added IPCC installation costs along with haulage costs to find the total cost associated with the in-pit crusher.

Rahmanpour, et al. (2013) Proposed a systematic approach to find the optimal in-pit crusher location, by formulating it as a single hub location problem to minimize haulage costs. Candidate locations were selected using analytical hierarchical process (AHP), considering six economic and eleven technical factors, beyond just haulage and installation costs unlike Taheri, et al. (2009). Hub-spoke network was used to connect all destinations and source locations, increasing haulage capacity. AHP provides quantitative estimates for qualitative factors, making it an effective tool for selecting candidate locations. However, delays and queuing during trans-shipment at hubs were not considered in the model.

Roumpos, et al. (2014) The authors developed an iterative method to minimize total transportation cost by finding the optimal location for a belt conveyor distribution point in a mine's perimeter. They used simulation to verify the model and found that the location of the waste dump and conveyor distribution point directly affect transportation costs. This model has advantages over Taheri, et al. (2009) and Konak, et al. (2007) from the context that it continuously calculates costs without requiring initial candidate locations. However, it only considers operating and capital costs and not operational uncertainties or irregular geometries, which can affect conveyor downtime and operating costs.

Paricheh, et al. (2016) proposed a heuristic model to find the optimum locations and movement time of the in-pit crusher in open pit mines hierarchically. The crusher location is optimised by a linear dynamic facility location model with an objective of minimising cost of haulage. The transfer time of crusher is optimised by maximizing the discounted cash flow throughout the life of the mine. This is an iterative model that keeps repeating the steps until the solution improves. Later, Paricheh, et al. (2017) developed another model with the objective of finding out the optimum in-pit crusher location to minimise the haulage cost by modelling it as a dynamic location problem based on the prime factors, such as haulage distance, that affect IPCC location. The results of the model in a case study of a hypothetical mine show that the application of IPCC will reduce cost by six percent from sixth year of mining, saving a total of one hundred and fifty million dollars throughout the mine life.

The models discussed so far are all strictly deterministic. Paricheh and Osanloo (2016) proposed a stochastic approach to determine the optimal crusher location for open pit mines under production and haulage cost uncertainty using stochastic facility location model. The authors formulated the model as a p-median problem with an objective of minimising the expected loss across all scenarios. P-median problem is a kind of a facility location problem where for a set of n demand points or customers and a set of m potential facility locations, the objective is to choose p (where $p \leq m$) facility locations from the set of m locations, such that the sum of distances between each customer and the nearest facility is minimised. The expected loss is the difference between the optimum haulage cost and the p-median haulage cost from each candidate location to the destinations. A case study using the model at Sungun Mine, Iran, to find two crusher locations across nine different equally likely scenarios for fixed, increasing and decreasing production and cost showed that the model is capable of minimising deviation between optimal and p-median haulage cost. However, the model does not work well if the value of p is less than 2.

There has not been many research formulations on finding the best candidate locations from which the optimum in-pit crusher location can be chosen. Paricheh and Osanloo (2019b) explored this opportunity to propose a search algorithm to identify practical and cost-effective candidate locations for in-pit crusher placement in open pit mines. In addition to conventional rules, such as topography and ramp intersection, the authors used block aggregation policies and six specific rules to significantly reduce the number of candidate locations. These rules included depth, pushback, required space, radius of influence, and economic value constraints. The algorithm was validated in Sungun mine and showed a reduction in candidate locations from two hundred and eighty-three to twenty-three. The algorithm does not consider geotechnical or shape restrictions when defining candidate locations.

7.1. Drawbacks of Crusher location Optimisation Models

- ✓ The major problem of the crusher location optimisation models is that the mine plan is not considered for location optimisation. Hence, it cannot guarantee NPV maximisation in the long term.
- ✓ The case study results are not reliable because most of them have been applied in hypothetical mines with simplified geometrical assumptions.
- ✓ There is not enough research work on finding the candidate crusher locations systematically. While Paricheh and Osanloo (2020) proposed a hierarchical approach to finding feasible candidate locations, most of the other models choose candidate locations randomly or based on shortest path without considering a real road network.
- ✓ IPCC design aspects need to be considered for optimal location determination (Dean, et al. 2015).

8. Contributions from Industry Professionals

Morris (2008) provides an overview of productivity issues in semi-mobile (SMIPCC) and full-mobile IPCC (FMIPCC) in real mining operations, without rigorous mathematical modelling. SMIPCC tends to have better overall utilisation than FMIPCC due to lesser dependence on shovel feed. The high service meter unit in IPCC systems, defined as the ratio of engine run time and effective working time, leads to distorted results while predicting fuel consumption from historic data. FMIPCC shows slightly better throughput than SMIPCC. This article is a good introduction to IPCC concerns and industry perspective.

McCarthy (2011) discussed the risks and challenges of implementing IPCC in place of truck shovel haulage systems in mining operations. The author highlighted the importance of proper management planning and training to overcome employee aversion to new technologies like IPCC, and provided information on the types, advantages, and risks associated with IPCC. However, the use of IPCC in large deep mines can be risky due to loss of slope stability and mobility. To address areas of uncertainty, the author recommended probabilistic risk assessment using Monte Carlo simulation during the planning stage and presented examples of decision-making based on risk assessment in the Sandvik mine by Snowden Mining Company. Overall, the article offers valuable insights for beginners to understand IPCC and its industry perspectives. Utley (2011) published a similar article that focused mostly on general ideas and challenges associated with implementing IPCC in large mines.

Dean, et al. (2015) discussed the benefits of using FMIPCC in deep mines such as cost savings and reduced emissions, but also acknowledged the challenges such as large investments and loss of flexibility. They proposed a theoretical design approach for implementing FMIPCC in deep mines using hydraulic excavators, with a model that includes pit widening by conveyor systems and mine sinking by truck-shovel. The use of hydraulic shovels allows for narrow bench widths to maintain high ramp angles necessary for deep mines, and the model proposes radial and parallel belt conveyor movements to minimize the frequency of belt extensions. While the model is innovative, it has not been practically executed in any deep mines, making it difficult to determine its usefulness and feasibility.

The efforts of the members of industry to address existing issues with introducing IPCC in new and existing mines can prove handy because it will help the companies to switch to IPCC with more confidence and assurance.

9. Comparative Studies

9.1. Environmental Comparison

Norgate and Haque (2013) looked at the advantages of using IPCC over Truck-shovel system in open pit mining from a different perspective. They presented a life cycle assessment for IPCC and ore sorting to highlight the potential of reduced greenhouse gas emission these technologies offer. Environmental regulations have made it imperative for large mining companies to ponder about CO2 emission reduction in mining and mineral processing stage. The study showed that IPCC offers 5% and 22% reduction in CO2 emission compared to traditional truck-shovel system for black coal based and natural gas-based electricity respectively. The problem with such studies is that they are highly subjective and the assumptions used might change the outcome of the result.

Awuah-Offei and Askari-Nasab (2009) presented a similar life cycle assessment (LCA) study which gleaned contradictory results to Norgate and Haque (2013). The results for a coal mine case study show that, for acidification potential, the truck system has thirty-two kg of equivalent sulphur dioxide per functional unit, compared to eight kg for the conveyor system. However, for global warming potential, the conveyor has two thousand eight hundred twenty kg of equivalent carbon dioxide per functional unit, compared to six hundred forty-eight kg for the truck option.

Erkayaoğlu and Demirel (2016) conducted a life cycle assessment of trucks and conveyors used in mining for their environmental impact in terms of climate change and acidification. They chose these categories as they have the maximum impact on the environment and human health, and data for these categories is usually reliable. Trucks are found more environmentally harmful than conveyors in terms of acidification due to their dependence on diesel fuel, while conveyors are more detrimental in terms of climate change as they use electricity produced primarily from lignite coal, which, upon burning, produces greenhouse gasses like CO2. This study highlights the importance of LCA as a tool for equipment selection in mining but should be used with caution as it is specific to Turkish mines and assumptions made in the study may not apply to other countries' mines.

A similar life cycle assessment study was presented by Fuming, et al. (2015) that concluded IPCC system to be more energy efficient and environment friendly compared to traditional truck-shovel system. The outcomes of the study reveal that the energy consumption of truck transportation was four to twelve times higher than that of the belt conveyor, the CO2 emissions from truck transportation were three to ten times higher than those of the belt conveyor and with the increase in the slope angle for transportation, the ratio of truck to belt conveyor for both energy consumption and carbon emissions gradually decreased in open-cut coal mines in China. A general outcome of these life cycle assessment studies is that IPCC is more environmentally sustainable than diesel trucks because of less dependence on fossil fuel.

9.2. Economic Comparison

The economical comparative studies mainly focus on the advantages and disadvantages of truck-shovel and IPCC systems in terms of the cost associated with them. Some studies present a financial comparison between fixed, semi-mobile and mobile IPCC systems. Koehler (2003), Schroder (2003) highlighted the technical and economic aspects of IPCC system to demonstrate the advantages it offers over the traditional truck-shovel system.

Klanfar and Vrkljan (2012) compared stationary and mobile crushers and plants in quarrying stone in terms of cost of processing, loading and transportation by a case study at Sungun mine, Iran. The results showed that mobile crusher offers about 11% cost saving compared to stationary crusher mostly because of its significant cost saving in transportation of material. This article

assumes that all the costs are known with certainty, which hardly happens in real operations. The results might vary substantially based on the size of the mine.

Londoño, et al. (2013) explored alternative configurations for pre-stripping in an open pit coal mine using IPCC and found that introducing parallel conveyor lines with spreaders can boost productivity by 9.4 – 12.6% and generate more profit compared to a single conveyor line, despite the higher equivalent unit cost. Simulation of five different IPCC configurations demonstrated that an IPCC system with three conveyors and four parallel conveyor lines could increase annual production by 20%, which compensates for the 15% higher operating cost than the single conveyor line. However, assumptions about process delay and failure distribution are crucial, and changes to these assumptions could affect the results significantly.

Dzakpata, et al. (2016) compared shovels, trucks, and IPCC based on operating time and productivity. Results showed that introducing IPCC can improve shovel productivity by 20-25% as shovels spend 40% of the operating time spotting for trucks, while conveyors offer 25% higher valuable operating time than trucks due to trucks' empty travel time. Although the study used multiple metrics, it is case-specific, and the authors did not disclose their data. Therefore, using the study's results without proper assumptions and modifications for other mines may not be useful.

De Werk, et al. (2017) compared Semi-mobile IPCC (SMIPCC) and traditional truck-shovel (TS) systems in terms of haulage cost in a hypothetical iron ore mine. Results show that although IPCC has higher capital cost, its total cost is lower due to lower operational cost. Sensitivity analysis indicates that TS is more sensitive to fuel prices than IPCC due to the smaller number of required trucks. While electricity price has not been as stable as it has been since 2016, the recent hike in electricity prices (25%) from 2020 to December 2022 is still lower than diesel price increase (97%) in this time frame in the USA (2022b; 2023a). Risk analysis via Monte Carlo Simulation in terms of electricity and fuel prices, TS and IPCC availability and truck fill factor shows that the range of minimum and maximum unit operating costs of IPCC is 10% narrower than TS. While this article verifies most of the cost advantage assumptions of IPCC over TS, the case study was run in a perfectly cone shaped hypothetical mine. The outcome of the comparison might vary substantially in real mines.

Another decision making method to choose between TS and SMIPCC was proposed by Nunes, et al. (2019). The aim of this study is to develop a methodology to compare transportation alternatives (TS and SMIPCC) and select the best one in terms of cost saving and environmental sustainability. The results from a Copper mine show that while the CAPEX of SMIPCC is 60% higher than TS, the OPEX is 43% lower because of low maintenance and labour cost, which results in a 34% saving in net present cost over a LOM of 20 years.

Bernardi, et al. (2020) used an ARENA simulation model to compare semi-mobile and fixed IPCC systems for open pit mines in terms of NPV and proximity to target production rate. The simulation was run for a simplified cone-shaped hypothetical mine with hourly costs, and results showed that semi-mobile IPCC generated 10% higher NPV and was closer to production targets. While the model yields quick results and can help decide on the type of IPCC system, the simplified cost model and mine geometry used may not represent typical mining project complexity. Further work is needed on the cost and geometrical assumptions to make this model applicable to a real and complex mine site.

9.3. Shortcomings of the Comparative Studies

- ✓ Environmental comparison via life cycle assessment is highly case sensitive and qualitative. The results of one case study is not applicable for another mine.
- ✓ Data required for life cycle assessment studies is difficult to get. If data collection is poor, the study will not lead to solid conclusions (Curran 2014).
- ✓ Contradictory outcomes to similar studies on environmental sustainability of IPCC and truck-shovel operations may result based on the type and geographical location of the mine (Awuah-Offei and Askari-Nasab 2009; Norgate and Haque 2013).

- ✓ Economic comparison between IPCC and TS systems is also case specific. The cost of labour and haulage vary substantially based on the geological location of a mine.

Despite the limitations of the life cycle assessment and economic comparison studies, they provide valuable insight on the environmental sustainability and economic viability of IPCC system compared to traditional haulage.

10. Simultaneous Optimisation of IPCC and Mine Plan

The most recent addition to IPCC literature is the simultaneous optimisation of mine planning, IPCC location and relocation. This integration is very important from the aspect of mine planning. The inclusion of IPCC affects the number of required haulage equipment, mining direction, availability of mineable faces or cuts which need to be considered while formulating the strategic or even operational plan. Otherwise, the NPV calculation and generated mining sequence could end up being sub-optimal.

Samavati, et al. (2018) explored the fact that there is almost no study for optimizing the operations with IPCC in open pit mines and estimating the costs of IPCC systems. This makes large mining companies averse to using IPCC system despite the advantages, such as, the low operating cost it offers over traditional trucks and shovels. This article points out the fact that while researchers mostly focus on finding an optimal in-pit crusher location for IPCC, there is not much concern about the integration of IPCC with mine planning and scheduling, without which it is very hard to estimate the costs and savings that might be generated by IPCC throughout the mine life. The authors proposed a research direction to discover the optimal location of the conveyors and how open pit mine planning would be affected by the modified precedence constraints due to the location of the conveyors and crushers inside the pit. This is a descriptive article that raised concerns about a few research agendas that must be explored to make IPCC integration more lucrative and risk free for large mining companies.

The research gap pointed out by Samavati, et al. (2018) has been explored by Paricheh and Osanloo (2019a), who proposes a MILP model to optimize the location of the in-pit crusher to minimize total haulage cost, fleet requirement, and maximize the NPV of the mine, taking into account the dynamic changes in block sequencing caused by the IPCC location and relocation. The model determines block destinations and extraction sequences while comparing to two existing benchmark models. Results showed a 2 to 4% increase in NPV, a 75% decrease in fleet requirement, and changes in extraction sequence from the existing benchmarks models. However, the model is deterministic, and its reliability could be improved by incorporating uncertainties associated with vital parameters like grade, price, and cost in real mines.

A more comprehensive approach to integrate long-term plan with fully-mobile IPCC (FMIPCC) conveyor locations was proposed by Samavati, et al. (2020). Their research proposes a mathematical model that simultaneously generates long time mine planning with optimum crusher and conveyor locations for IPCC with an objective of maximizing net profit over the life of mine. They solved the model with three different relaxation techniques using their proposed heuristic and direct MILP solver, where the heuristics required only 10% time of exact solver to find near optimal solution. While the model has not been applied to a real mine yet, the case study was run in a hypothetical mine that is geologically similar to copper porphyry deposits in Australia.

A framework for simultaneous optimisation of long-term mine scheduling with semi-mobile IPCC was developed by Liu and Pourrahimian (2021). The authors proposed an integer linear programming model that maximises NPV by maximizing block values and minimising haulage and crusher relocation cost. They solve the model for several candidate conveyor and crusher locations and the one that generates the maximum NPV is considered as the optimum conveyor/crusher location. The candidate crusher locations are determined using a pit rotation approach developed by Hay, et al. (2020). Assuming the conveyor locations to be fixed in one side of the pit throughout the mine life, this model shows that the conveyor location can significantly impact the NPV of a mine.

The latest attempt to integrate long-term plan with IPCC location and relocation time has been proposed by Shamsi, et al. (2022). The objective of this study is to maximise the NPV of an open pit mine, considering SMIPCC, TS capital and operating cost, and find the optimum locations and relocation time of crushers constrained by mining and processing capacity, blending requirements etc. Unlike Samavati, et al. (2020), this model does not consider the location and relocation of the conveyors. The case study in a copper mine shows that while the capital is $74M higher for SMIPCC than the traditional truck-shovel system, it generates 70% higher NPV over the life of mine. This model can be used as decision making tool to choose between TS and SMIPCC systems in large open pit mines.

10.1. Areas to Improve

The simultaneous optimisation of mine planning with IPCC is very new and requires a lot of work to be put in to make them suitable to be applied in a real mining project. The major limitations to be overcome are summarised below.

- The existing models are all still in theoretical level. They have not been applied to a real mine yet.
- The models developed so far are all deterministic and cannot consider uncertainties associated with geology or IPCC operations.
- We are yet to find out the effect of IPCC on short-term or operational level planning. Most of the simultaneous optimisation models are concerned with strategic mine planning.
- IPCC integration to mine planning is difficult because of the complex design of conveyor, belt distribution points and dynamic crusher locations (Samavati, et al. 2018).

Building upon the limited research work that exists will lead to more comprehensive simultaneous optimisation model in future.

11. Others

Some of the recent research work related to IPCC fall outside the five categories discussed above. For example, a significant contribution to IPCC literature was made by Ritter (2016), who proposed a method for calculating the annual capacity of SMIPCC system considering the random delays that occur due to system performance and inter connection between several parts. The system induced delays have been determined by a discrete event simulation model. The case study shows that the SMIPCC capacity is substantially affected by system delays and the capacity has an inversely proportional relationship with mean repair time. An economic comparison between TS and IPCC system proved SMIPCC to be cheaper than TS for the same annual capacity. This method of determining SMIPCC annual capacity is the first numerical method that considers random system behaviour. A simulation of the proposed numerical model of in a hypothetical coal deposit show that the capacity of a SMIPCC system reaches an optimum in terms of cost per tonne, which is 24% lower than a truck and shovel system (Ritter and Drebenstedt 2019).

A comparative study was published by Abbaspour, et al. (2018), where the different types of transportation systems (truck-shovel and IPCC) are evaluated based on safety (such as accidental death) and social indexes (higher number of employees). FMIPCC presented the highest safety index in contrast with SMIPCC, which showed the lowest. In addition, Truck-Shovel and SMIPCC systems demonstrated the highest social index because of benefiting from higher number of employees and hours of training. In contrast, FMIPCC ranked the last in the social index. Such system dynamic models are highly dependent on the variables, which depend on the judgement of the modeler. Hence, the results are not always reliable. The model has not been applied to any real mine yet.

Abbaspour and Drebenstedt (2020) used system dynamics modelling to determine the optimum transition time from Truck-shovel to IPCC. The case study shows that whereas TS system is

preferable at the first five years of a mining project, FMIPCC system shows a better economic performance in the rest of the mine's life.

Shamsi and Nehring (2021) determined the optimum depth at which it is the most convenient to switch to SMIPCC from truck-shovel by scenario analysis. The economic analysis in a cone shaped hypothetical mine with 4 pushbacks showed that switching to IPCC from truck-shovel from the second phase at a depth of 335m generates the maximum discounted cost savings. This model is based on a lot of simplified assumptions on mine geometry and the results will vary depending on the depth and phases of mine.

Wachira, et al. (2021) developed a methodology to determine SMIPCC performance based on mine productivity index. The study found that a reduction in loading equipment (shovel) reduces the truck requirement by 33%. The mine productivity is higher with multiple loading equipment than a single shovel. The case study in a hypothetical mine shows mine productivity index is higher for SMIPCC system than traditional TS system. Table 2 in Appendix presents a detailed comparison of the aspects and objectives optimised among IPCC publications post 2007.

Gong, et al. (2023a) and Gong, et al. (2023b) introduced a new concept called near face stockpile (NFS) mining, which combines the in-pit crushing and conveying IPCC system with a pre-crusher stockpile. This idea of NFS showed an overall improvement in production quantity and NPV compared to traditional mining method.

12. Relevant Optimization Models Suitable for Mine Planning

The capacitated vehicle routing problem (CVRP), a well-established concept in industrial engineering, holds potential for mine planners, as it allows for the optimization of material handling costs through the application of vehicle routing principles to haulage management. Essentially, the vehicle routing problem seeks to fulfil customer demands while working with finite resources, with the ultimate aim of selecting the most efficient or shortest route to minimize movement costs. This section will explore a selection of vehicle routing problem literature to demonstrate the value of these concepts in mining engineering.

Xiao, et al. (2012) proposed a CVRP model to minimise fuel consumption by considering Fuel Consumption Rate (FCR) as a load dependent function using simulated annealing algorithm with a hybrid exchange rule. Experimental results show that the proposed model can reduce fuel consumption by 5% on average compared to the classical CVRP model. This model can be used to manage the trade-off between the total distance and the priorities of serving customers with larger demands. The model in its current state of art cannot assume factors such as road condition, driver behaviour etc. on fuel consumption.

A similar model was proposed by Feng, et al. (2017) with normally distributed vehicle speed and fixed vehicle cost to minimize fixed cost and fuel consumption using a non-linear objective function that is linearized. They used a simulated annealing algorithm to achieve optimal or near optimal solutions, which outperforms CPLEX and simulated annealing approach when there are many destinations. The model shows that fuel consumption is always larger for stochastic vehicle speed than for fixed speed model. However, the model does not account for randomness of demand and the speed distribution is not necessarily normal.

Feld, et al. (2019) proposed a hybrid solution approach using a quantum annealer device to minimize total distance in CVRP. However, the comparison with classical 2-phase heuristics method did not show any significant advantage in terms of solution quality or computation time. The study suggests a method to split complex problems and solve them in a hybrid way using a quantum annealer, but further research is needed to assess the effect of hardware on problem mapping efficiency and the use of additional tools like QBSolv, a software tool developed to solve large scale optimisation problems.

Sarasola, et al. (2016), Errico, et al. (2016), Marinaki and Marinakis (2016) and many other researchers have worked on capacitated vehicle routing problem formulation. The objective of introducing IPCC in big mines is to reduce the number of trucks to minimise haulage cost. The

fleet management in mine planning might be optimised by applying the CVRP approach because the basic idea of meeting production target (mill demand) by limited resource (fleet) with minimum cost is the same in both cases.

The emission minimisation vehicle routing problem (EVRP) formulation methodologies similar to Bektaş and Laporte (2011), Figliozzi (2010), Franceschetti, et al. (2013), Jabali, et al. (2012) etc., might be applicable to life cycle assessment studies for IPCC and TS system in mines because the general objective of EVRP is to reduce the greenhouse gas emission while solving the CVRP.

Another arena of operations research that must be explored more is the facility location problem. While Paricheh, et al. (2016), Rahmanpour, et al. (2013) used facility location models to find optimum in-pit crusher locations, there is still a lot of opportunity to formulate more efficient models to optimise IPCC location and relocation using this particular field of study. Other significant research work that can be looked at are Nikbin and Moradi Afrapoli (2023), Moradi-Afrapoli and Askari-Nasab (2022) etc.

13. Future Research Direction

As discussed in the previous sections, mines are becoming deeper and the average ore grade is depleting (McCarthy 2011; Osanloo and Paricheh 2020), which leaves mines with only two options going ahead: switching to underground mining which is not feasible in most cases because the total setup needs to be changed or introducing IPCC to exploit the benefits of a lower operating cost and longer life span than truck-shovel system. This detailed review of the short-term planning and IPCC literature shows that, while most of the articles concerning IPCC are focusing typically on conveyor design or finding an optimal crusher location inside mines based on the cost of traveling from crusher to destinations assuming a predefined and fixed strategic mine plan, some articles are comparing the pros and cons of IPCC with traditional truck-shovel system to promote IPCC system to the mining industry.

This review highlights the fact that the majority of the case studies pertaining to IPCC have been based on hypothetical mines, with simplified assumptions made about mine geometry or operational costs. The widespread adoption of IPCC technology by mining companies has been limited, leading to a scarcity of data on IPCC installation and capital costs, as well as on how changes in mine geometry can accommodate a crusher inside the pit. This lack of data has made it difficult, if not impossible, to validate research formulations against real data. Without such validation, it is challenging to comment on the scalability of any research model. To promote more comprehensive and realistic mine planning with IPCC, it is crucial for mining companies and researchers to collaborate and facilitate the free exchange of data. This will not only aid in validating existing models but also support their improvement.

The comparisons among the most recent short-term planning and IPCC literature show that while very few models can generate a strategic plan with IPCC in place, such as Paricheh and Osanloo (2019a), Samavati, et al. (2020), Shamsi, et al. (2022), Liu and Pourrahimian (2021) etc., there is hardly any short-term planning model with IPCC integration. To make things worse, there is no study that can help mine planners estimate the cost of IPCC systems in a systematic manner considering all the variables and uncertainties associated with it, forcing mine planners to use intuition and experience to come up with a cost estimate that are mostly error-prone and affect the planned NPV in a negative manner (Samavati, et al. 2018).

Commercial tools like Geovia Whittle, Minesched, XPAC etc., can generate long or short-term production schedule for traditional truck-shovel haulage systems but to the best of our knowledge, there is no such commercial tool that can do the same for IPCC system in place. Therefore, it is evident that while IPCC is considered to the future of open pit mines, production sequencing (both long and short-term) considering in-pit crusher is still under-developed and neglected. While strategic planning with IPCC needs to find out the optimal locations of IPCC as a function of time to maximise the NPV, short-term sequencing needs to consider the effects of IPCC location and relocation over time, such as, change in production capacity, haulage

distance etc. to come up with a practical production schedule that will sync with the long-term plan.

Operations research tools, such as, transportation problem, vehicle routing, facility location etc. need to be used more rigorously in mining literature so that the existing gaps can be filled in and mathematical models and commercial tools capable of generating strategic and short-term planning with IPCC can be developed. The following sub-section will propose a brief research proposal for short-term planning optimisation with Semi-Mobile IPCC.

14. A Brief Research Proposal

The authors propose a methodology to generate a near optimal short-term planning schedule by optimal allocation of shovel. The schedule can be generated for both IPCC and traditional truck shovel haulage. The goal is to develop a short-term planner that can compare scenarios with IPCC and traditional truck-shovel mining method in terms of profits earned and cost of haulage in a specific period of mine life to decide on the optimal material handling system. Some of the existing issues this research work intends to address are:

1. Reduce or eliminate manual intervention in shovel allocation to dig locations.
2. Considering profit maximisation for optimum shovel allocation unlike existing short-term planning models that consider cost minimisation only.
3. Demonstrate the effect of IPCC on short-term planning.

The model assumptions are:

- The IPCC system is semi-mobile.
- Uncertainty of ore grade and price is not taken into account in the initial stages of the study.
- The optimum locations, relocation time of the crusher and conveyor length and design are known throughout the life of mine from strategic planning.
- There is no waste crusher. Waste material is hauled to waste dump by trucks.
- The ore and waste faces are known from long-term plan.
- There is no stockpiling. Material goes to either waste dump or processing plant.
- Queuing models, as applied by some researchers, will not be applied in this study, although it may provide further improvement in the solutions.
- This study does not focus on the dispatching stage in its current state of art.
- The shovel allocations are made based on haulage cost minimisation and profit maximisation. Capital investment for IPCC system, shovel movement cost etc. are not considered.
- Lost production due to equipment failure and planned maintenance is not considered at the current stage of the model.

The proposed MILP model has three operational objectives: 1. Maximize profit earned by ore material per period, 2. Meet production requirement to feed the mill to its capacity, 3. Minimize haulage cost. The objective function consists of three components. The first component calculates the cost of hauling ore material to crusher or mill and waste material to waste dumps respectively, using regular diesel trucks. The second part calculates the cost of conveying ore material from crusher to processing plant. The last component calculates the profit earned from selling ore. The model should be solved in mining cut level. The mining blocks can be aggregated using clustering algorithms proposed by Tabesh and Askari-Nasab (2013) or Tabesh and Askari-Nasab (2019).
The problem can be formulated as a minimization problem in MATLAB, where the objective is the minimization of, f = cost of transporting material to crusher or waste dump from mine by trucks + cost of conveying ore material from crusher to processing plant – profit
The following Figure 3 shows the transportation of waste and ore with and without in-pit crusher in place. The materials are mined from the mining faces by shovels and then loaded to trucks.

The waste material are transported all the way to the waste dumps by the waste trucks. The ore material will be hauled by the ore trucks to the in-pit crusher from mining faces and then conveyed to plant in the scenario with IPCC. In the scenario without IPCC, the ore material will be hauled all the way by trucks from the pit to the plant crusher.

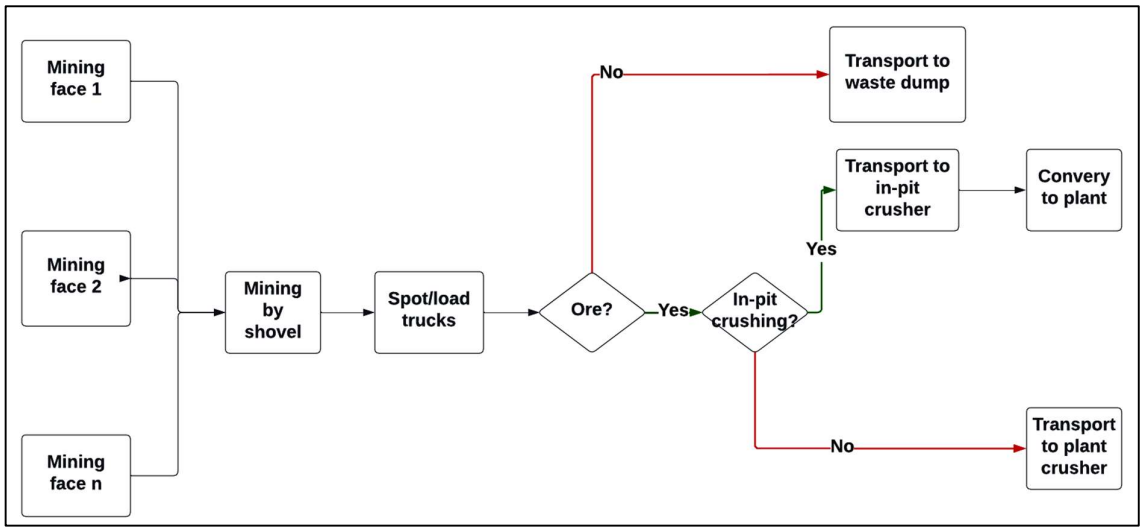


Figure 3. Flow of material from mine to crusher, plant and waste dump.

The distance of each face from the crusher and waste dump will be fed to the model as a road network graph. The objective function will be optimised subject to shovel allocation, grade blending, minimum plant requirement, maximum allowable grade variation and IPCC location constraints to achieve required production and grade targets set by strategic plan through accommodating crusher within ultimate pit limit. Optimum allocation of shovels to mining faces will extract required tonnage of material to feed the plant. The idea is to present two scenarios, one with IPCC and the other one with traditional truck haulage and compare the results to find out the overall revenue generated and haulage cost incurred in each of the scenarios. The comparison of results should enable mine planners to decide on the better haulage option for a specific year of mine life and verify whether the SMIPCC offers cost benefits by meeting long-term production targets within short-term planning horizon of 1 to 3 years.

14.1.1. Expected Outcomes

The proposed research is expected to deliver the following outcomes.

1. The difference in ore and waste production for cases without and with IPCC to see if the monthly production target can be met with IPCC system in place. The total production is expected to drop when IPCC is installed due to the IPCC location constraints. The results should demonstrate how significant is this dip in production and how badly it impacts the profits earned.

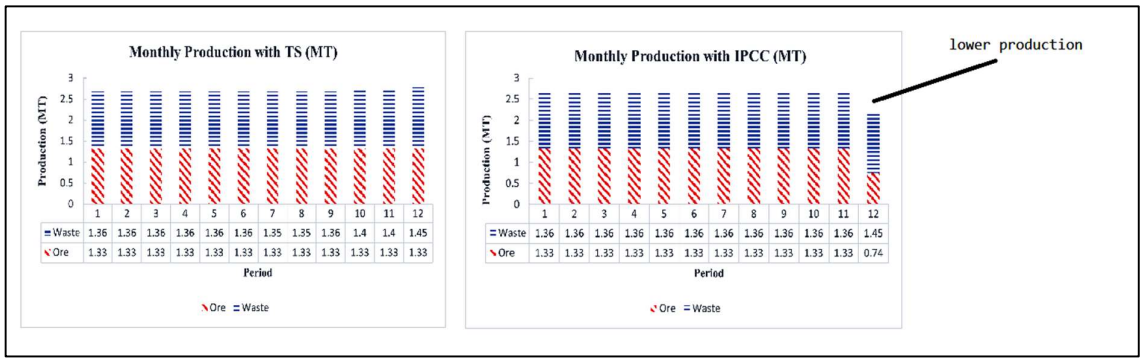


Figure 4. An example of production dip with IPCC.

2. The installation of IPCC will prevent the faces that house the crusher from being mined. It will also impact the mining of the precedence faces too. The results of the proposed model will demonstrate the effect of housing the crusher inside the mine on the short-term schedule.

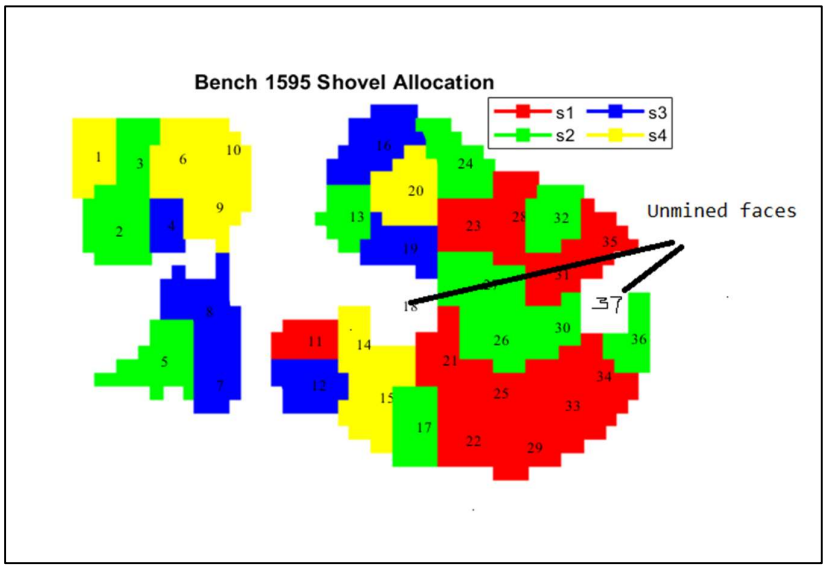


Figure 5. Example of shovel allocation to mining cuts.

3. The results should verify if the cost saving in haulage due per year to IPCC installation is large enough to offset the huge capital investment required for IPCC over the life of mine.
4. The results are expected to delineate the impact of IPCC installation on shovel efficiency.

15. Conclusion

IPCC is the future of open pit mining. For the industry to have a smooth transition from traditional truck-shovel system to IPCC, a lot of work is required to be done in both academic and commercial sectors of mining engineering. Mathematical models and commercial tools that can produce long-term, short-term and operational plans need to be created so that IPCC can be more mainstream in the mining industry and bring about the revolution it can deliver.

16. References

[1] 2018 Global Fuel Prices Chart. Pp. IEA, Global fuel price changes, 2005-2018, IEA, Paris https://www.iea.org/data-and-statistics/charts/global-fuel-price-changes-2005-2018.

[2] 2022a Petroleum and Other Liquids: U.S. Energy Information Administration. https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMD_EPD2D_PTE_NUS_DPG&f=M.

[3] 2022b US Average Retail Price of Electricity (I:USARPE). USA: YCHARTS. https://ycharts.com/indicators/us_average_retail_price_of_electricity_total.

[4] 2023a Average Fuel Prices in the USA. USA: U.S. Department of Energy. https://afdc.energy.gov/data/10326.

[5] 2023b Putting Price on Carbon Pollution. Canada: Government of Canada. https://www.canada.ca/en/environment-climate-change/services/climate-change/pricing-pollution-how-it-will-work/putting-price-on-carbon-pollution.html.

[6] Abbaspour, H., and C. Drebenstedt, 2020. Determination of transition time from truck-shovel to an ipcc system considering economic viewpoint by system dynamics modelling. 28th International Symposium on Mine Planning and Equipment Selection, MPES 2019, December 2, 2019 - December 4, 2019, Perth, WA, Australia, 2020, pp. 289-295. Springer.

[7] Abbaspour, H., C. Drebenstedt, and S. R. Dindarloo, 2018. Evaluation of safety and social indexes in the selection of transportation system alternatives (Truck-Shovel and IPCCs) in open pit mines. Safety Science 108:1-12.

[8] Awuah-Offei, K., and H. Askari-Nasab, 2009. Valuation of Belt Conveyor and Truck Haulage Systems in an Open Pit Mine using Life Cycle Assessment. The Canadian Institute of Mining, Metallurgy and Petroleum Bulletin 102:1-6.

[9] Bektaş, T., and G. Laporte, 2011. The Pollution-Routing Problem. Transportation Research Part B: Methodological 45(8):1232-1250.

[10] Ben-Awuah, E., Y. Pourrahimian, and H. Askari-Nasab, 2010. Hierarchical Mine Production Scheduling using Discrete-Event Simulation. International Journal of Mining and Mineral Engineering 2:137-158.

[11] Bernardi, L., M. Kumral, and M. Renaud, 2020. Comparison of fixed and mobile in-pit crushing and conveying and truck-shovel systems used in mineral industries through discrete-event simulation. Simulation Modelling Practice and Theory 103:102100.

[12] Blom, M. L., C. N. Burt, and P. J. Stuckey, 2014. A decomposition-based heuristic for collaborative scheduling in a network of open-pit mines. INFORMS Journal on Computing 26(4):658-676.

[13] Blom, M., A. R. Pearce, and P. J. Stuckey, 2016. Short-term scheduling of an open-pit mine with multiple objectives. Engineering Optimization 49:1-19.

[14] Blom, M., A. R. Pearce, and P. J. Stuckey, 2017. Short-term scheduling of an open-pit mine with multiple objectives. Engineering Optimization 49(5):777-795.

[15] Blom, M., A. R. Pearce, and P. J. Stuckey, 2018. Short-term planning for open pit mines: a review. International Journal of Mining, Reclamation and Environment 33(5):1-22.

[16] Bodon, P., T. Sandeman, and C. Stanford, 2011. Modeling the mining supply chain from mine to port: A combined optimization and simulation approach. Journal of Mining Science 47:202-211.

[17] Both, C., and R. Dimitrakopoulos, 2020. Joint stochastic short-term production scheduling and fleet management optimization for mining complexes. Optimization and Engineering 21(4):1717-1743.

[18] Bozorgebrahimi, E., R. A. Hall, and G. H. Blackwell, 2003. Sizing equipment for open pit mining - A review of critical parameters. Institution of Mining and Metallurgy. Transactions. Section A: Mining Technology 112(3):A171-A179.

[19] Can, L., and I. E. Grossmann, 2021. A Review of Stochastic Programming Methods for Optimization of Process Systems Under Uncertainty. Frontiers Chemical Enginnering, DOI: https://doi.org/10.3389/fceng.2020.622241. 2(1).

[20] Chilès, J. P. , and P. Delfiner, 2012. Geostatistics: Modeling Spatial Uncertainty. 2 vols. Volume 2. Paris, France: John Wiley & Sons, Inc., ISSN: 9781118136188, DOI: 10.1002/9781118136188

[21] Curran, M., A., 2014. Strengths and Limitations of Life Cycle Assessment. *In* Background and Future Prospects in Life Cycle Assessment. W. Klöpffer, ed. Pp. 189-206. Dordrecht: Springer Netherlands.

[22] De Werk, M., B. Ozdemir, and M. Kumral, 2017. Cost analysis of material handling systems in open pit mining: Case study on an iron ore prefeasibility study. The Engineering Economist 62(4):369-386.

[23] Dean, M., P. Knights, and M. Nehring, 2015. Selection and Planning of Fully Mobile IPCC Systems for Deep Open-Pit Metalliferous Applications. *In* AusIMM 2015 3rd International Future Mining Conference. Sydney, Australia.

[24] Dellino, G., C. Meloni, and H. Pierreval, 2014. Simulation-optimization of complex systems: Methods and applications. Simulation Modelling Practice and Theory 46:1-3.

[25] Dimitrakopoulos, R., and A. Jewbali, 2013. Joint stochastic optimisation of short and long term mine production planning: Method and application in a large operating gold mine. Transactions of the Institutions of Mining and Metallurgy, Section A: Mining Technology 122(2):110-123.

[26] Dzakpata, I., P. Knights, and M. Nehring, 2016. Truck and Shovel Versus In-Pit Conveyor Systems: a Comparison Of The Valuable Operating Time. *In* Proceedings of the 16thCoal Operators' Conference. Pp. 463-476. Univeristy of Wolongong.

[27] Eivazy, H., and H. Askari-Nasab, 2012. A mixed integer linear programming model for short-term open pit mine production scheduling. Transactions of the Institutions of Mining and Metallurgy, Section A: Mining Technology 121(2):97-108.

[28] Elkan C., and K. Noto, 2008. Learning classifiers from only positive and unlabeled data. *In* Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining. Pp. 213 - 220.

[29] Erkayaoğlu, M., and N. Demirel, 2016. A comparative life cycle assessment of material handling systems for sustainable mining. Journal of Environmental Management 174:1-6.

[30] Errico, F., G. Desaulniers, and L. M. Rousseau, 2016. A priori optimization with recourse for the vehicle routing problem with hard time windows and stochastic service times. European Journal of Operational Research 249(1):55-66.

[31] Feld, S., C. Roch, and T. Gabor, 2019. A Hybrid Solution Method for the Capacitated Vehicle Routing Problem Using a Quantum Annealer. Frontiers in ICT 6(13):1-13.

[32] Feng, Y., R. Q. Zhang, and G. Jia, 2017. Vehicle Routing Problems with Fuel Consumption and Stochastic Travel Speeds. Mathematical Problems in Engineering 2017:6329203.

[33] Figliozzi, M., 2010. Emissions Minimization Vehicle Routing Problem. Transportation Research Record: Journal of the Transportation Research Board 2197.

[34] Fioroni, M. M., L. A. G. Franzese, and T. J. Bianchi, 2008. Concurrent simulation and optimization models for mining planning. Proceedings of 40th Conference on Winter Simulation, 2008, pp. 759-767.

[35] Franceschetti, A., D. Honhon, and T. Bektaş, 2013. The time-dependent pollution-routing problem. Transportation Research Part B: Methodological 56:265-293.

[36] Fu, M. C., 2015. Handbook of Simulation Optimization. Volume 216: Springer New York, NY. DOI: https://doi.org/10.1007/978-1-4939-1384-8S.

[37] Fuming, L., C. Qingxiang, and C. Shuzhao, 2015. A comparison of the energy consumption and carbon emissions for different modes of transportation in open-cut coal mines. International Journal of Mining Science and Technology 25(2):261-266.

[38] Gholamnejad, J., 2008. A zero-one integer programming model for open pit mining sequences. Journal- South African Institute of Mining and Metallurgy 108:759-762.

[39] Gong, Hongshuo, A. Moradi Afrapoli, and H. Askari-Nasab, 2023a. Integrated simulation and optimization framework for quantitative analysis of near-face stockpile mining. Simulation Modelling Practice and Theory 128:102794.

[40] Gong, Hongshuo, et al. 2023b. Near-face stockpile open pit mining: a method to enhance NPV and quality of the plant throughput. International Journal of Mining, Reclamation and Environment 37(3):200-215.

[41] Grodzevich, O., and O. Romanko, 2006. Normalization and Other Topics in Multi-Objective Optimization. Proceedings of the Fields–MITACS Industrial Problems Workshop, 2006, pp. 89 - 101.

[42] Hay, E., M. Nehring, and P. Knights, 2020. Ultimate pit limit determination for semi mobile in-pit crushing and conveying system: a case study. International Journal of Mining, Reclamation and Environment 34(7):498-518.

[43] Jabali, O., T. Van Woensel, and T. De Kok, 2012. Analysis of Travel Times and CO2 Emissions in Time-Dependent Vehicle Routing. Production and Operations Management 21(6):1060-1074.

[44] Jewbali, A., and R. Dimitrakopoulos, 2018. Stochastic mine planning-example and value from integrating long-and short-term mine planning through simulated grade control, Sunrise Dam, Western Australia. *In* Advances in Applied Strategic Mine Planning. Pp. 173-190.

[45] Klanfar, M., and D. Vrkljan, 2012. Benefits of using mobile crushing and screening plants in quarrying crushed stone. AGH Journal of Mining and Geoengineering : quarterly of AGH University of Science and Technology Vol. 36:167-175.

[46] Koehler, F., 2003. In-pit crushing system the future mining option. Proceedings of Mine Planning and Equipment Selection (MPES), Melbourne, 2003, pp. 371-376. Australasian Institute of Mining and Metallurgy.

[47] Konak, G., A. H. Onur, and D. Karakus, 2007. Selection of the optimum in-pit crusher location for an aggregate producer. Journal of the Southern African Institute of Mining and Metallurgy 107(3):161-166.

[48] Kozan, E., and S. Q. Liu, 2016. A new open-pit multi-stage mine production timetabling model for drilling, blasting and excavating operations. Mining Technology 125(1):47-53.

[49] Kozan, E., S. Liu, and R. Wolff, 2013. A short-term production scheduling methodology for open-pit mines. Proceedings of the 36th Application of Computers and Operations Research in The Mineral Industry (APCOM) Symposium, 2013, pp. 465 - 473.

[50] L'Heureux, G., M. Gamache, and F. Soumis, 2013. Mixed integer programming model for short term planning in open-pit mines. Transactions of the Institutions of Mining and Metallurgy, Section A: Mining Technology 122(2):101-109.

[51] Liu, D., and Y. Pourrahimian, 2021, A Framework for Open-Pit Mine Production Scheduling under Semi-Mobile In-Pit Crushing and Conveying Systems with the High-Angle Conveyor. Mining 1(1):59-79.

[52] Liu, S. Q., and E. Kozan, 2017. Integration of mathematical models for ore mining industry. International Journal of Systems Science: Operations & Logistics 6:1-14.

[53] Londoño, J. G., P. F. Knights, and M. S. Kizil, 2013. Modelling of In-Pit Crusher Conveyor alternatives. Mining Technology 122(4):193-199.

[54] Manriquez, F., H. González, and M. V. Nelson, 2019. Short-term open-pit mine production scheduling with hierarchical objectives. *In* 39th International Symposium on Application of Computers and Operations Research in the Mineral Industry (APCOM 2019). Pp. 443-452. Wroclaw, Poland.

[55] Manríquez, F., J. Pérez, and N. Morales, 2020. A simulation–optimization framework for short-term underground mine production scheduling. Optimization and Engineering 21(3):939-971.

[56] Marinaki, M., and Y. Marinakis, 2016. A Glowworm Swarm Optimization algorithm for the Vehicle Routing Problem with Stochastic Demands. Expert Systems with Applications 46:145-163.

[57] Matamoros, M. E. V., and R. Dimitrakopoulos, 2016. Stochastic short-term mine production schedule accounting for fleet allocation, operational considerations and blending restrictions. European Journal of Operational Research 255(3):911-921.

[58] McCarthy, R. J., 2011. In-Pit Crushing and Conveying: Fitting a Square Peg in a Round Open Pit: Canadian Institute of Mining, Metallurgy and Petroleum.

[59] Moradi-Afrapoli, Ali, and Hooman Askari-Nasab, 2022. Advanced Analytics for Surface Extraction. *In* Advanced Analytics in Mining Engineering: Leverage Advanced Analytics in Mining Industry to Make Better Business Decisions. A. Soofastaei, ed. Pp. 181-203. Cham: Springer International Publishing.

[60] Moradi Afrapoli, A., and H. Askari-Nasab, 2017. Mining fleet management systems: a review of models and algorithms. International Journal of Mining, Reclamation and Environment 33(1):1-19.

[61] Morris, P., 2008. Key Production Drivers in In Pit Crushing and Conveying (IPCC) Studies. The Southern African Institute of Mining and Metallurgy:12.

[62] Mousavi, A., E. Kozan, and S. Q. Liu, 2016a. Comparative analysis of three metaheuristics for short-term open pit block sequencing. Journal of Heuristics 22(3):301-329.

[63] ousavi, A., E. Kozan, and S. Q. Liu, 2016b. Open-pit block sequencing optimization: A mathematical model and solution technique. Engineering Optimization 48:1-19.

[64] Nehring, M., P. F. Knights, and M. S. Kizil, 2018. A comparison of strategic mine planning approaches for in-pit crushing and conveying, and truck/shovel systems. International Journal of Mining Science and Technology 28(2):205-214.

[65] Nelis, G., and N. Morales, 2022. A mathematical model for the scheduling and definition of mining cuts in short-term mine planning. Optimization and Engineering 23(1):233-257.

[66] Nikbin, Vahid, and Ali Moradi Afrapoli, 2023. A Multiple Objective Hybrid Algorithm for Daily Ore Blend in Oil Sands Mines. International Journal of Mining, Reclamation and Environment:1-16.

[67] Norgate, T., and N. Haque, 2013. The greenhouse gas impact of IPCC and ore-sorting technologies. Minerals Engineering 42:13-21.

[68] Nunes, R., H. Junior, and G. Tomi, 2019. A decision-making method to assess the benefits of a semi-mobile in-pit crushing and conveying alternative during the early stages of a mining project. REM - International Engineering Journal 72:285-291.

[69] Osanloo, M., and M. Paricheh, 2020. In-pit crushing and conveying technology in open-pit mining operations: a literature review and research agenda. International Journal of Mining, Reclamation and Environment 34(6):430-457.

[70] Paduraru, C., and R. Dimitrakopoulos, 2018. Adaptive policies for short-term material flow optimization in a mining complex. Mining Technology: Transactions of the Institute of Mining and Metallurgy 127(1):56-63.

[71] Paricheh, M., and M. Osanloo, 2016. Determination of the optimum in-pit crusher location in open-pit mining under production and operating cost uncertainties. 6th International Conference on Computer Applications in the Minerals Industries, Istanbul, Turkey.

[72] icheh, M., and M. Osanloo, 2019a. Concurrent open-pit mine production and in-pit crushing–conveying system planning. Engineering Optimization 52(3):1-16.

[73] icheh, M., and M. Osanloo, 2019b. A New Search Algorithm for Finding Candidate Crusher Locations Inside Open Pit Mines. Proceedings of the 28th International Symposium on Mine Planning and Equipment Selection, 2019b.

[74] icheh, M., and M. Osanloo, 2020. A New Search Algorithm for Finding Candidate Crusher Locations Inside Open Pit Mines. Proceedings of the 28th International Symposium on Mine Planning and Equipment Selection - MPES 2019, Cham, 2020, pp. 10-25. Springer International Publishing.

[75] Paricheh, M., M. Osanloo, and M. Rahmanpour, 2016. A heuristic approach for in-pit crusher and conveyor system's time and location problem in large open-pit mining. International Journal of Mining, Reclamation and Environment 32(1):35-55.

[76] Paricheh, M., M. Osanloo, and M. Rahmanpour, 2017. In-Pit Crusher Location as a Dynamic Location Problem. The Southern African Institute of Mining and Metallurgy 117(6):599 - 607.

[77] Quigley, M., and R. Dimitrakopoulos, 2019. Incorporating geological and equipment performance uncertainty while optimising short-term mine production schedules. International Journal of Mining, Reclamation and Environment 34(5):362-383.

[78] Rahmanpour, M., M. Osanloo, and N. Adibi, 2013. An approach to determine the location of an in pit crusher in open pit mines. 23rd International Mining Congress and Exhibition of Turkey, IMCET 2013 1:141-149.

[79] Ritter, R., 2016. Contribution to the capacity determination of semi-mobile in-pit crushing and conveying systems, Faculty of Geosciences, Geoengineering and Mining Technische Universität Bergakademie Freiberg.

[80] Ritter, R., and C. Drebenstedt, 2019. Output prediction of Semi Mobile In Pit Crushing and Conveying

[81] Systems (SMIPPC). *In* Scientific and Practical Studies of Raw Material Issues, Vol. 1. London: Taylor & Francis Group. ISBN : 978-0-367-86153-7.

[82] Rodovalho, E. da. C., H. M. Lima, and G. De Tomi, 2016. New approach for reduction of diesel consumption by comparing different mining haulage configurations. Journal of Environmental Management 172:177-185.

[83] Roumpos, C., P. Partsinevelos, and A. Vlachou, 2014. The optimal location of the distribution point of the belt conveyor system in continuous surface mining operations. Simulation Modelling Practice and Theory 47:19-27.

[84] Samavati, M., D. L. Essam, and M. Nehring, 2018. Open-Pit Mine Production Planning and Scheduling: A Research Agenda. Data and Decision Sciences in Action, Cham, 2018, pp. 221-226. Springer International Publishing.

[85] Samavati, M., D. Essam, and M. Nehring, 2020. Production planning and scheduling in mining scenarios under IPCC mining systems. Computers & Operations Research 115:104714.

[86] Sandeman, T., C. Fricke, and P. Bodon, 2011. Integrating optimization and simulation - A comparison of two case studies in mine planning. *In* Proceedings of the 2010 Winter Simulation Conference. Pp. 1898-1910.

[87] Sarasola, B., K. F. Doerner, and V. Schmid, 2016. Variable neighborhood search for the stochastic and dynamic vehicle routing problem. Annals of Operations Research 236(2):425-461.

[88] Schroder, D. L., 2003. Schroder, D.L., 2003, The use of in-pit crushing and conveying methods to significantly reduce transportation costs by truck. *In* Coaltrans Asia Conference, . Bali.

[89] Shamsi, M., and M. Nehring, 2021. Determination of the optimal transition point between a truck and shovel system and a semi-mobile in-pit crushing and conveying system. Journal of the Southern African Institute of Mining and Metallurgy (121):497-504.

[90] Shamsi, M., Y. Pourrahimian, and M. Rahmanpour, 2022. Optimisation of open-pit mine production scheduling considering optimum transportation system between truck haulage and semi-mobile in-pit crushing and conveying. International Journal of Mining, Reclamation and Environment 36(2):142-158.

[91] Shishvan, M. S., and J. Benndorf, 2014. Performance optimization of complex continuous mining system using stochastic simulation. *In* Engineering Optimization IV - Proceedings of the 4th International Conference on Engineering Optimization. Lisbon.

[92] Shishvan, M. S., and J. Benndorf, 2016. The effect of geological uncertainty on achieving short-term targets: A quantitative approach using stochastic process simulation. Journal of the Southern African Institute of Mining and Metallurgy 116:259-264.

[93] Shishvan, M. S., and J. Benndorf, 2017. Operational Decision Support for Material Management in Continuous Mining Systems: From Simulation Concept to Practical Full-Scale Implementations. Minerals 7:116.

[94] Smith, M. L., 1998. Optimizing short-term production schedules in surface mining: Integrating mine modeling software with AMPL/CPLEX. International Journal of Surface Mining, Reclamation and Environment 12(4):149-155.

[95] Tabesh, M., and H. Askari-Nasab, 2013. Automatic Creation of Ore-Selection and Blast Polygons using Clustering Algorithms.

[96] Tabesh, Mohammad, and Hooman Askari-Nasab, 2019. Clustering mining blocks in presence of geological uncertainty. Mining Technology 128(3):162-176.

[97] Taheri, M., M. Irannajad, and P. Ataee, 2009. An approach to determine the locations of in-pit crushers in deep open-pit mines. 9th International Multidicsciplinary Scientific Geoconference and EXPO, SGEM 2009, June 14, 2009 - June 19, 2009, Albena, Bulgaria, 2009. Vol. 1, pp. 341-347. International Multidisciplinary Scientific Geoconference.

[98] Thomas, A., G. Singh, and M. Krishnamoorthy, 2013. Distributed optimisation method for multi-resource constrained scheduling in coal supply chains. International Journal of Production Research 51(9):2740-2759.

[99] Thomas, A., J. Venkateswaran, and M. Krishnamoorthy, 2014. A resource constrained scheduling problem with multiple independent producers and a single linking constraint: A coal supply chain example. European Journal of Operational Research 236(3):946-956.

[100] Topf, A., 2017. In-pit crushing and conveying systems changing the way ore is moved: mining.com. https://www.mining.com/in-pit-crushing-systems-changing-the-way-ore-is-moved/.

[101] Torkamani, E., and H. Askari-Nasab, 2015. A linkage of truck-and-shovel operations to short-term mine plans using discrete-event simulation. International Journal of Mining and Mineral Engineering 6(2):97-118.

[102] Upadhyay, S. P., and H. Askari-Nasab, 2016. Truck-shovel allocation optimisation: A goal programming approach. Transactions of the Institutions of Mining and Metallurgy, Section A: Mining Technology 125(2):82-92.

[103] Upadhyay, S. P., and H. Askari-Nasab, 2017. Dynamic shovel allocation approach to short-term production planning in open-pit mines. International Journal of Mining, Reclamation and Environment 33(1):1-20.

[104] Upadhyay, S. P., J. Doucette, and H. Askari-Nasab, 2021. Short-term production scheduling in open pit mines with shovel allocations over continuous time frames. International Journal of Mining and Mineral Engineering 12(4):292-308.

[105] Urbanucci, L., 2018. Limits and potentials of Mixed Integer Linear Programming methods for optimization of polygeneration energy systems. Energy Procedia 148:1199-1205.

[106] Utley, R. W., 2011. In-pit Crsuhing. Volume 2: SME Mining Engineering Handbook, Society for Mining, Metallurgy and Exploration, ISBN : 978-0-87335-264-2.

[107] Wachira, D., J. Githiria, and M. Onifade, 2021. Determination of semi-mobile in-pit crushing and conveying (SMIPCC) system performance. Arabian Journal of Geosciences 14:1-13.

[108] Xiao, Y., Q. Zhao, and I. Kaku, 2012. Development of a fuel consumption optimization model for the capacitated vehicle routing problem. Computers & Operations Research 39(7):1419-1431.

17. Appendix

Table 2. Comparison among key aspects of IPCC publications.

Comparison of post 2010 IPCC papers	Key Aspects					Objectives										Solution Tools
	A1	A2	A3	A4	A5	O1	O2	O3	O4	O5	O6	O7	O8	O9	O10	O11	NS
Konak et al. (2007)	No	No	F,SM	√	×	×	×	×	×	√	×	×	√	×	×	×	NS
Phil Morris (2008)	No	No	F,SM	×	×	×	×	√	×	×	×	×	×	×	×	×	NS
Taheri et al. (2013)	No	No	F	√	×	×	×	×	×	×	√	×	√	×	×	×	NS
McCarthy (2011)	No	No	F,SM, FM	×	×	×	×	√	×	×	×	×	×	×	×	×	NS
Utley (2011)	No	No	F,SM, FM	×	×	×	×	√	×	×	×	×	×	×	×	×	NS
Klanfer, Vrkjln (2012)	No	No	F,FM	√	×	×	×	√	×	×	×	×	√	×	×	×	NS
Rahmanpour et al. (2013)	No	No	SM	√	×	×	×	×	×	√	×	√	√	×	×	×	NS
Roumpos et al. (2014)	No	No	F,SM, FM	√	×	×	×	×	√	×	×	×	√	×	×	×	MATLAB
Londono et al. (2013)	No	No	F,SM, FM	√	×	×	×	×	√	×	×	×	×	×	×	×	NS
Norgate, Haque (2013)	No	No	F,SM, FM	√	×	×	√	×	×	×	×	×	×	×	×	×	Simapro
Dean et al. (2015)	No	No	FM	√	×	×	×	×	√	×	×	×	√	×	×	×	NS
Erkayaoglu, Demirel (2016)	No	No	F,SM, FM	√	×	×	√	×	×	×	×	×	×	×	×	×	Simapro 7.3
Ritter (2016)	No	No	SM	√	√	√	×	×	×	×	×	×	×	×	×	√	ARENA /VBA
Paricheh, Osanloo (2016)	No	No	SM	√	√	×	×	×	×	√	×	×	√	×	×	×	CPLEX
Paricheh et al. (2016)	No	No	SM	√	×	×	×	×	×	√	√	×	×	×	√	×	GAMS, Excel
De Wark et al.(2017)	No	No	SM	√	×	√	×	×	×	×	×	×	×	×	×	×	NS
Paricheh et al. (2017)	No	No	SM	√	×	×	×	×	×	√	×	×	√	×	×	×	GAMS
Abbaspour et al. (2018)	No	No	F,SM, FM	√	×	×	√	×	×	×	×	×	×	√	×	×	NS
Abbaspour, Carsten (2019)	No	No	FM	√	×	√	×	×	×	×	×	×	√	×	×	×	NS
Nunes et al. (2019)	No	No	SM	√	×	√	×	×	×	×	×	×	√	×	×	×	Excel VBA

Comparison of post 2010 IPCC papers	Key Aspects					Objectives										Solution Tools
	A1	A2	A3	A4	A5	O1	O2	O3	O4	O5	O6	O7	O8	O9	O10	O11	NS
Paricheh, Osanloo (2019a)	Yes	No	SM	√	×	×	×	×	×	√	×	×	√	×	√	×	CPLEX
Paricheh, Osanloo (2019b)	No	No	F,SM	√	×	×	×	×	×	×	×	√	×	×	×	×	NS
Bernardi et al. (2020)	No	No	F,SM	√	×	×	×	√	×	×	×	×	×	×	√	×	ARENA
Samavati et al (2020)	Yes	No	FM	√	×	×	×	×	√	√	×	×	×	×	√	×	Gurobi
Shamsi, Nehring (2021)	No	No	SM	√	×	√	×	×	×	×	×	×	√	×	×	×	NS
DingBang, Yahsar (2021)	Yes	No	SM	√	×	×	×	×	√	×	√	×	√	√	×	×	MATLAB/CPLEX 12.7
Wachira et al. (2021)	No	No	SM	√	×	×	×	×	×	×	×	×	×	×	×	√	NS
Shamsi et al. (2022)	Yes	No	SM	√	×	×	×	×	×	√	√	×	√	×	√	×	CPLEX 12.7

A1 - Integration with long-term plan

A2 - Integration with short-term plan

A3 - IPCC type

A4 - Case study

A5 - Stochastcity

O1 - Economic comparison with TS

O2 - Environmental comparison with TS

O3 - Comparison among IPCCs (Economic)

O4 - Optimum conveyor design/ exit location determination

O5 - Optimum Crusher Location determination

O6 - Crusher relocation time optimisation

O7 - Candidate crusher location determination

O8 - Transportation cost minimisation

O9 - IPCC risk assessment

O10 - NPV maximisation

O11 - IPCC capacity/performance determination

F – Fixed

SM – Semi-mobile

FM – Fully-mobile

Table 3. Comparison among most recent publication on short-term mine planning.

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Stochastic or Deterministic	IPCC/ TS
Eivazy and Askari-Nasab (2012)	Block extraction sequence generation	12 to 36 months	CPLEX	Minimise cost of mining, processing, material movement and waste rehabilitation **subject to** head grade, precedence and capacity constraints	Deterministic	TS
Liu, Kozan (2012), Liu, Kozan, Wolff (2013,2016)	Block extraction with equipment scheduling; multi-stage, multi-resource scheduling	Not specified	C++	Minimise makespan of mining activities drilling, blasting and excavation **subject to** capacity of mining equipment and precedence constraints	Deterministic	TS
L'Heureux et al. (2013)	Block extraction, shovel allocation drilling and blasting schedule.	3 months	IBM ILOG CPLEX	Minimise cost of shovel movement, drilling and blasting cost **subject to** precedence of activities, capacity and blending constraints	Deterministic	TS
Mousave et al. (2016b)	Block sequencing problem with equipment scheduling	Six months	CPLEX	Minimise the total mining cost which includes rehandling and holding costs, misclassification and drop-cut costs **constrained by** precedence relationship machine capacity, grade requirements and processing demands	Deterministic	TS
Mousave et al. (2016a)	A comparative study of three meta heuristic approaches (tabu search, simulated annealing and a hybrid of these two) to short-term mine sequencing.	NS	NS	An MIP model to minimise the stockpile rehandling cost **constrained by** upper and lower bounds of ore grade.	Deterministic	TS

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Stochastic or Deterministic	IPCC/ TS
Kozan, Liu (2016)	Multi-stage mine production timetabling model for drilling, blasting and excavating operations	18 weeks	IBM ILOG CPLEX	Maximise the throughput and minimise the total idle times of equipment at each stage of drilling, blasting and excavation **subject to** equipment capacity, speed, ready times subject to precedence constraints.	Deterministic	TS
Liu, Kozan (2017)	An innovative mine management system by integrating a series of mathematical models for long-term, mid-term block sequencing and operational level planning of equipment with a job-shop scheduling model to achieve an overall mining efficiency	18 weeks	CPLEX	The long and medium term MIP models maximise the net present value of the blocks to be mined throughout the life of mine and for a specific period respectively and the operational level MIP minimises the makespan and tardiness in job completion times **subject to** block precedence and capacity constraints.	Deterministic	TS
Blom et al. (2014,2016)	A decomposition based heuristic model to solve a set of mine-side optimisation problems and a port-side blending problem	13 weeks	IMB CPLEX	Meeting blending targets and maximizing equipment use in a multi-mine, multiple port network **constrained by** capacity and blending constraints	Deterministic	TS
Blom (2017)	A rolling planning horizon-based MIP model to generate multiple short-term production schedules	13 weeks	IMB CPLEX	Optimise equipment use and shovel movement **constrained by** precedence relationships, blending requirements, equipment availabilities and trucking hours considering multiple processing paths.	Deterministic	TS

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Stochastic or Deterministic	IPCC/ TS
Upadhyay, et al. (2021)	Shovel allocation optimization over continuous time frame	20 weeks	CPLEX	Maximizing shovel utilisation, minimising deviation in production and grade from target, minimising shovel movement **subject to** production capacity, grade blending and precedence constraints.	Deterministic	TS
Nelis, Morales(2022)	Optimization of short-term plan by simultaneous generation of mining cuts	5 weeks	Gurobi	Maximizing profit **subject to** mining capacity, precedence, mining cut size and maximum number of mining cuts constraints.	Deterministic	TS
Upadhyay, S., Askari-Nasab (2016, 2017)	Simulation optimisation model to generate optimum mining schedule by shovel allocation	12 months	CPLEX, ARENA	Maximizing shovel utilisation, minimising deviation in production and grade from expected/target, minimising shovel movement **subject to** production capacity, grade blending and precedence constraints.	Operational uncertainty	TS
Manriquez et al. (2019)	A framework to optimise short-term planning of open pit mines	NS	Python	Minimising maximum deviation between ore tonnage sent to plant and plant capacity, minimising maximum deviation between metal fines and the expected metal fines in processing plant and minimising overall shovel fleet movement cost minimisation **subject to** grade blending and precedence constraints.	Deterministic	TS
Manriquez et al. (2020)	Simulation optimisation model to generate short-term extraction sequence	18 months	UDESS	Maximise value of extraction **subject to** precedence, blending and equipment availability constraints.	Operational uncertainty	TS
Matamoros, Dimitrakapoulos (2016)	Simultaneous optimisation of fleet and production schedules	12 months	CPLEX, C++	Eight component objectives to minimise the cost of extraction, haulage time under uncertainty of trucks' haulage time and availability, loss of shovel production and geological risks **subject to** capacities and blending constraints.	Stochastic (geological and fleet uncertainty)	TS

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Stochastic or Deterministic	IPCC/ TS
Paduraru, Dimitrakopoulos (2018)	Shows how new information, such as updated estimates on the characteristics of extracted material, can be integrated into the short-term planning process	50 weeks	NS	Based on the characteristic vector of a block, determining the optimum destination for that block to impose the largest immediate improvement on cash flow **constrained by** block precedences and processing capacities.	Geological uncertainty	TS
Matamoros, Jewbali (2013, 2018)	A multi-stage planning process that incorporates potential short-term variability in the long-term planning process.	NS	NS	Maximises NPV and minimises deviation in planned production, where a set of possible realizations of future grade control data is generated based on the grade of material in mined out areas of the mine site **satisfying** block precedence constraints.	Geological and operational uncertainty	TS
Bodon, Sandman (2010, 2011)	Model shows how integrating optimisation within a simulation allows a more accurate representation of the system, providing a better solution although with a longer run time.	9 days	Lingo	Maximise tonnes mined and shipped, minimise the deviation of the quality of all mine and port stockpiles and meet blending requirements **constrained by** equipment and port capacity and precedence constraints for a supply chain consisting of pit, port and ships.	Operational Uncertainty	TS
Shishvan, Bendorf (2014, 2016, 2017)	Stochastic simulation approach to predict performance and reliability of complex continuous mining operations for optimal decision making in short-term production planning	7days	Arena	Minimise production deviation and maximise equipment utilisation **subject to** processing capacities and equipment availability.	Geological Uncertainty and equipment uncertainty	TS
Rahmanpour, Osanloo (2016)	Stochastic optimisation to capture the effects of geological uncertainties on short-term mine planning	30 months	NS	Minimise cost of mining **subject to** equipment capacity, ore quality and mill demand constraints	Geological Uncertainty	TS

Comparison of post 2010 short-term papers	key Aspects	Time horizon	Solution tool	Objectives	Stochastic or Deterministic	IPCC/ TS
Quigley, Dimitrakapol ous (2019)	Improvement of Matamoros, Dimitrakapolous model (2016)	12 months	CPLEX	Generate short term schedule to minimise cost of shovel movement and production deviation, deviation of tonnage and grade sent to plants and maximise truck hours of the allocated fleet **constrained by** processing capacity, equipment availability considering uncertainty of geology, shovel performance and truck cycle time.	Geological and equipment uncertainty	TS

Table 4. List of acronyms.

Acronym	Abbreviation
NPV	Net present value
OPEX	Operational expense
Capex	Capital Expense
SMIPCC	Semi-mobile IPCC
FMIPCC	Fully-mobile IPCC
LP	Linear programming
MILP	Mixed integer linear programming
DES	Discrete event simulation
GHG	Greenhouse gas

Short-term Planning of Open Pit Mines with Semi-Mobile IPCC: A Shovel Allocation Model[1]

Nasib Al Habib[1], Eugene Ben-Awuah[2] and Hooman Askari-Nasab[1]
Mining Optimization Laboratory (MOL)
[1] University of Alberta, Edmonton, Canada
[2] Laurentian University, Sudbury, Canada

ABSTRACT

In-pit crushing and conveying (IPCC) is considered a suitable alternative to truck haulage in open pit mines because it offers a lower operating cost than a truck-shovel system. It also reduces truck haulage distance and truck requirements. One of the IPCC variations is the semi-mobile system, which is relocated every two to five years. The short-term plan needs to be updated accordingly, based on the crusher's optimal location and relocation time. To the best of our knowledge, short-term planning with IPCC is an area of research that has not been explored extensively yet and hardly any model can generate short-term schedules considering an IPCC in place. This research work proposes a mixed integer programming model to generate short-term production plans and near-optimal shovel allocation to mining faces, within a time horizon of 12 months. The objective of the model is to minimize the cost of material handling and maximize revenue, with respect to plant requirement, maximum allowable tonnage variation and IPCC location constraints, and the production and NPV targets set by the strategic plan. An iron ore mine case including a semi-mobile IPCC system with one relocation is used as the case study to verify the proposed model. The comparison of results between scenarios with and without IPCC justifies the use of IPCC in the iron ore mine from a short to medium-term perspective. The project can be considered a pioneering work in the arena of short-term mine planning with the IPCC.

Keywords: IPCC, optimization, haulage

1. Introduction

This paper proposes a short-term planning methodology by near-optimal shovel allocation in the presence of IPCC or traditional truck-shovel haulage. It is a general short-term planning model that is applicable to all types of open pit mines. The most significant contribution of this research is the generation of short-term mining sequences with IPCC as the major means of transportation. The model takes into account the revenue earned from selling ore along with the cost of production and haulage from a short to medium-term perspective. Most of the existing short-term planning models focus on cost minimization without focusing on profit maximization. The biggest challenge to optimizing shovel allocation by profit maximization is the contradictory nature of the objective

[1] This paper is under review for publication in the International Journal of Mining, Environment and Reclamation

ISBN: 978-1-55195-503-2

function, which requires simultaneous maximization of revenue and minimization of cost by meeting production targets. The number of variables increases exponentially with an increase in the number of benches and mining faces. Solving the model to develop short-term mining sequences within a reasonable time has also been a substantial challenge in this research.

Mining is a highly capital-intensive operation and proper production planning is required to avoid the sub-optimality of the overall setup, including all the equipment utilization. The primary objective of any mining project is to maximize the net present value (NPV) by keeping the cost at a minimum. Mine planning can be divided into long-term and short-term planning based on the planning time horizon and the objectives being optimized. While the long-term plan is created at the strategic level to maximize the NPV throughout the life of mine, the short-term planning aims at optimizing the operational activities like shovel allocation, grade blending to meet head grade requirements at the plant, truck requirement etc. to help achieve the ultimate long-term schedule. The time horizon of short-term planning can be monthly, weekly or even daily.

Optimal utilization of the equipment used in mining operations is of vital importance because the haulage costs may account for over 50% of the total operating cost in a truck-shovel operation (Moradi Afrapoli and Askari-Nasab 2017). The optimal utilization of the equipment can only be achieved by efficient utilization of all the assets involved, to meet the production targets set by the long-term production plan. Therefore, optimal allocation of assets such as shovels and trucks as part of the short-term production scheduling is of utmost importance.

Mied integer programming (MIP) models have been used extensively to generate short-term schedules of open pit mines. Most of the modern short-term planning models are MIP based with explicit precedence constraints applied. Smith (1998), was the first to popularize the use of precedence constraints in mine planning and scheduling. The model uses an MIP for constructing short-term schedules with explicit accessibility constraints, requiring the nine blocks above a block to be mined before that block can be accessed. Gholamnejad (2008) proposed a binary integer programming model to solve the short-term mine scheduling problem to decide which blocks of ore and waste must be mined in which period (shifts, days, weeks or months) by satisfying several operational and geometrical constraints simultaneously. Eivazy and Askari-Nasab (2012) solved a short-term planning MIP model under several different scenarios, in which the direction of mining varies with different mining precedence constraints. The objective is to minimize the overall cost of mining operations including mining, processing, haulage, re-handling and rehabilitation costs.

L'Heureux, et al. (2013) proposed a detailed mathematical optimization model for short-term planning, with operational details for a period of up to three months. The objective is to minimize operational costs of trucks' and shovels' activity, drilling and blasting. The authors solved the problem for up to 5 shovels, 90 periods and 132 faces. Kozan, et al. (2013) modelled drilling, blasting and mining of blocks, and allocation of equipment to these activities with an objective of minimizing the make-span (elapsed time between the start and end of a schedule). Later, Kozan and Liu (2016) formulated another short-term planning model to maximize the throughput and minimize the total idle times of equipment at each stage of drilling, blasting and excavation, subject to equipment capacity, speed, read times and activity precedence constraints. The latest contribution of Liu and Kozan (2017) was an is an innovative mine management system. The suggested approach combines various mathematical models to determine the ultimate pit limit in the long-term and medium-term block sequencing, while also optimizing equipment planning with a job-shop scheduling model to enhance mining efficiency. Overall, this methodology aims to improve mining efficiency by integrating various planning and scheduling models. Blom, et al. (2017) proposed a MIP model for generating multiple short-term production schedules that optimize equipment and shovel use while taking into account constraints such as blending requirements, equipment availability, trucking hours, and precedence relationships among tasks. The model uses a rolling planning horizon approach and considers multiple processing paths.

Integration of simulation with MIP is a tool that has been used by some researchers to account for the uncertainty that exists in mining operations such as, equipment failure, haulage etc. Upadhyay and Askari-Nasab (2016), and Upadhyay and Askari-Nasab (2017) developed an MIP-based short-term planning model that incorporates simulation to enable proactive decision-making in the dynamic mining environment. The model synchronizes operational plans with long-term planning to minimize opportunity costs, optimize production, and enhance equipment utilization. The authors solved the MIP model to optimally allocate shovels to meet production and grade requirement and minimize shovel movement time. Manríquez, et al. (2020) proposed a similar simulation-optimization framework to increase the adherence of short-term mining schedules to actual execution for underground mining operation. The framework generates an initial schedule using a MILP model embedded in UDESS, a software implemented via Python and can be used through scripts or graphical interface. The model is then simulated using any discrete event simulation (DES) software to replicate the schedule and estimate equipment utilization. . The authors claim the model to be general and applicable to open pit mining as well. Gong, et al. (2023a) formulated an integrated simulation-optimization approach for short-term planning with a new conceptual mining method called the near-face stockpile (NFS), which combines the in-pit crushing and conveying IPCC system with a pre-crusher stockpile. The simulation results revealed a 5% improvement in overall production for an oil sands mine case study.

The short-term planning models discussed so far are all designed to generate schedules assuming truck-shovel haulage system. A close look at the IPCC literature shows that many of the research works focus on optimizing the crusher location. Examples are Konak, et al. (2007), Taheri, et al. (2009), Rahmanpour, et al. (2013), Paricheh, et al. (2016), Paricheh (2017), Paricheh and Osanloo (2019b) etc. All these studies present methodologies to find the optimum crusher location, candidate crusher locations and/or optimum relocation time of crusher, assuming that the long-term plan was generated considering IPCC.

The life cycle assessment studies like Norgate and Haque (2013), Awuah-Offei and Askari-Nasab (2009), Erkayaoğlu and Demirel (2016), Fuming, et al. (2015) present comparisons between IPCC and truck haulage system or among different IPCC systems in terms of environmental sustainability. The results of these studies are highly case specific and varies substantially based on the geological location of the mine and types of trucks and IPCC systems used. However, most of these life cycle assessment studies identify IPCC as the more environmentally sustainable haulage option over trucks.

While there are studies, such as, Paricheh and Osanloo (2019a), Samavati, et al. (2020), Shamsi, et al. (2022), Liu and Pourrahimian (2021), Gong, et al. (2023b) etc., that justify the use of in-pit crushing in long-term by simultaneous optimization of IPCC location and long-term plan, to the best of our knowledge, except there is hardly any research work that does the same in operational or short-term level. Haulage is one of the largest sources of expense in any open pit mining operation. Several fleet optimization models, such as, (Mirzaei-Nasirabad, et al. 2023; Moradi Afrapoli, et al. 2019a; Moradi Afrapoli and Askari Nasab 2020; Moradi Afrapoli, et al. 2019b; Moradi Afrapoli, et al. 2022) have been formulated to minimize the cost of the truck fleet in open-pit mining operations. IPCC has the potential to reduce this cost and in turn maximize the profit. Hence it is crucial to explore the effects of IPCC on short-term planning of open pit mines. Several key decisions regarding IPCC, such as optimum location, relocation time, conveyor design and length etc., are made in the strategic level of mine planning. Therefore, short-term planning needs to investigate the changes in schedules that occur because of housing and moving a crusher inside the pit over time. It is also important to verify if the operational plans can be synced with the long-term plan to deliver the desired NPV of the mine in presence of IPCC.

This research formulates a short-term planning methodology to generate monthly production schedules by optimum shovel allocation. This is a general shovel allocation model that can generate

short-term schedule for both truck-shovel haulage and IPCC systems. The model has been used to compare scenarios with IPCC and traditional truck shovel haulage system to determine which one provides more cost saving and generates higher revenue from a short-term perspective within a time horizon of one year. This research can be marked as one of the pioneering works on short-term planning of open pit mines with IPCC.

2. Problem Definition

This research study aims to demonstrate the effects of IPCC installation on short-term planning by generating near-optimal schedules. The proposed model is intended to be used as a tool to compare IPCC and truck haulage systems to identify the better haulage options for a specific year of mine life.

The proposed short-term planning methodology optimally allocates shovels to the mining faces, which are an aggregation of blocks to reduce the number of variables, meet production requirements, reduce the cost of haulage and maximize the revenue per period. The model will generate monthly schedules for a 12-month planning time horizon. The idea is to present two scenarios, one with IPCC and the other with traditional truck haulage, and compare the results to find out the overall revenue generated and haulage cost incurred in each scenario. The difference in scheduling or extraction sequence based on shovel allocation will also be highlighted to demonstrate how IPCC installation affects the mine plan from an operational viewpoint. Comparing results should enable mine planners to decide on the better option haulage for cost saving and higher revenues earned for a specific year of mine life.

The model's objectives include:

1. Maximizing revenue earned by ore material per period.
2. Meeting production requirements to feed the mill to its capacity.
3. Minimizing ore haulage cost.

The model's development, implementation and verification to compare schedules with semi-mobile IPCC and traditional truck-shovel haulage systems will be shown in section 3.

2.1. Scope and Assumptions of the Model

The proposed model provides a tool to generate and compare short-term schedules for open pit mines. The developed MILP is a general allocation model that can generate schedules for truck-shovel haulage and IPCC systems. For shovel allocation, the model considers both haulage cost minimization and revenue maximization per period, unlike the models proposed by Upadhyay and Askari-Nasab (2016), Upadhyay and Askari-Nasab (2017) and Manríquez, et al. (2020), where the revenue component was missed. The proposed model can be integrated with haulage simulation models to account for operational uncertainty and can be extended to find the optimal number of trucks required in a specific period of mine life. The model is developed based on the following assumptions:

1. The IPCC system is semi-mobile and only used for ore crushing and conveying.
2. The optimum locations and relocation time of the crusher are known throughout the life of mine from the strategic mine plan.
3. The ore and waste faces are known from long-term plans. Hence, ore material will go to the mill or crusher, and waste material will go to the waste dump.
4. Ore shovels are locked to ore faces, and waste shovels are locked to waste faces.
5. There is no stockpiling.
6. The model does not consider ore blending in its current state of the art.

7. The model does not consider multiple processing destinations.
8. Production loss due to shovel movement time is not considered.
9. Production loss due to equipment failure and maintenance is not considered.
10. The model is strictly deterministic.
11. The mill requirement is constant throughout the planning horizon.

3. Model Formulation

The objective function, variables, parameters and the constraints of the MILP model are described in this section.

3.1. Objective Function

The objective of the model is to maximize the total profit generated by the mined material. The objective function consists of five components. The first component calculates the mining cost of the material. The second and third components calculate the cost of hauling ore material to the crusher or mill and the waste material to the waste dumps using diesel trucks. The fourth part calculates the cost of conveying ore material from the crusher to the processing plant. The last component calculates the difference between the revenues earned from and the processing cost of ore. The flow of ore and waste material from source to destination is displayed in Figure 1. The materials are mined from the mining faces by shovels and then loaded onto trucks. The waste material is transported to the waste dumps by the waste trucks. The ore material will be hauled by the ore trucks to the in-pit crusher from mining faces, then conveyed to the plant in the scenario with IPCC. In the scenario without IPCC, the ore material will be hauled by trucks from the pit to the plant crusher.

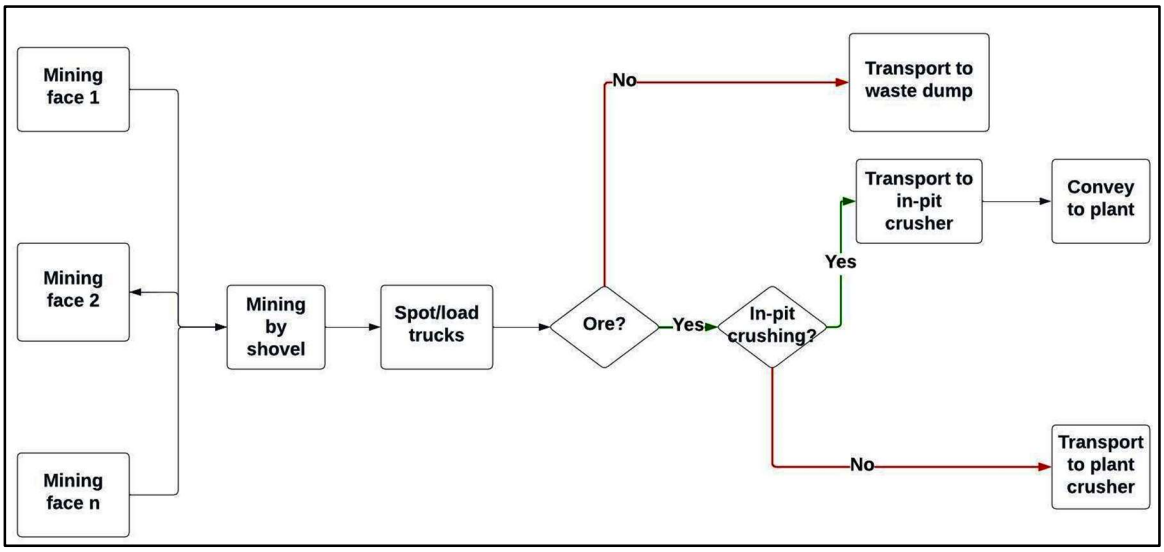


Figure 1: Flow of material from mine to crusher, plant and waste dump.

The objective function is defined as the minimization of the cost of transporting material to the crusher or waste dump from the mine by trucks, plus the cost of conveying ore material from the crusher to the processing plant, minus the profit earned from selling ore. Mathematically, the objective function can be represented as Equation:

$$\text{Min, f} = \sum_{p\in P,t\in T,f\in F} x_{p,f,t} \times RM_{p,f} \times TT \times M_c + \sum_{p\in P,t\in T,f\in F_{ore}} x_{p,f,t} \times RM_{p,f} \times TT \times D_{f,r} \times H_t + \sum_{p\in P,t\in T,f\in F_{waste}} x_{p,f,t} \times RM_{p,f}.TT \times D_{f,w} \times H_t + \sum_{p\in P,t\in T,f\in F_{ore}} x_{p,f,t} \times$$

$$RM_{p,f} \times TT \times C \times H_c - \sum_{p \in P, t \in T, f \in F_{ore}} x_{p,f,t} \times RM_{p,f} \times TT \times (R_k - PR_c) \quad (1)$$

Where the variables, parameters and indexes are,

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

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
H_t	$/tonneKm	Transportation cost per unit
H_c	$/tonneKm	Conveying cost per unit
M	-	A big number
R_k	$/tonne	Iron ore price

M_c	\$/tonne	Mining cost per unit
PR_c	\$/tonne	Processing cost per unit
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

4. Constraints

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Equation 2 ensures that only one shovel can be assigned to a face in a specific period. Every shovel is allowed to be allocated to 2 faces at any given time of a period by equation 2. This constraint enables the shovels to move to a new face whenever the working face is mined out. Equation 3, combined with Equation 10, ensures that a shovel can always move to the next face in a period if a face is mined out.

Equation 4 puts an upper limit on ore material extraction in a period. It guarantees that the ore extraction does not exceed the mill capacity in a period. The model naturally tries to maximize ore production as it aims to maximize revenues earned per period. Hence, the upper limit is set on ore production so it does not overproduce, as we are not considering stockpiling now. Equation 5, however, sets a lower limit on the total waste material to be mined in each period. The model tries to minimize waste mining as waste material increases haulage costs and does not contribute to revenue. Therefore, this constraint ensures that the tonnage of waste mined in a period is at least such that the total available waste material is mined out at the end of the 12 periods. Changing the value of the stripping ratio will increase or decrease the tonnage of waste mined. Hence, this constraint guarantees that the model applies to other case studies with more benches and available material to be mined.

The total tonnage of each face TM_f is assigned to the $l_{f,t}$variable in the initial period by equation 6. Equation 7 keeps track of the remaining tonnage of each face at the end of a period. This constraint lets the model know when a face is mined out so that it can update the variable $m_{f,t}$, which is controlled by Equations 8 and 9 and becomes 1 when $l_{f,t}$becomes very small. Therefore, the $m_{f,t}$ variable is used to keep track of the mined-out faces.

Equation 10 takes care of the fact that if a face has been mined out, it stays mined out in the next periods so that the model does not allocate any shovels to that face in future. Equation 11 strengthens equation 2 by controlling when a shovel can be assigned to more than one face in a period. The right-hand side of this constraint looks over all the faces and takes a very large value if shovel 's' is not assigned to the face in that period. For the faces shovel is allocated to, last part of the constraint will become zero and remaining portion may take a value of 1 or 2. If the shovel was working on the face in the previous period and still hasn't finished mining it, maximum number of faces the shovel can work on can be 1, but if the face is mined out completely, $m_{f,t}$ will become 1 and thus the shovel will be allowed to be assigned to another face. For the new face, as $s_{p,f,t-1}$ and $m_{f,t}$ will be zero, the constraint will still hold true and allow the shovel to be assigned to two more faces in that period.

Equation 12 forces a shovel to stay in the same face unless it is mined out so that the shovels do not make unnecessary movements from the working faces. Equation 13 is the IPCC location constraint. It does not let a shovel to be assigned to a face in a period if the crusher is located on that face during that period. The right-hand side of the constraint becomes zero for the scenario without IPCC in the mine and the model behaves like a traditional shovel allocation model for truck haulage.

Equation 14 ensures that the total material mined by all the shovels from a face across all the periods does not exceed the total material available in that face. Equation 15 is the precedence constraint. The precedence among faces are known from the long-term plan. This constraint ensures that a face f cannot be mined before the precedence faces (f') are completely mined out. Equation 16 is the

shovel availability constraint, which guarantees that the fraction of time a shovel works in several faces in a period does not exceed the shovel availability.

The model has been solved using a rolling-planning horizon technic to reduce the runtime. The model looks 3 months ahead while assigning the shovels to the faces. It assigns shovels to faces for the first three periods at first. Then it investigates the next three periods, assigns shovels to the available faces and so on. The periods are denoted by P in Figure 2 that demonstrates the rolling-planning horizon time frame used in the model.

Optimization Time frame											
P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
Decision Time Frame(T)											

Figure 2. Optimization and decision time frame of the model.

5. Case Study

The case study presents two scenarios in an iron mine with IPCC and a traditional truck-shovel mining method to verify the model. The short-term schedule will be generated for the 11th year of mine life. Four benches at elevations 1595m, 1610m, 1730m and 1745m are available to be mined with a total 16MT (mega tonnes) of ore and 35MT of waste. There is only one mill to process the ore material. The in-pit or plant crusher requirement is 2700 tons per hour. The monthly crusher requirement is 1.33MT assuming 16 hours of operation in a day with 2 eight-hour shifts. The mine layout for the eleventh year is shown in Figure 3. The distances from each face to the waste dump, crusher and plant are calculated using the nodes in the road network. The grade of the designed ramps is 8%. The length of the conveyor belt for the IPCC scenario is 2550 m, which comes from the strategic plan.

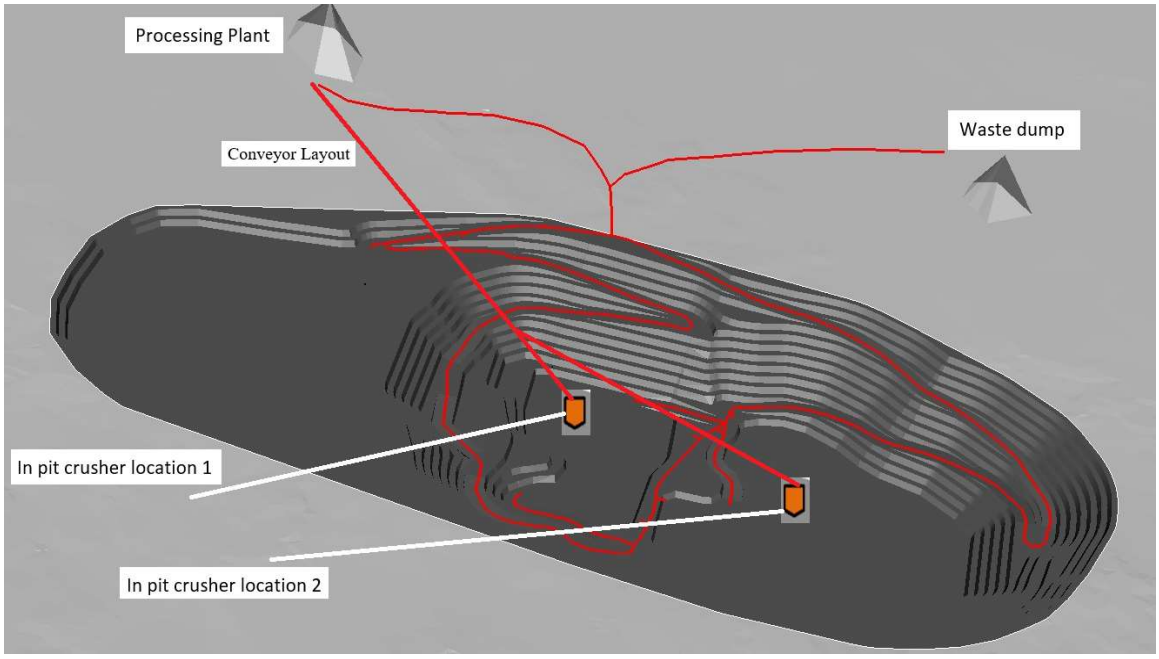


Figure 3. Pit layout with roads and ramps in year 11.

The element of interest in the mine is the magnetic weight recovery of iron (MWT). The grade and tonnage distribution of MWT in year 11 is presented in Figure 4.

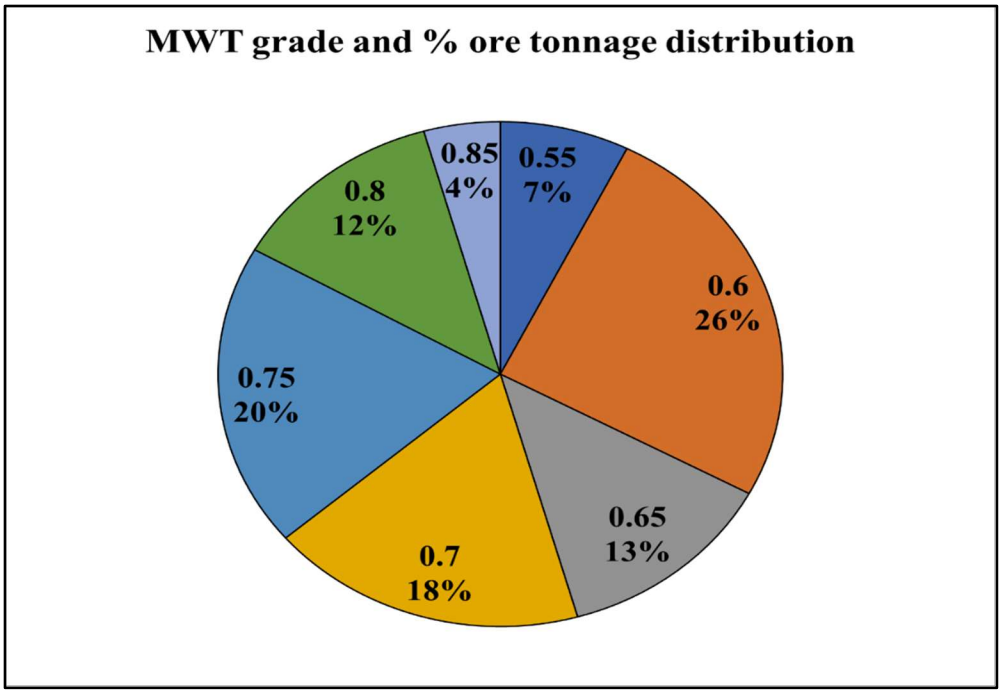


Figure 4. Grade and tonnage distribution of MWT.

A hierarchical clustering algorithm has been used (Tabesh and Askari-Nasab 2013) to aggregate similar blocks together to generate 170 mining faces (polygons) out of 4200 blocks to be mined in year 11 within the four available benches. A more advanced clustering algorithm by Tabesh and Askari-Nasab (2019) has not been used in this paper as geological uncertainty of the material is not part of this model in its current state of the art.The clustered ore and waste faces on 1595 and 1610 benches are shown in the Figure 5 and Figure 6 for illustration purposes. The other two benches contain waste faces only. The numbers in the figures represent the face IDs on the benches.

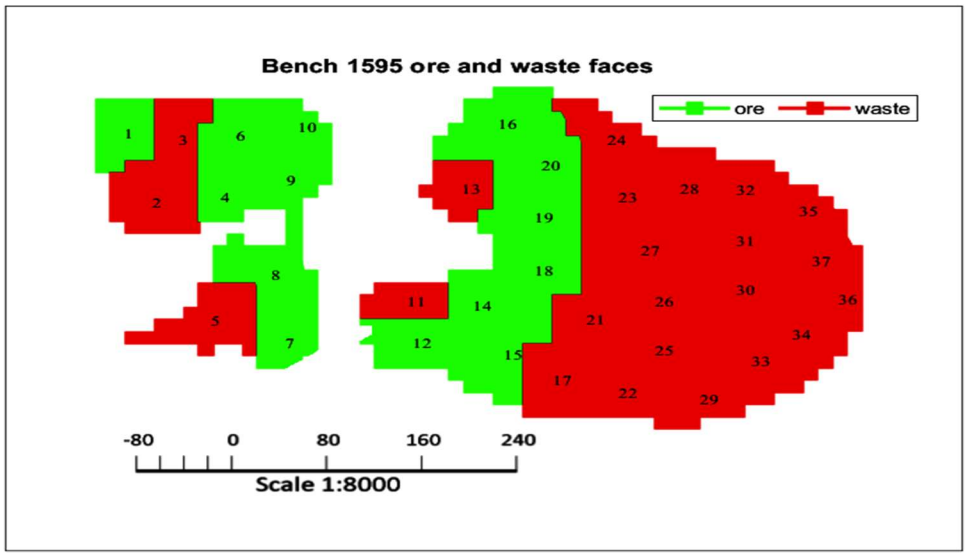


Figure 5. Clustered faces on bench 1595.

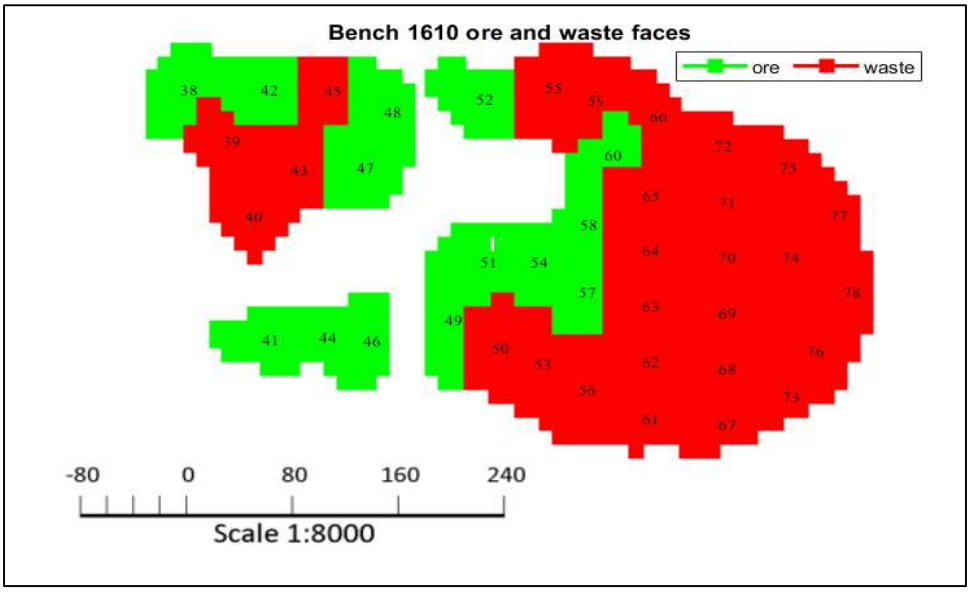


Figure 6. Clustered faces on bench 1610.

The mine employs five shovels, including two Hit 2500 shovels (shovel indexes 1 and 2) specifically for ore and three Hit 5500Ex shovels (shovel indexes 3, 4 and 5) only for waste mining. The Hit 2500 shovels have a bucket capacity of approximately 12 tons and a bucket cycle time of about 22 seconds, whereas Hit 5500Ex shovels have a bucket capacity of roughly 22 tons and a bucket cycle time of about 23 seconds.

The mine employs Cat 785C and Cat793C trucks with nominal capacities of 140 tons and 240 tons, respectively, to haul the material mined from the faces. Cat 785C trucks are locked to ore shovels, and thus, they may be loaded only by Hit 2500 shovels, whereas Hit 5500Ex shovels can only load Cat 793C trucks. The truck requirement for both scenarios are calculated and compared to investigate the change in fleet size requirement.

6. Results

The MIP model is solved for two scenarios: one with semi-mobile IPCC and one with Truck-shovel only. The two scenarios are differentiated by Equation 12, which controls whether the mine has an in-pit crusher. The model runs for twelve months in four steps where it allocates shovels to faces for three months, saves the results and then looks for available faces for the coming three months. The model is formulated and solved in MATLAB 2021(B). The scenario without IPCC (scenario 1) took 219 seconds to run, and the IPCC scenario (scenario 2) took 237 seconds in a Dell XPS machine with 16 GB RAM. The optimality gaps in both cases are less than 0.5%. The problem has 24,480 variables, and the rolling planning horizon reduced the computational expense substantially. A comparison of the solution quality and computation time among the global solution approach and several rolling planning time horizon solution technics used is shown in Table 1.

Table 1: Comparison of solution quality and computation time.

Solution Approach	Scenario 1		Scenario 2	
	Solution time	Optimality gap	Solution time	Optimality gap (per rolling horizon)
Global Solution	20 hours	8.35%	20 hours	7%

approach				
Rolling time horizon of 6 months	700 sec	3%	759 sec	2.8%
Rolling time horizon of 4 months	319 sec	1.1%	350 sec	1.05%
Rolling time horizon of 3 months	219 sec	0.44%	237 sec	0.5%

The computational time to find an optimal or near-optimal schedule is crucial for short-term mine planning as it is dynamic. The reduction of computing time from 20 hours to only 240 seconds makes the model usable for an actual mining operation. The optimality gap also reduces significantly when each scenario's solution space is compressed. A comparison of the optimal results and generated schedules are presented in the following sections.

7. Scenario 1 (No IPCC)

This scenario represents a conventional truck-shovel (TS) mining operation where trucks haul the mined material to the plant crusher and waste dump. Pragmatic and near-optimal shovel assignment to the faces is the model's primary goal. Shovel positions and the working periods are summarized to analyze the allocation decisions made by the model. The model does not take shovel movement time into account. A shovel availability of 80% is assumed to account for the lost time for movement among faces and maintenance. The optimal objective function value for this scenario is $1957M. Figure 7, Figure 8, Figure 9 and Figure 10 display the mining periods for bench 1595, 1610, 1730 and 1745 respectively. Here p1 to p12 denote the twelve periods in the time horizon.

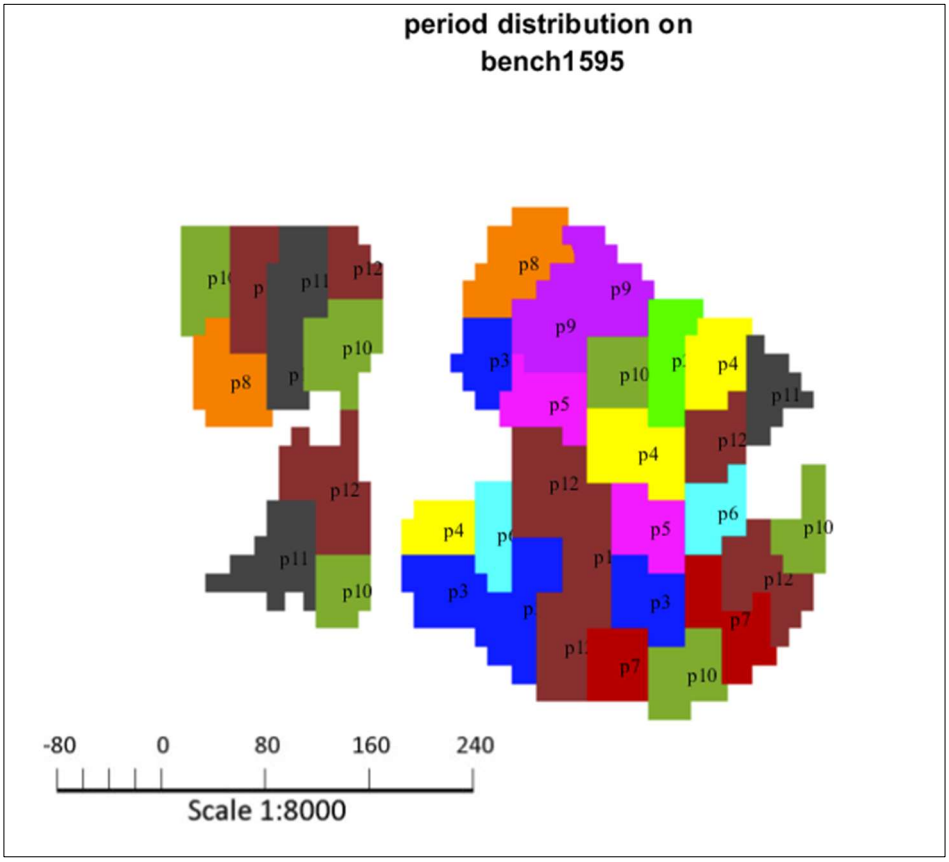


Figure 7. Mining periods of faces on bench 1595.

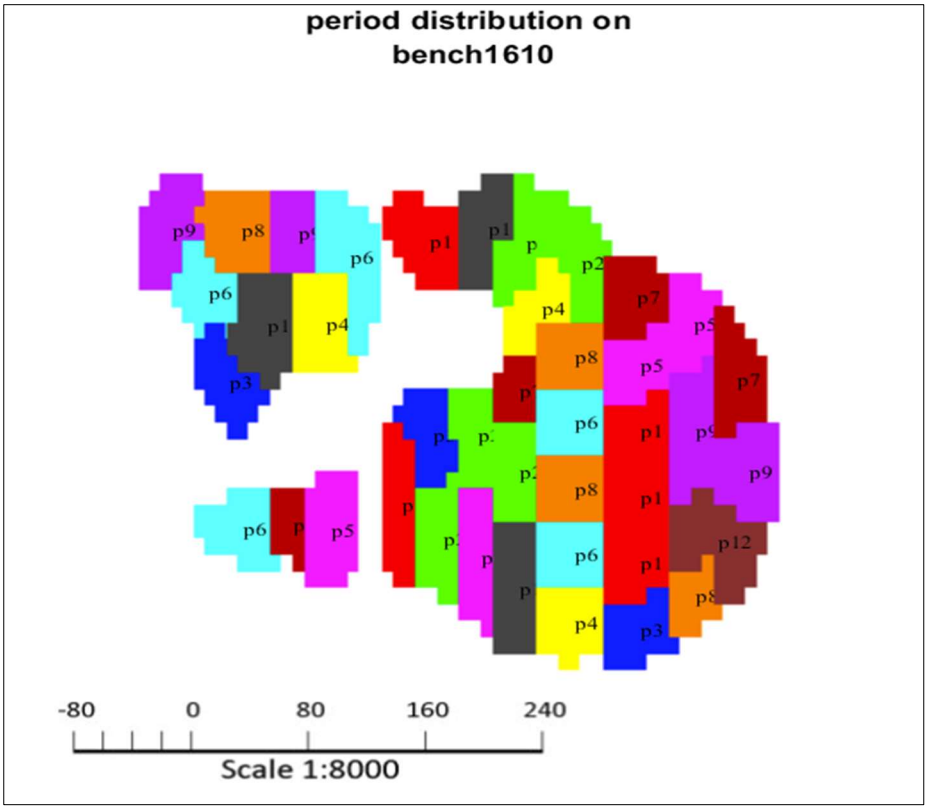


Figure 8. Mining period of faces on bench 1610.

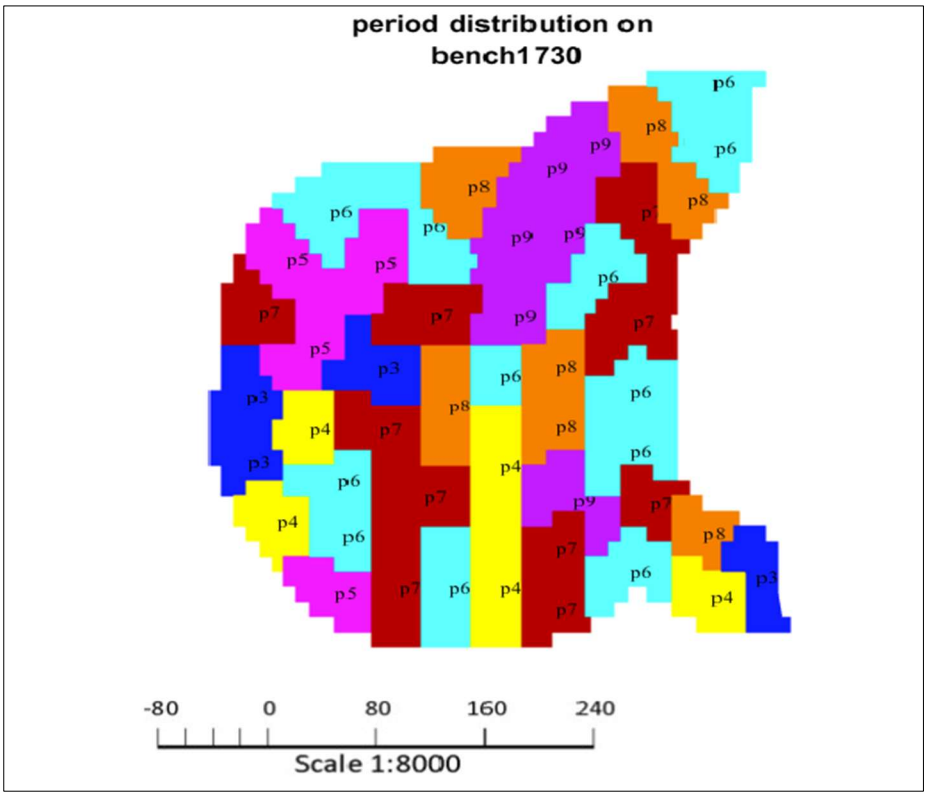


Figure 9. Mining period of faces on bench 1730.

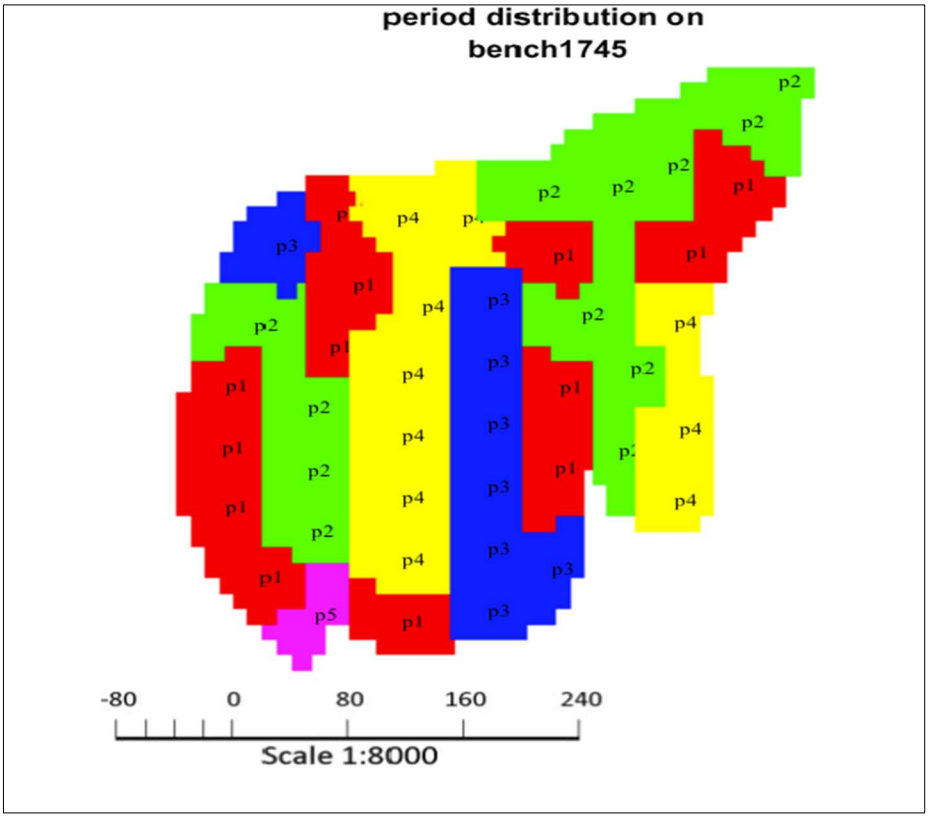


Figure 10. Mining period of faces on bench 1745.

The top bench on 1745 m is mined within the first five periods. The next bench on 1730m elevation is being mined within period 3 and period 9. Both these benches are waste benches and mining on bench 1730 starts from a later period than bench 1745 because of the precedence relationships that exist among several faces of these two benches. The model assigns shovels to ore bench 1610 from period 1 but mining starts at bench 1595 from period 2 because of the vertical precedences that exist between these two benches. Generally, the waste faces are mined in the earlier periods than ore faces for both benches at 1595m and 1610m elevation because the waste faces precede the ore faces in many of the cases.

The following Figure 11, Figure 12, Figure 13, and Figure 14 demonstrate the shovel assignment to the four benches at 1595m, 1610m, 1730m and 1745m respectively. The five shovels are indicated by s1 to s5 in the figures.

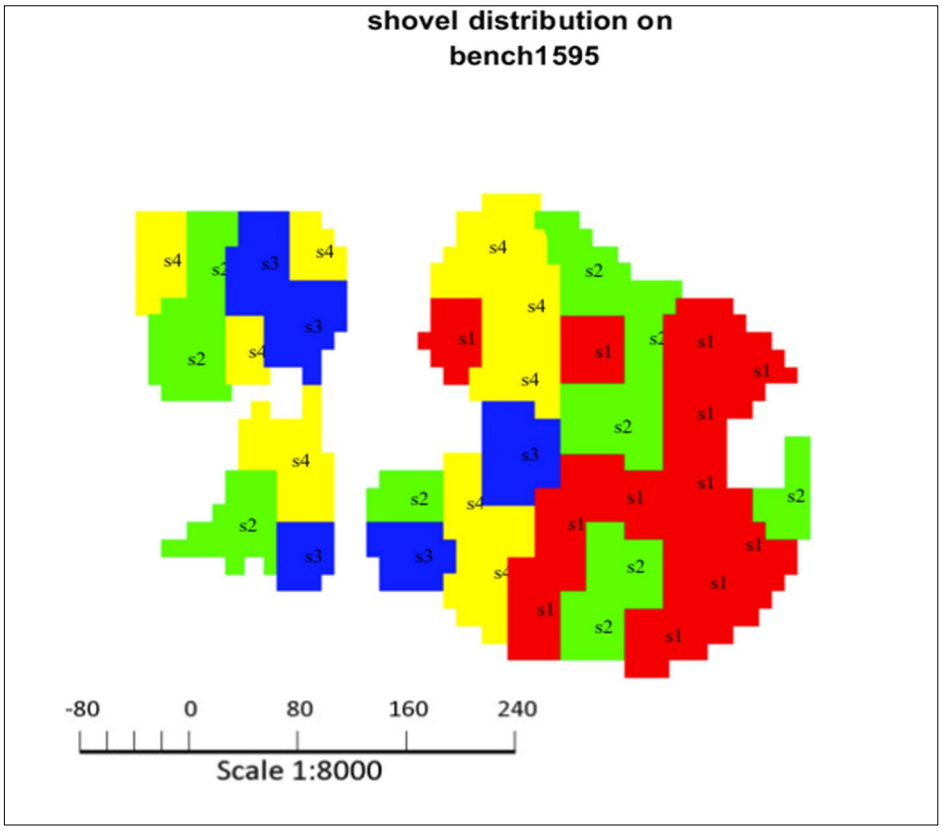


Figure 11. Shovel allocation on bench 1595.

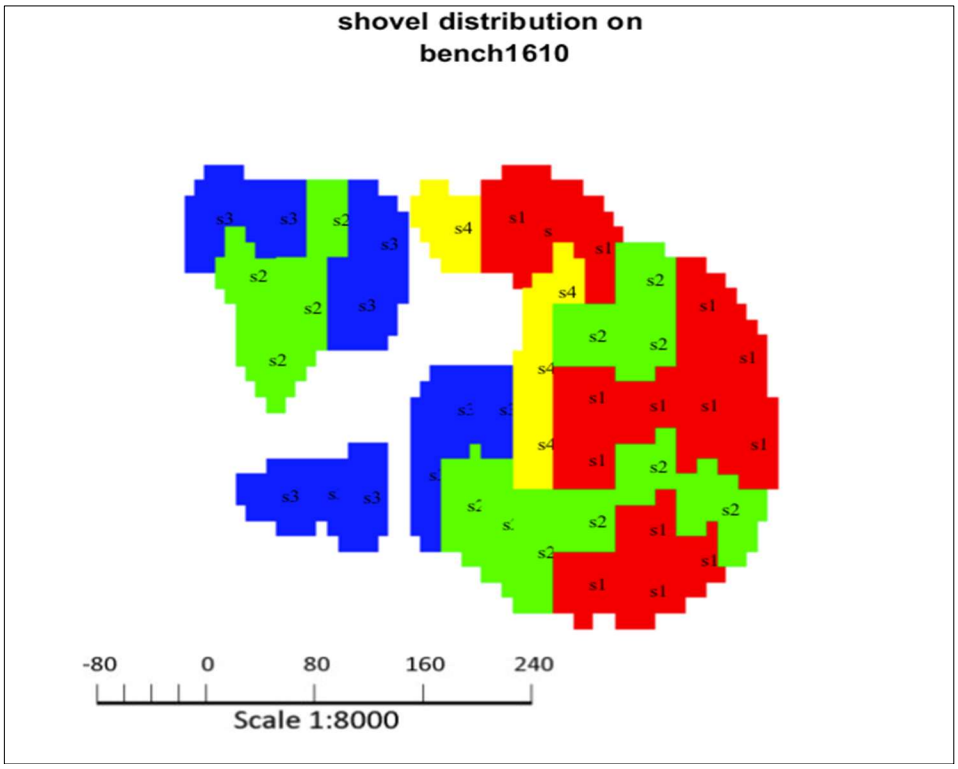


Figure 12. Shovel allocation on bench 1610.

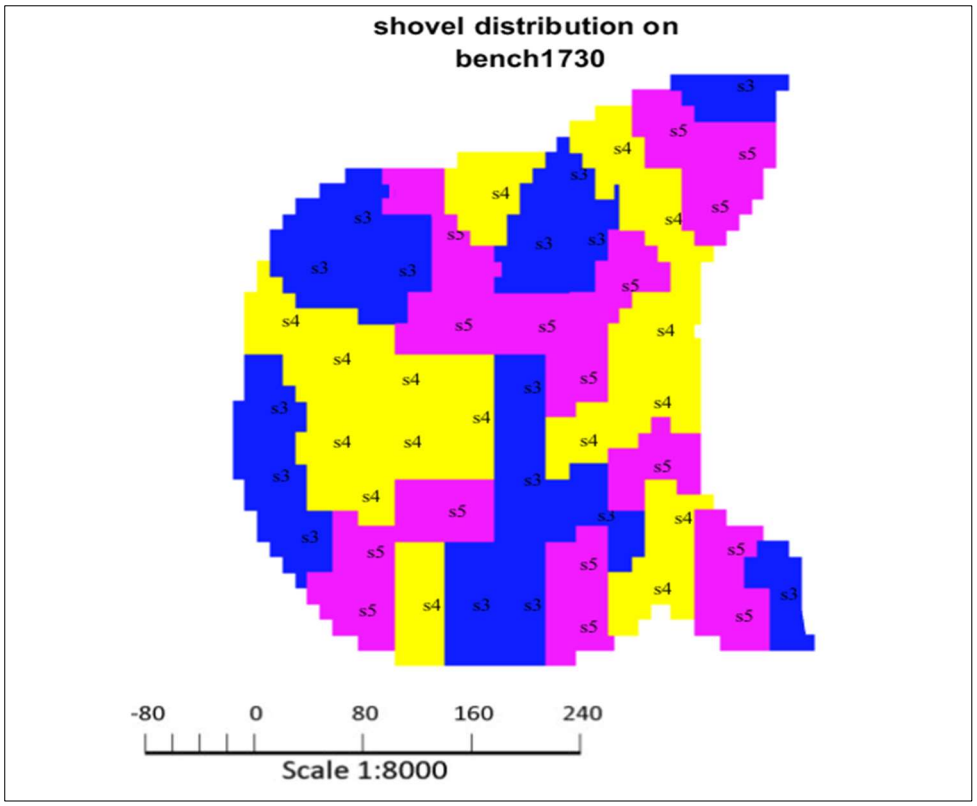


Figure 13. Shovel allocation on bench 1730.

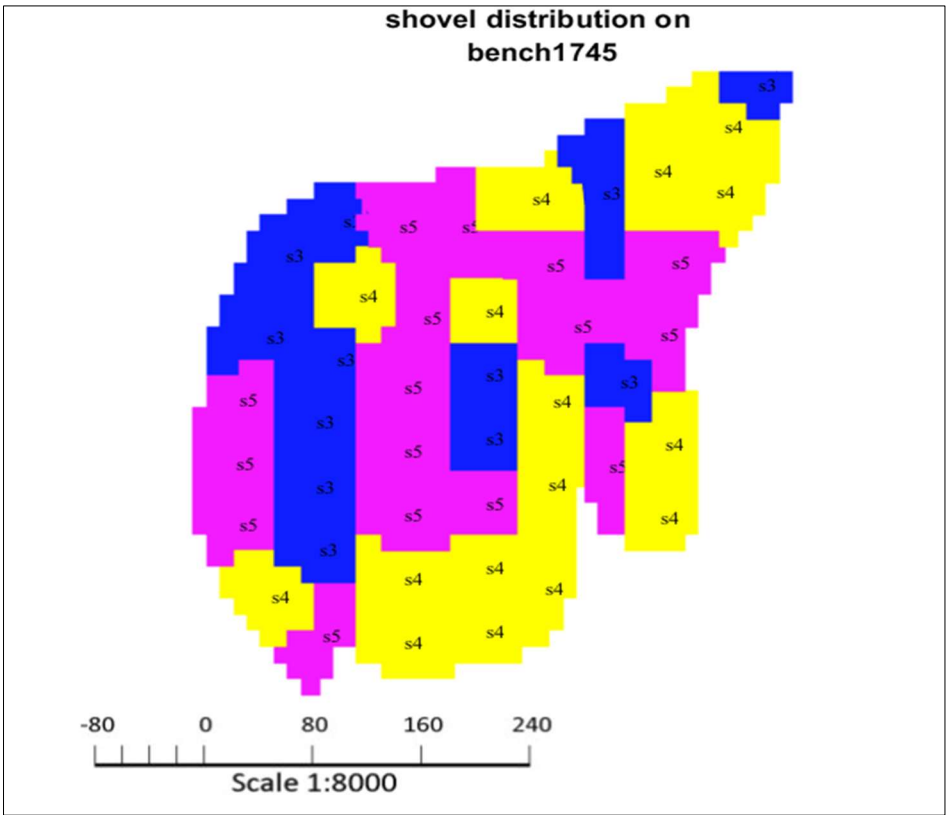
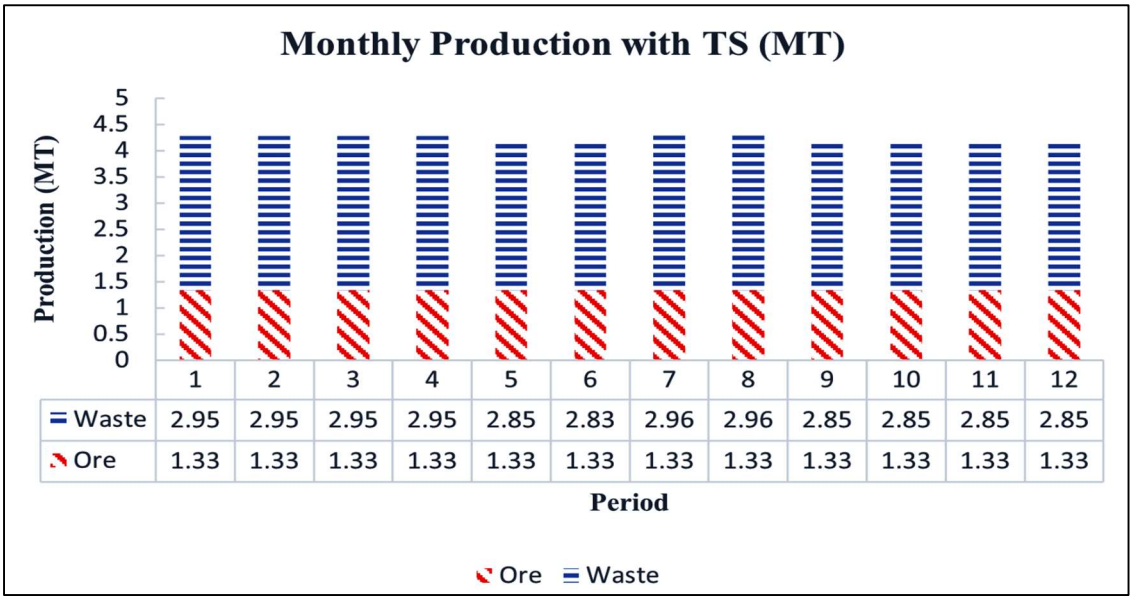


Figure 14. Shovel allocation on bench 1745.

Shovel 5 works solely on the two waste benches at 1730m and 1745m along with shovel 3 and shovel 4. Shovel 3 and shovel 4 also mine the waste faces on the bottom two benches at 1610m and 1595m elevation. Shovel 1 and shovel 2 are ore shovels. Hence these two shovels work only on the bottom two ore benches at elevations 1610m and 1595m. The shovels do not look for the nearest faces for next assignment after a face is mined out because the model does not minimize shovel movement costs or movement time in its current state. The allocations demonstrate that the model is capable of assigning shovels to faces respecting the precedence relationships and the production requirements. All the faces are mined within the 12 months optimization time frame making sure that the production target of the strategic plan is met.

Figure 15 shows the monthly production of ore and waste. The production of ore is uniform throughout the 12 periods which ensures that the mill is fed to its capacity. The waste production is also fairly uniform too with slight variation of less than 1.5% across the planning horizon.



	1	2	3	4	5	6	7	8	9	10	11	12
Waste	2.95	2.95	2.95	2.95	2.85	2.83	2.96	2.96	2.85	2.85	2.85	2.85
Ore	1.33	1.33	1.33	1.33	1.33	1.33	1.33	1.33	1.33	1.33	1.33	1.33

Figure 15. Monthly ore and waste production for scenario 1.

The ore and waste truck requirement has been calculated based on the production requirement, truck cycle time and shovel capacity. The average one-way distance from all the faces to the plant crusher is 5km and the one-way distance to the waste dump is 3.2kms. The loaded and empty haul speed are estimated from the rimpull characteristics curve for CAT 785C and CAT 793C trucks. The equation used to calculate the truck requirement is,

$$N_h = \frac{P_h \times TC_{ch}}{60 \times L_h \times E} \quad (17)$$

Where, N_h = Number of trucks required

P_h = Production rate per hour

TC_{ch} = Truck cycle time

L_h = Nominal truck load

E = Operating efficiency

The required number of ore and waste trucks for this scenario is 13 and 11 respectively assuming a 65% efficiency.

8. Scenario 2 (IPCC)

This scenario assumes an in-pit crusher for ore crushing. The trucks haul the mined material to the crusher. The crushed material is conveyed to the processing plant by a 2.5km long conveyor belt. The crusher is located on face 3 over the first six months and face 18 for the rest of the periods. Equation 12 prevents mining of the faces that house the crusher for the IPCC scenario. The optimal objective value is \$1969M. Figure 16, **Error! Reference source not found.**, Figure 18 and Figure 19 display the resulting mining periods of the faces for bench 1595, 1610, 1730 and 1745 respectively.

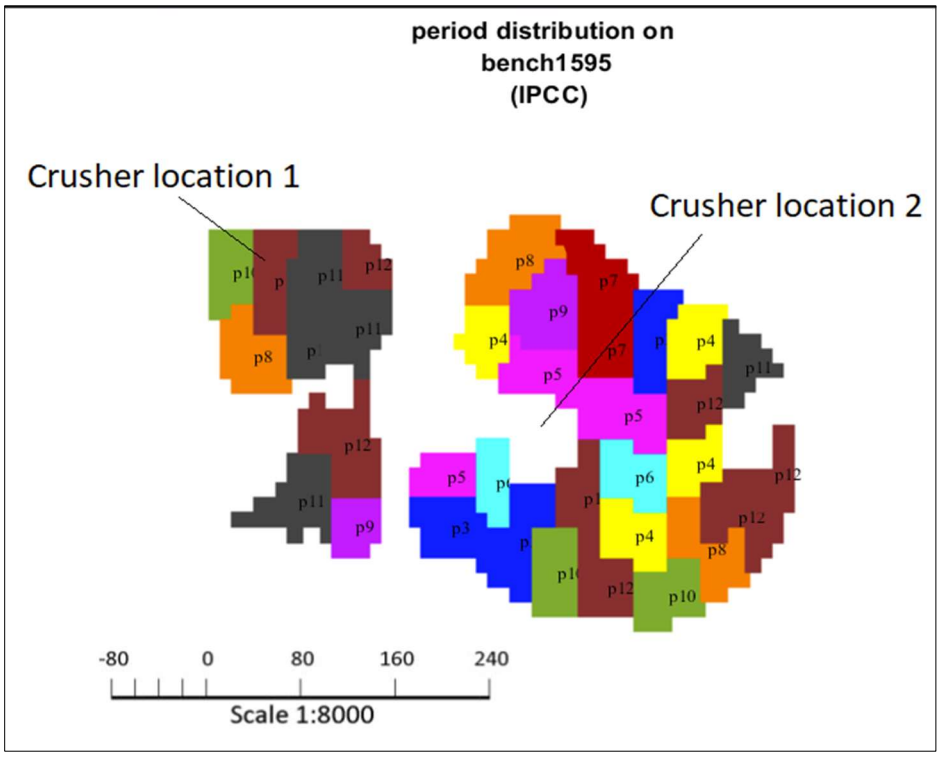


Figure 16: Mining period of faces on bench 1595

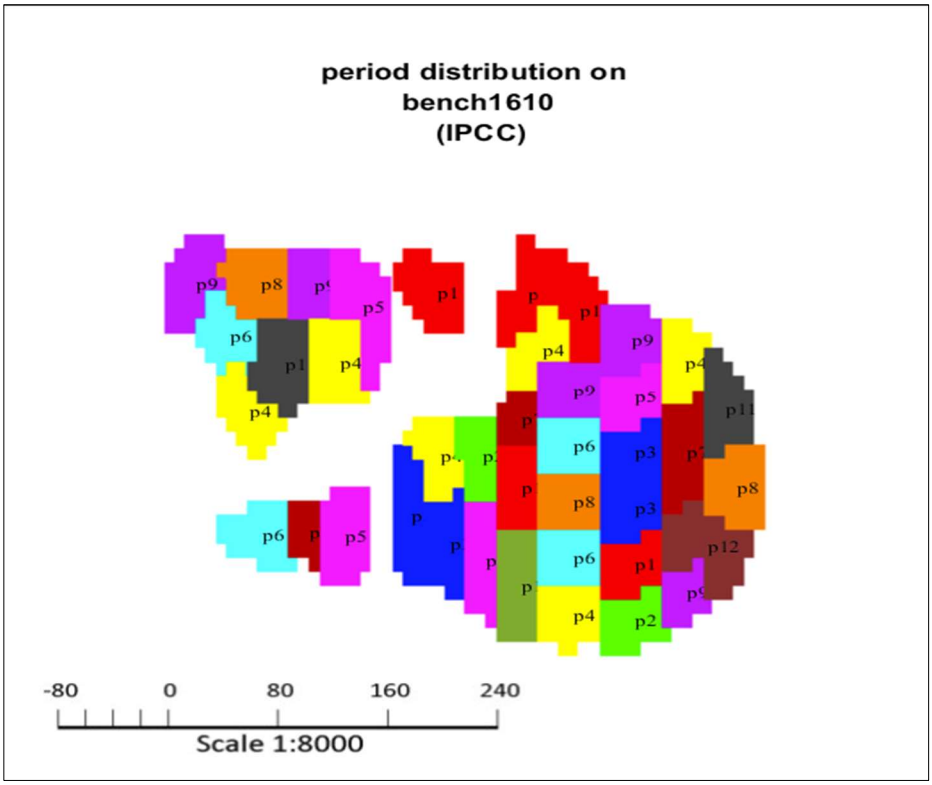


Figure 17. Mining period of faces on bench 1730.

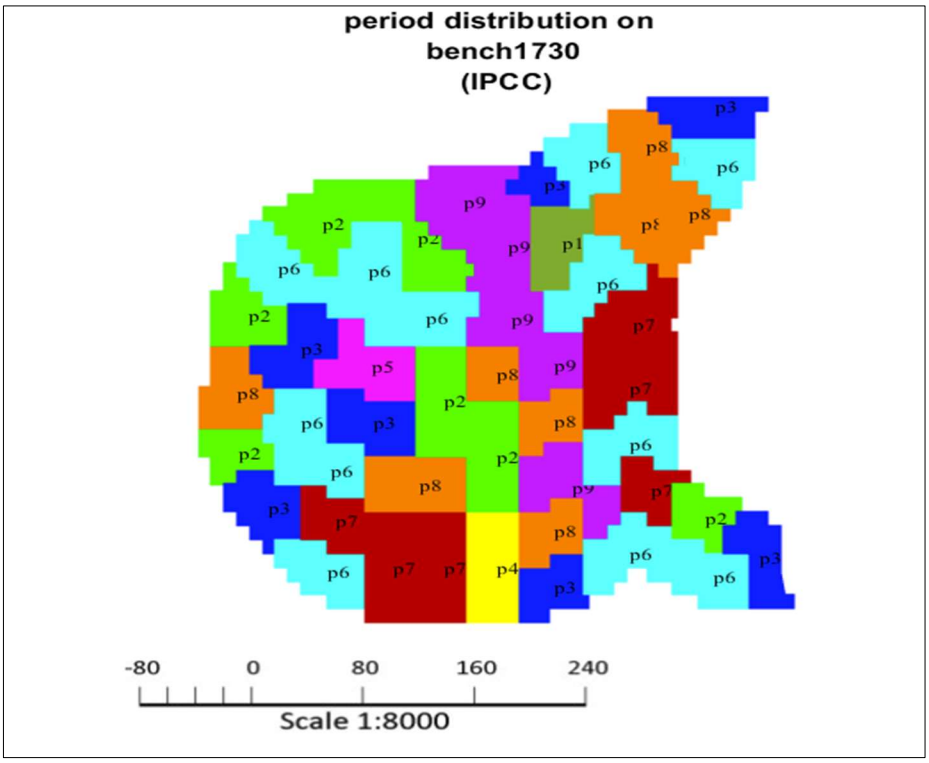


Figure 18. Mining period of faces on bench 1730.

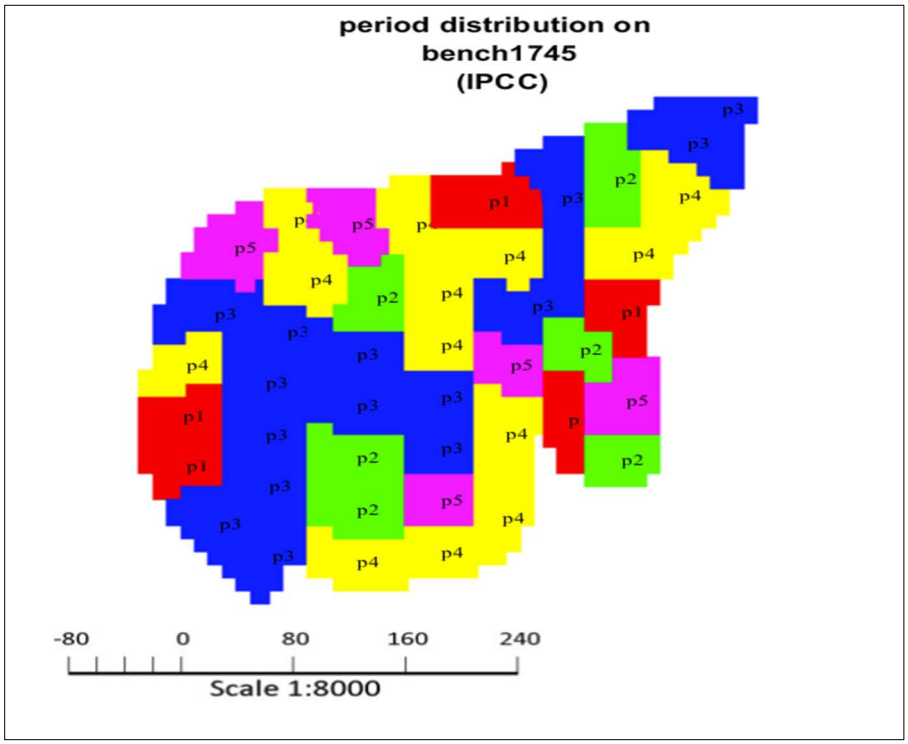


Figure 19. Mining period of faces on bench 1745.

The faces of bench 1595 starts from period 3 while mining in bench 1610 starts from the first period. The waste faces are generally mined in earlier months compared to ore faces just like the

previous scenario. This proves that the shovel assignments are made respecting the precedence relations. The crusher was located on face 3 of bench 1595 from period 1 to 6 and it has been mined on period 12. Face 18 has been left unmined as the crusher has been located here from period 6 onwards. This face has to be mined when the crusher is relocated in a next period. Face 3 on bench 1595 has been mined on the twelfth period. These results confirm that the model is well capable of providing schedules respecting the locations of the IPCC. The two waste benches at 1730m and 1745m are being mined out in a similar manner to scenario 1. These two benches do not have the IPCC on them at any given time of the planning horizon, which justifies the similar mining sequence of these benches between the scenarios in consideration.

Shovel allocation to the benches are delineated in Figure 20, Figure 21, Figure 22, and Figure 23 for bench 1595m, 1610m, 1735m and 1745m respectively.

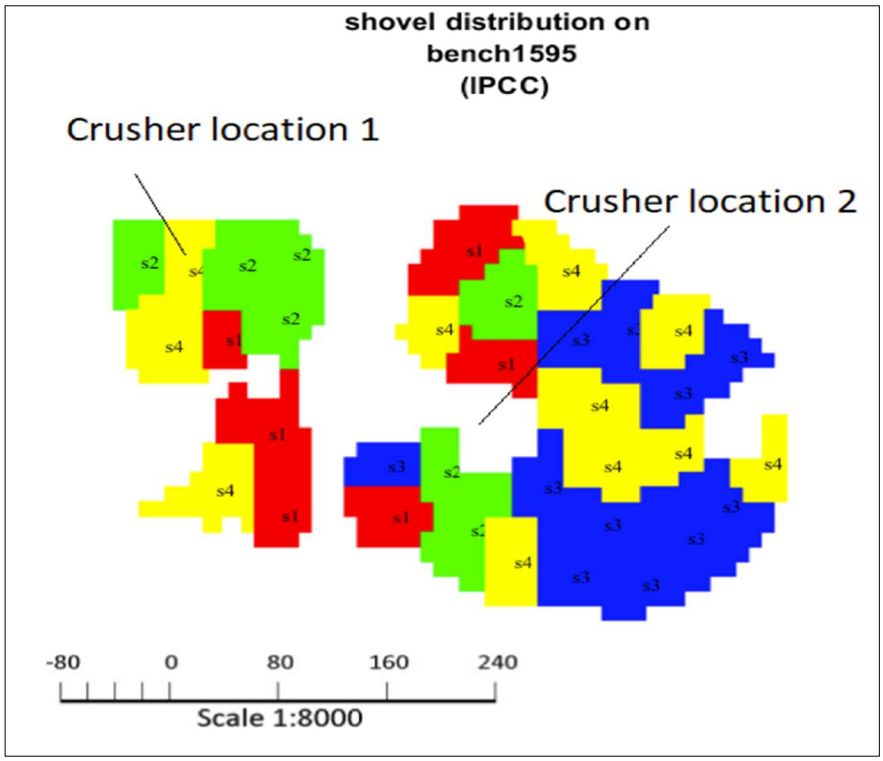


Figure 20. Shovel allocation on bench 1595.

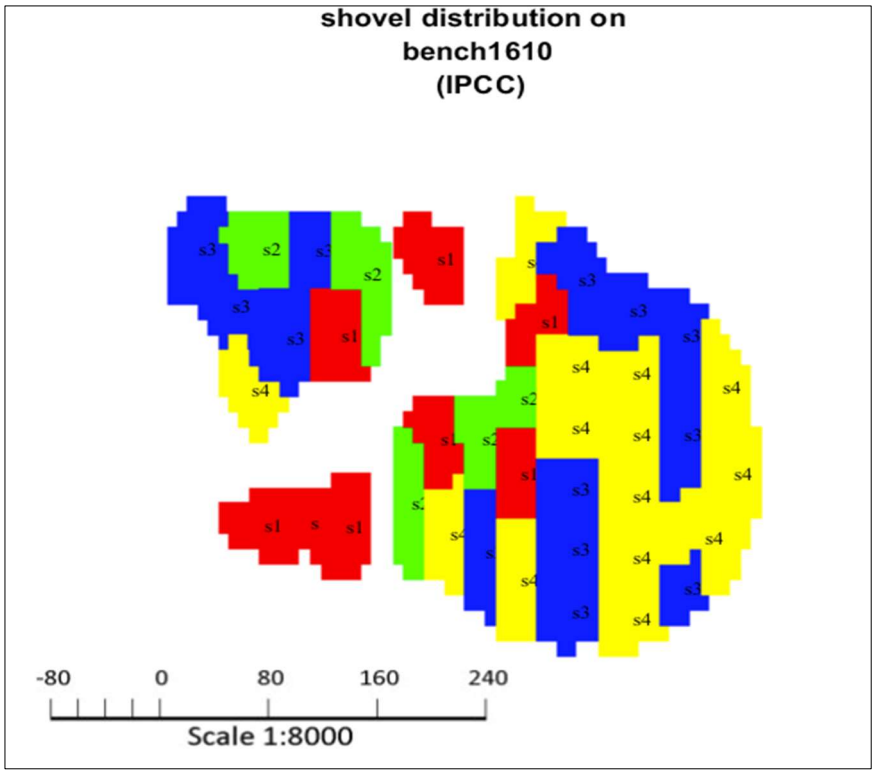


Figure 21. Shovel allocation on bench 1610.

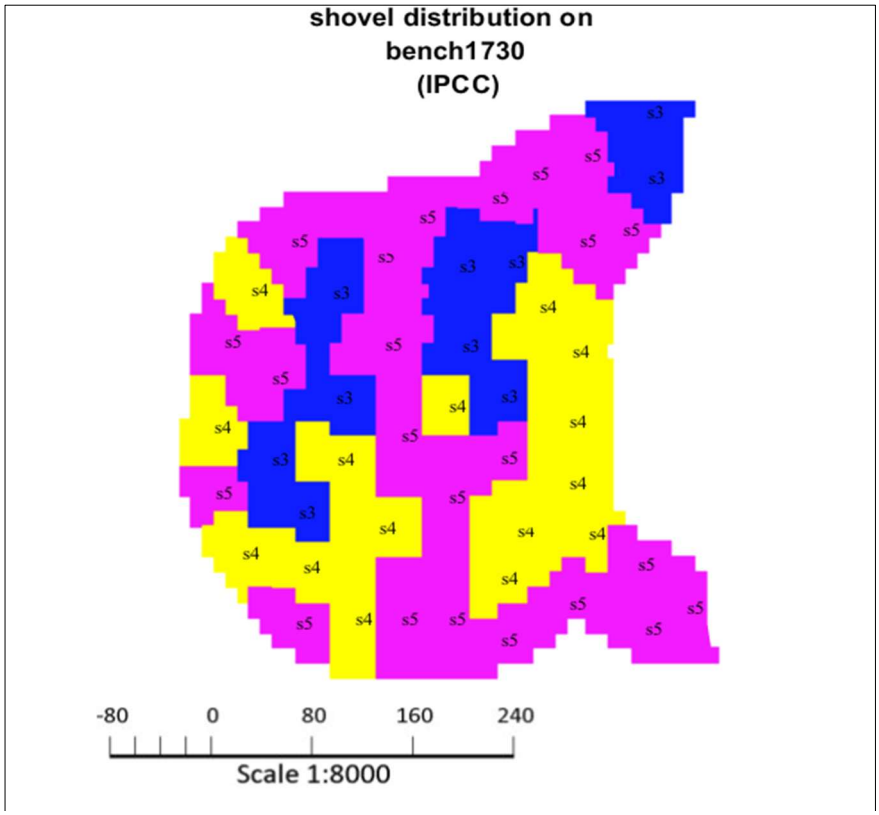


Figure 22. Shovel allocation on bench 1730.

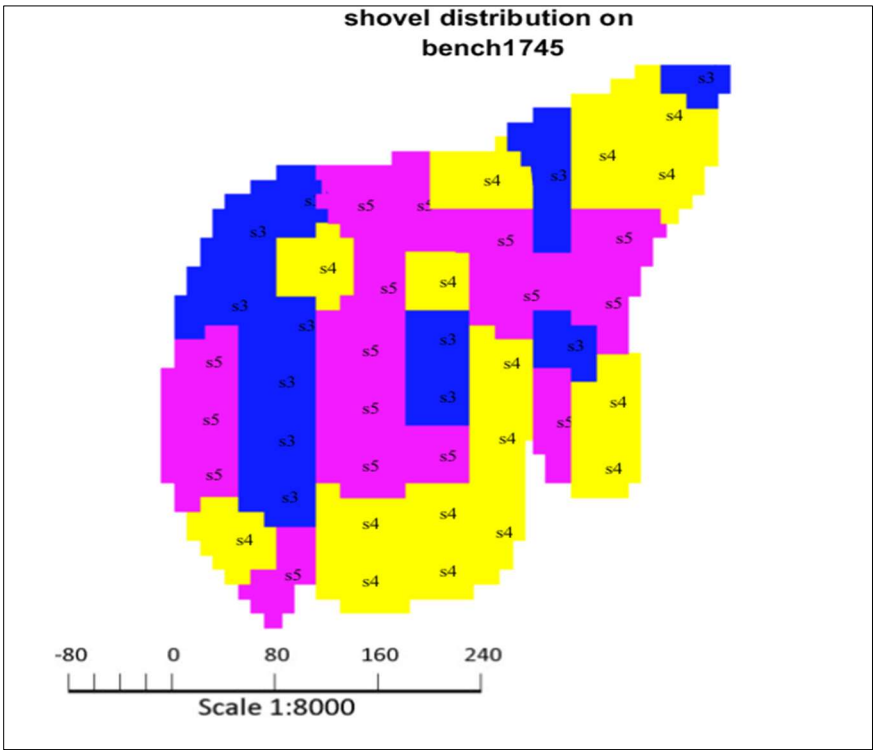
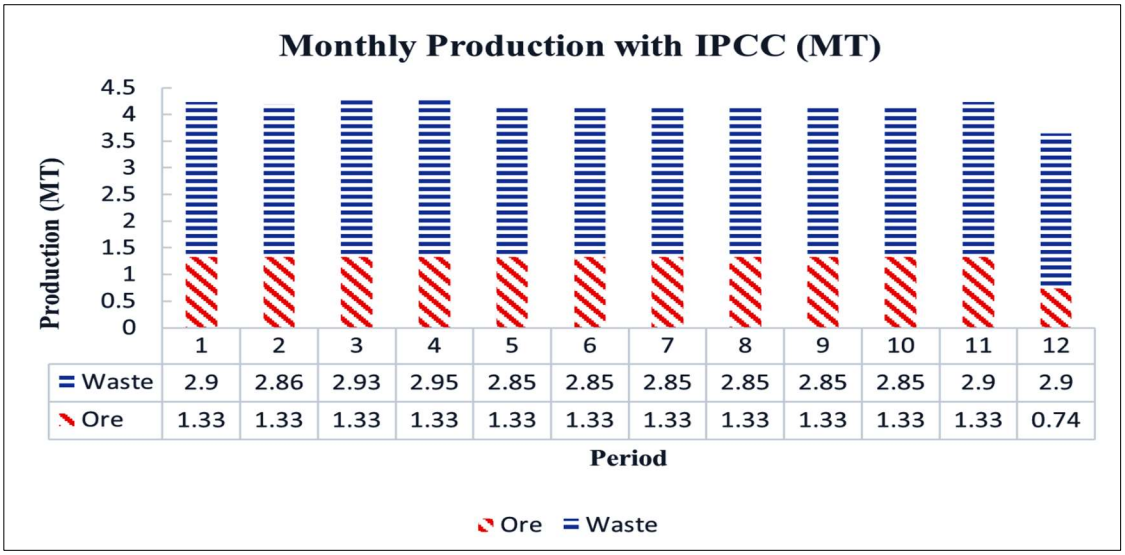


Figure 23. Shovel allocation on bench 1745.

The only face that is left unmined is face 18 on bench 1595, as shown in Figure 20, because this face is housing the IPCC from period 6 onwards. Shovel 5 dedicatedly works on the top two waste benches like the previous scenario. Shovel 1 and 2 mines the ore faces from the bottom two benches at 1595m and 1610m elevation. The assignment of shovels also verifies the model's capacity to provide short-term planning schedules with semi-mobile IPCC.

Figure 24 shows the production of ore and waste for this scenario. The ore production is low in the last period because of unavailability of enough ore faces on this period. The production of ore and waste otherwise is steady and meets the crusher requirements and the long-term production target for the rest of the periods.



	1	2	3	4	5	6	7	8	9	10	11	12
Waste	2.9	2.86	2.93	2.95	2.85	2.85	2.85	2.85	2.85	2.85	2.9	2.9
Ore	1.33	1.33	1.33	1.33	1.33	1.33	1.33	1.33	1.33	1.33	1.33	0.74

Figure 24. Monthly ore and waste production for scenario 2.

The required number of ore and waste trucks for this scenario is 9 and 11 respectively with a 65% efficiency.

9. Discussion of Results

The purpose of introducing IPCC systems to open pit mines is to reduce the number of trucks required, truck haulage cost and distance. Figure 25 shows that the truck requirement for scenario 2 with IPCC is 35% lower than scenario 1 with no IPCC. The waste truck requirement does not change as the waste transportation method does not change across the scenarios. This outcome proves the hypothesis that the introduction of IPCC reduces the required number of trucks.

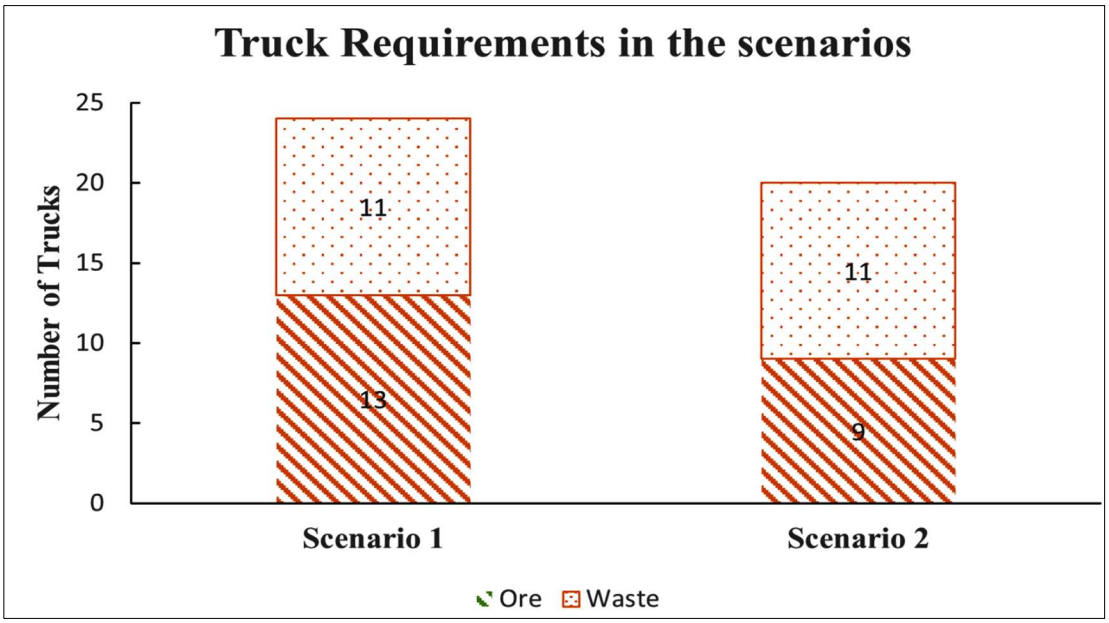


Figure 25. Ore truck requirement for scenarios without IPCC and with IPCC.

Now we will investigate the impact of IPCC on ore haulage cost. Table 2 summarizes the total ore haulage cost over the planning horizon, the mean and standard deviation of ore haulage cost per period for both the scenarios. The annual ore haulage cost is $37M lower with IPCC in scenario 2 compared to scenario 1 with only truck haulage. The mean haulage cost per period for scenario 1 and scenario 2 is $6.87M and $3.78M respectively. The standard deviation of haulage cost is higher in the scenario with IPCC compared to the scenario with no IPCC. The reason of the higher standard deviation in scenario 2 is the lower ore haulage cost ($2M) in the last period compared to the other periods due to the lower production of ore. The lower production of ore in the last period occurred due to the unavailability of ore faces.

Table 2: Summary of ore haulage cost for two scenarios.

Cost Summary	Scenario 1	Scenario 2
Total Haulage Cost (M$)	82.45	45.32
Mean Haulage Cost Per Period (M$)	6.87	3.78
Standard Deviation of Haulage Cost Per Period (%)	41.97	55.70

Figure 26 shows the ore haulage cost comparison between scenarios across all periods within the

time horizon. The ore haulage cost hovers around $4.5 to $5.5 per kilometer per period for scenario 1 with truck haulage and it is between $2.5 to $3.5 per kilometer per period for the scenario with IPCC. The sharp dip in haulage cost in the last period of scenario 2 represents the lower ore production in that period.

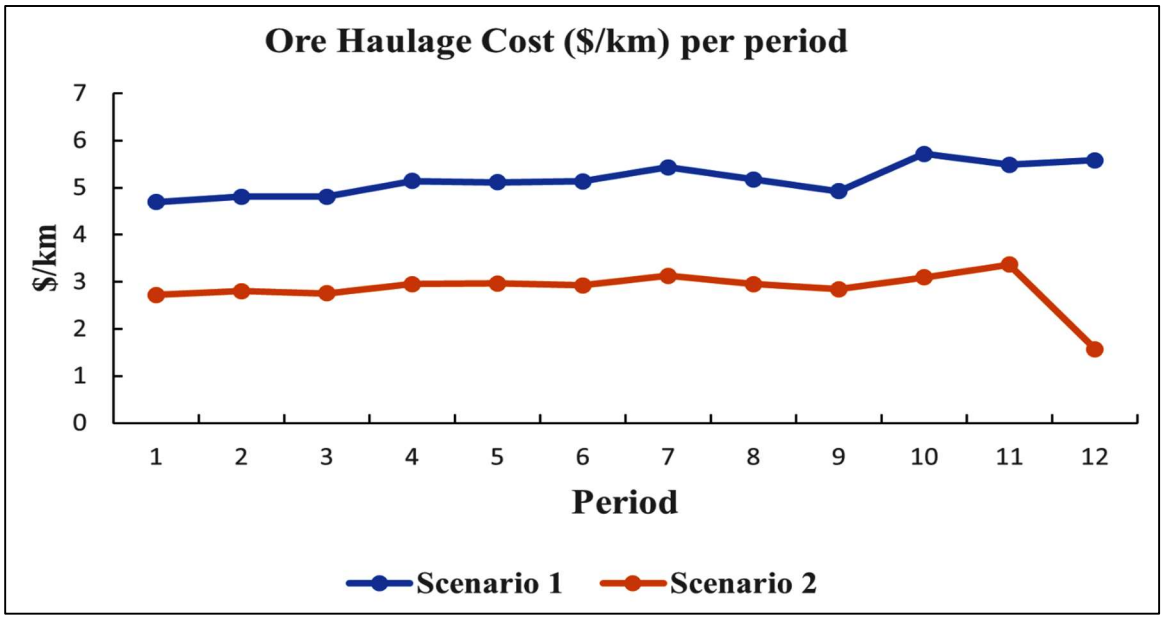


Figure 26. Comparison of ore haulage cost per period between scenarios.

The impact of increasing truck operating cost has been checked for both scenarios. Figure 27 shows the impact of increasing truck operating cost on ore haulage for both the scenarios.

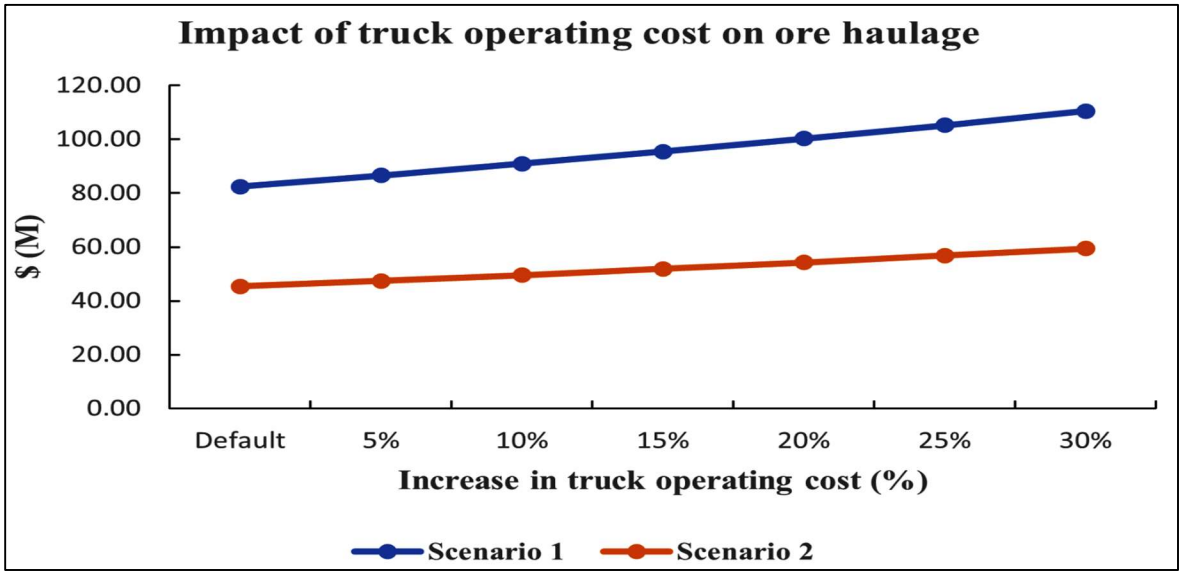


Figure 27. Sensitivity of ore transport cost to increasing truck operating cost.

The percent change in ore haulage cost is slightly sharper in scenario 1 with truck haulage compared to scenario 2. Superimposing the curves of Figure 27 shows that a 30% increase in truck operating cost increases ore haulage cost by 34% and 31% for scenario 1 and scenario 2 respectively, as shown in Figure 28.

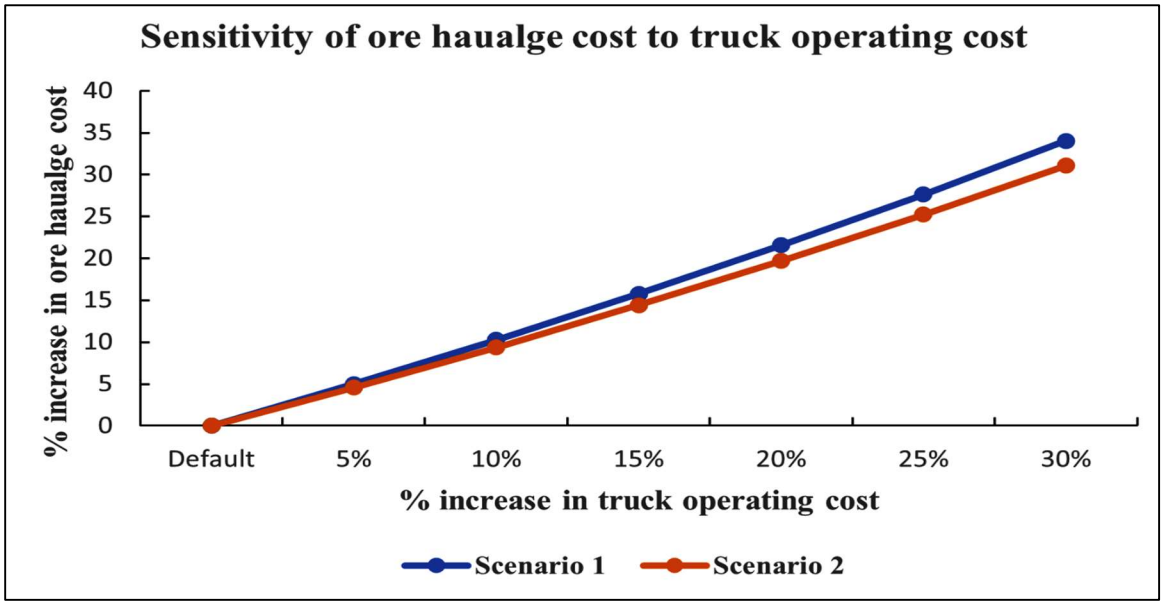


Figure 28. Truck operating cost vs haulage cost.

The analysis presented in Table 2 and Figure 25, Figure 26, Figure 27 and Figure 28 substantiates the fact that the installation of IPCC reduces haulage cost, truck requirements and delineates the impact of increasing truck operating cost on haulage from an operational perspective.

We have calculated the shovel efficiency for all five shovels over the 12 periods. Equation 18 shows the shovel efficiency formulation.

$$\textbf{Shovel efficiency}, \vartheta = \boldsymbol{availability} \times \boldsymbol{utilization} \quad (18)$$

Utilization is being defined as the percent of time a shovel is busy working in faces in a period in this equation. A comparison of shovel efficiencies for all the five shovels for the scenarios with and without IPCC is presented in Figure 29.

The shovel efficiency is slightly higher for the ore shovels compared to waste shovels in both the scenarios. The difference in shovel efficiency between scenarios is negligible. The general trend, however, is that all the shovels have slightly higher efficiency in scenario 1 (no IPCC) than in scenario 2 (IPCC). The reason behind this is the slightly higher ore and waste production in scenario 1 with regular truck haulage. The ore production is significantly low in the last period of scenario 2 with IPCC because of the unavailability of ore faces. The waste production in this scenario is also about 0.5MT less than scenario 1.

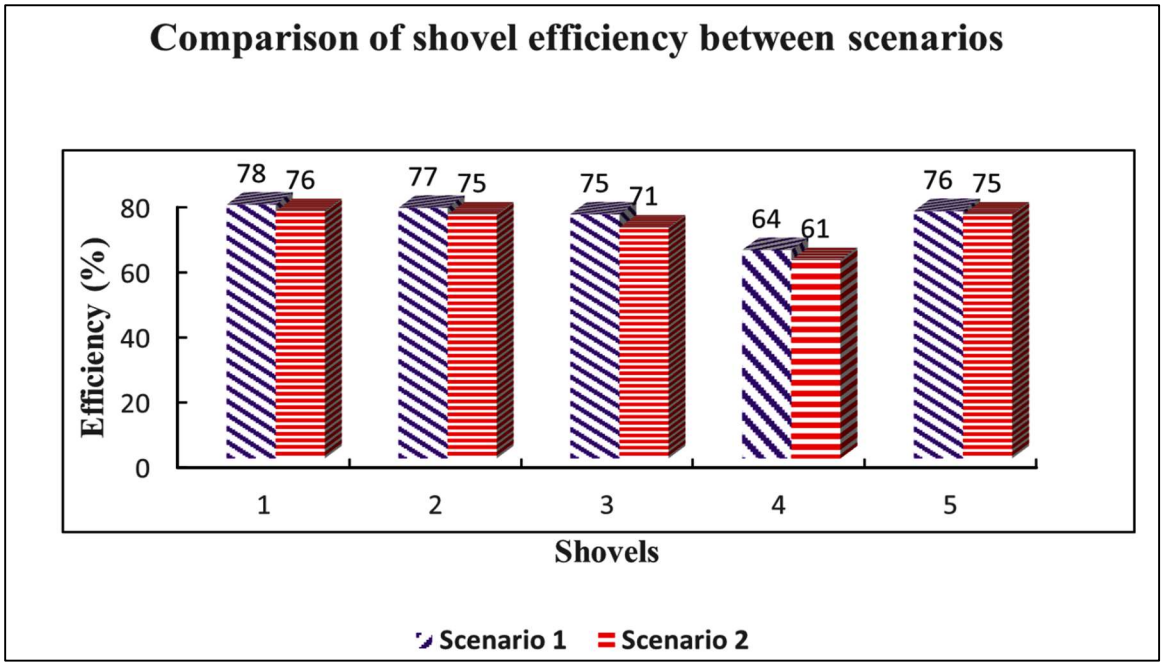


Figure 29. Shovel efficiency comparison between scenarios.

Figure 30 shows the optimal objective function values for both the scenarios. The objective function value is $12M higher for scenario 2 with IPCC, which justifies the use of IPCC in the mine in year 11. Although the total production is slightly lower for scenario 2, the mill requirement is fulfilled and the difference in production compared to scenario 1 is insignificant.

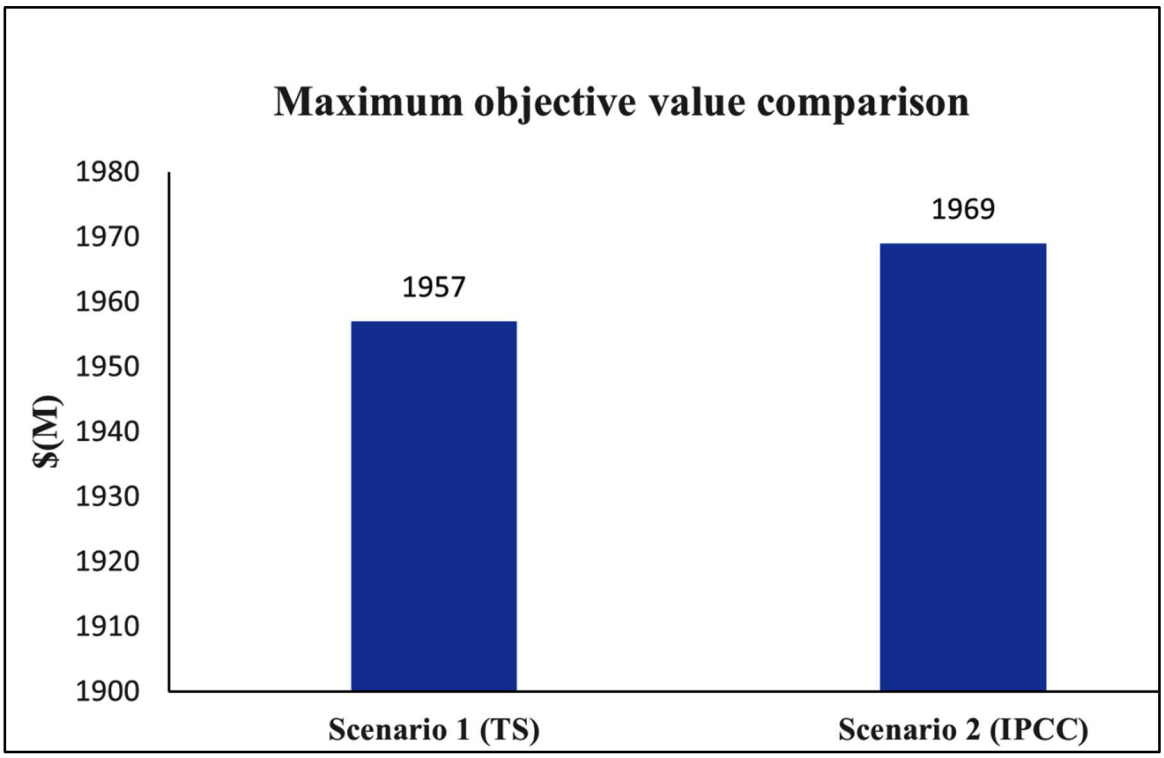


Figure 30. Comparison of (revenue - cost) between scenario 1 and scenario 2.

10. Conclusion and Future Work

The proposed shovel allocation model shows an approach to select a better haulage option for mines and a unique approach towards short-term planning with IPCC. The results show that the scenario with IPCC, scenario 2, generates 0.66% higher objective function value, which is the difference between revenue and haulage cost, compared to the scenario with no IPCC, scenario 1. The truck requirement and ore haulage cost in scenario 2 is also 35% and 43% lower than scenario 1, respectively. Since both scenarios have been able to meet the long-term production target for year 11, introduction of IPCC in year 11 is justified in the mine in terms of haulage cost saving and revenue generation.

While the model performs well for the case study, it has the following discrepancies.

- The model allocates shovels without considering ore blending requirements.
- The model does not consider shovel movement cost and does not constraint shovel movements between benches. This is the reason why in several periods, the model does not look for the nearest face to make the next shovel allocation. However, the model makes sure that the shovel movements are restricted within the immediate upper or lower bench once a face is mined out.
- The model does not consider the capital investment required for IPCC installation.
- The model cannot consider any operational uncertainty in its current state.

Constraining the model by blending requirements and shovel movement between benches to minimize shovel movement costs will generate more realistic shovel allocations. Combining the model with a haulage simulation model will enable it to capture uncertainties associated with haulage operations. These modifications in future will make the model more compelling and provide a more comprehensive tool for short-term production planning and analysis purposes.

11. References

[1] Awuah-Offei, K., and H. Askari-Nasab, 2009. Valuation of Belt Conveyor and Truck Haulage Systems in an Open Pit Mine using Life Cycle Assessment. The Canadian Institute of Mining, Metallurgy and Petroleum Bulletin 102:1-6.

[2] Blom, M., A. R. Pearce, and P. J. Stuckey, 2017. Short-term scheduling of an open-pit mine with multiple objectives. Engineering Optimization 49(5):777-795.

[3] Eivazy, H., and H. Askari-Nasab, 2012. A mixed integer linear programming model for short-term open pit mine production scheduling. Transactions of the Institutions of Mining and Metallurgy, Section A: Mining Technology 121(2):97-108.

[4] Erkayaoğlu, M., and N. Demirel, 2016. A comparative life cycle assessment of material handling systems for sustainable mining. Journal of Environmental Management 174:1-6.

[5] Fuming, L., C. Qingxiang, and C. Shuzhao, 2015. A comparison of the energy consumption and carbon emissions for different modes of transportation in open-cut coal mines. International Journal of Mining Science and Technology 25(2):261-266.

[6] Gholamnejad, J., 2008. A zero-one integer programming model for open pit mining sequences. Journal- South African Institute of Mining and Metallurgy 108:759-762.

[7] Gong, Hongshuo, A. Moradi Afrapoli, and H. Askari-Nasab, 2023a. Integrated simulation and optimization framework for quantitative analysis of near-face stockpile mining. Simulation Modelling Practice and Theory 128:102794.

[8] Gong, Hongshuo, et al., 2023b. Near-face stockpile open pit mining: a method to enhance NPV and quality of the plant throughput. International Journal of Mining, Reclamation and Environment 37(3):200-215.

[9] Konak, G., A. H. Onur, and D. Karakus, 2007. Selection of the optimum in-pit crusher location for an aggregate producer. Journal of the Southern African Institute of Mining and Metallurgy 107(3):161-166.

[10] Kozan, E., and S. Q. Liu, 2016. A new open-pit multi-stage mine production timetabling model for drilling, blasting and excavating operations. Mining Technology 125(1):47-53.

[11] Kozan, E., S. Liu, and R. Wolff, 2013. A short-term production scheduling methodology for open-pit mines. Proceedings of the 36th Application of Computers and Operations Research in The Mineral Industry (APCOM) Symposium, 2013, pp. 465 - 473.

[12] L'Heureux, G., M. Gamache, and F. Soumis, 2013. Mixed integer programming model for short term planning in open-pit mines. Transactions of the Institutions of Mining and Metallurgy, Section A: Mining Technology 122(2):101-109.

[13] Liu, D., and Y. Pourrahimian, 2021. A Framework for Open-Pit Mine Production Scheduling under Semi-Mobile In-Pit Crushing and Conveying Systems with the High-Angle Conveyor. Mining 1(1):59-79.

[14] Liu, S. Q., and E. Kozan, 2017. Integration of mathematical models for ore mining industry. International Journal of Systems Science: Operations & Logistics 6:1-14.

[15] Manríquez, F., J. Pérez, and N. Morales, 2020. A simulation–optimization framework for short-term underground mine production scheduling. Optimization and Engineering 21(3):939-971.

[16] Mirzaei-Nasirabad, Hossein, et al., 2023. An optimization model for the real-time truck dispatching problem in open-pit mining operations. Optimization and Engineering.

[17] Moradi Afrapoli, A., and H. Askari-Nasab, 2017. Mining fleet management systems: a review of models and algorithms. International Journal of Mining, Reclamation and Environment 33(1):1-19.

[18] Moradi Afrapoli, A., M. Tabesh, and H. Askari-Nasab, 2019a. A stochastic hybrid simulation-optimization approach towards haul fleet sizing in surface mines. Mining Technology: Transactions of the Institute of Mining and Metallurgy 128(1):9-20.

[19] Moradi Afrapoli, Ali, and Hooman Askari Nasab, 2020. A stochastic integrated simulation and mixed integer linear programming optimisation framework for truck dispatching problem in surface mines. International Journal of Mining and Mineral Engineering 11:257.

[20] Moradi Afrapoli, Ali, Mohammad Tabesh, and Hooman Askari-Nasab, 2019b. A multiple objective transportation problem approach to dynamic truck dispatching in surface mines.

[21] Moradi Afrapoli, Ali, Shiv Prakash Upadhyay, and Hooman Askari-Nasab, 2022. A nested multiple-objective optimization algorithm for managing production fleets in surface mines. Engineering Optimization:1-14.

[22] Norgate, T., and N. Haque, 2013. The greenhouse gas impact of IPCC and ore-sorting technologies. Minerals Engineering 42:13-21.

[23] Paricheh, M., 2017. In-pit crusher location as a dynamic location problem. Journal of the Southern African Institute of Mining and Metallurgy 117:599-607.

[24] Paricheh, M., and M. Osanloo, 2019a. Concurrent open-pit mine production and in-pit crushing–conveying system planning. Engineering Optimization 52(3):1-16.

[25] Paricheh, M., and M. Osanloo, 2019b. A New Search Algorithm for Finding Candidate Crusher Locations Inside Open Pit Mines. Proceedings of the 28th International Symposium on Mine Planning and Equipment Selection, 2019b.

[26] Paricheh, M., M. Osanloo, and M. Rahmanpour, 2016. A heuristic approach for in-pit crusher and conveyor system's time and location problem in large open-pit mining. International Journal of Mining, Reclamation and Environment 32(1):35-55.

[27] Rahmanpour, M., M. Osanloo, and N. Adibi, 2013. An approach to determine the location of an in pit crusher in open pit mines. 23rd International Mining Congress and Exhibition of Turkey, IMCET 2013 1:141-149.

[28] Samavati, M., D. Essam, and M. Nehring, 2020. Production planning and scheduling in mining scenarios under IPCC mining systems. Computers & Operations Research 115:104714.

[29] Shamsi, M., Y. Pourrahimian, and M. Rahmanpour, 2022. Optimisation of open-pit mine production scheduling considering optimum transportation system between truck haulage and semi-mobile in-pit crushing and conveying. International Journal of Mining, Reclamation and Environment 36(2):142-158.

[30] Smith, M. L., 1998. Optimizing short-term production schedules in surface mining: Integrating mine modeling software with AMPL/CPLEX. International Journal of Surface Mining, Reclamation and Environment 12(4):149-155.

[31] Tabesh, M., and H. Askari-Nasab, 2013. Automatic Creation of Ore-Selection and Blast Polygons using Clustering Algorithms.

[32] Tabesh, Mohammad, and Hooman Askari-Nasab, 2019. Clustering mining blocks in presence of geological uncertainty. Mining Technology 128(3):162-176.

[33] Taheri, M., M. Irannajad, and P. Ataee, 2009. An approach to determine the locations of in-pit crushers in deep open-pit mines. 9th International Multidicsciplinary Scientific Geoconference and EXPO, SGEM 2009, June 14, 2009 - June 19, 2009, Albena, Bulgaria, 2009. Vol. 1, pp. 341-347. International Multidisciplinary Scientific Geoconference.

[34] Upadhyay, S. P., and H. Askari-Nasab, 2016. Truck-shovel allocation optimisation: A goal programming approach. Transactions of the Institutions of Mining and Metallurgy, Section A: Mining Technology 125(2):82-92.

[35] Upadhyay, S. P., and H. Askari-Nasab, 2017. Dynamic shovel allocation approach to short-term production planning in open-pit mines. International Journal of Mining, Reclamation and Environment 33(1):1-20.

Simultaneous Optimization of In-pit Crusher Locations and Long-Term Planning of Open Pit Mines

Alireza Kamrani, Hooman Askari-Nasab, Yashar Pourrahimian and Mohammad Mahdi Badiozamani
Mining Optimization Laboratory (MOL)
University of Alberta, Edmonton, Canada

ABSTRACT

In-pit crushing and conveying system (IPCC) is a solution to decrease the haulage costs in open-pit mining. These costs could be due to the progressive depth of a pit leading to lengthy roads and creating a huge truck maintenance cost. They also could be because of moving towards reducing carbon footprints by using battery electric vehicles (BEVs). Having a shorter route is likely more practical for the BEVs where there are multiple problems if they are to be implemented on a longer road. Some of the challenges are recharging times, variable electrical load tradeoffs, and hauling on steep ramps. In this study, the goal is to propose a generalized optimization model which uses the road network to find the best in-pit locations of the crusher and generates a mine schedule that maximizes the Net Present Value (NPV). Applying this model will enable us to decrease the haulage distance per tonnage of transferable material and optimize the mine plan simultaneously. The model has been verified by applying it to an iron mine case study with two pushbacks. The result shows a significant NPV improvement compared to an out-pit crusher scenario.

1. Introduction

Material handling plays a crucial role in open pit mining operations, encompassing truck haulage and/or conveyor transport. One innovative approach to optimize this process is the use of In-Pit Crushing and Conveying systems (IPCC). This system consists of placing the crusher inside the pit, while the conveyor is positioned in a safe area alongside the benches and outside the pit. The main objective of the IPCC system is to efficiently transfer materials from the mining faces to the processing plant, reducing the reliance on truck haulage and thereby increasing overall efficiency. The success of an open-pit mining operation heavily relies on the reliability of the IPCC system. Factors such as equipment reliability, maintenance, and design play a crucial role in ensuring the practicality and effectiveness of the system. For instance, the location and capacities of the crusher and conveyor are critical design factors that should be integrated into the overall mine planning and design. Ignoring these factors could lead to disruptions in the extraction sequence of the blocks and even impact the ultimate pit limit design (UPL), which determines the final shape and size of the pit. To better understand the concept, refer to Figure 1, which illustrates a schematic view of the mine with two pushbacks, demonstrating the relative locations of different haulage equipment in the presence of the IPCC system.

ISBN: 978-1-55195-503-2

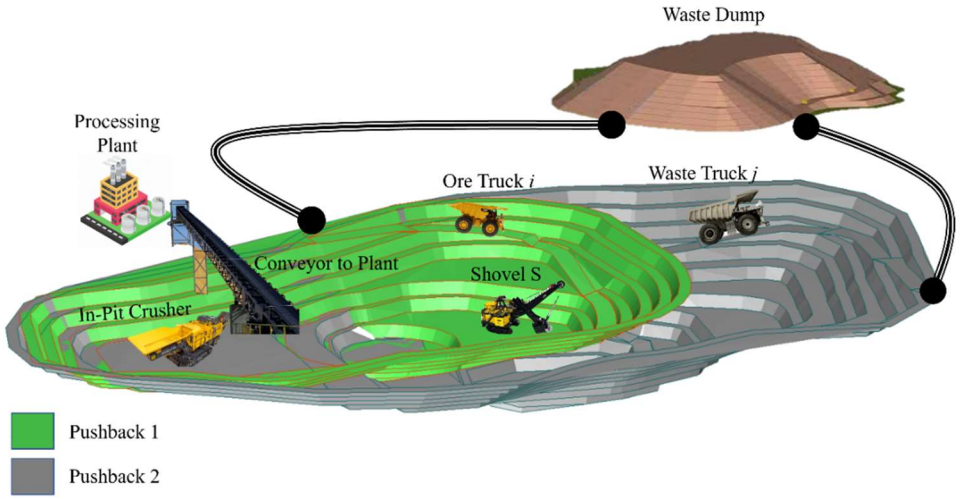


Figure 1. Schematic view of two open pit mine pushbacks with the relative locations of different equipment including semi-mobile IPCC.

This paper proposes a long-term planning methodology to optimize the NPV while minimizing the haulage costs of transporting material to the best locations of the IPCC and conveying them outside of the mining area to the processing plant. While some of the related constraints of this model is similar to the general open pit long-term planning models, there are specific objective function and necessary constraints to make it applicable for finding the best locations and relocation times of the IPCC which in this case is assigned to crush only the ore material inside of the pit. The model takes into account the road network and utilizes the shortest path function to find the minimum travel distance between the loading and dumping spots. Road network is a series of haul roads which connects loading points and dumping points within the mining cuts to inside or outside of the pit (Moradi-Afrapoli & Askari-Nasab, 2022). The important issues in the IPCC location finding in accordance with maximizing the NPV are the contradictory nature and non-linearity of the objective function. Therefore, finding a way to linearize the objective function was one of the biggest challenges of this research.

Mining is an endeavor that demands substantial capital investment, and its success hinges on meticulous production planning to prevent any suboptimal outcomes, particularly regarding equipment utilization. The fundamental goal of any mining project is to maximize the net present value (NPV) while minimizing costs. To achieve this, mine planning is divided into two key phases: long-term planning and short-term planning. Each phase is designed to optimize specific objectives and is based on the planning time horizon. Long-term planning takes place at the strategic level and revolves around maximizing NPV over the entire lifespan of the mine. This comprehensive plan considers various factors such as ore reserves, mineral grades, and economic conditions to devise a sustainable and profitable mining strategy. Conversely, short-term planning focuses on operational optimization within specific timeframes. It aims to enhance day-to-day efficiency by streamlining processes, ensuring optimal equipment utilization, and adapting to changing market conditions.

Throughout history, there has been a consistent endeavor to find ways to incorporate In-Pit Crushing and Conveying systems (IPCC) into open pit mining operations, considering various technical, environmental, design, and planning factors. The 20th century witnessed numerous attempts to explore the feasibility of utilizing IPCC, with particular focus on addressing its technical aspects. These efforts involved studying the installation processes and identifying necessary adjustments to the pit geometry. One significant area of attention in the implementation of IPCC was the modification of pit slopes to accommodate the conveyor ramp design. This adjustment aimed at reducing the overall costs associated with slope reduction, thereby optimizing the conveyor system's efficiency. The exploration of using high slope conveyors was also part of these trials, as it presented

another potential solution to improve the functionality and practicality of the IPCC system. (Dos Santos & Stanisic, 1986; Lonergan & Barua, 1985; Sturgul, 1987).

Based on Al Habib et al. (2023) post 2010 there are around 32 papers investigating IPCC option only four of which are about the incorporation of long-term planning and IPCC. Al Habib et al. (2023) says this number reduces to zero when it comes to the short-term planning and IPCC reconciliation. In recent times, the emphasis of researchers has shifted towards conducting investigations aimed at identifying optimal, near optimal or even best placements for in-pit crushers within mining operations. These studies delve into the intricate task of pinpointing strategic locations where the in-pit crusher can be situated. These identified locations present an array of benefits, ranging from technical advantages to economic gains (Konak et al. 2007; Rahmanpour et al., 2014; Roumpos et al., 2014). In 2023, Gong et al. proposed a MILP model for solving a near face stockpile where there is a crusher next to the stockpile to crush the blended material. Based on them, this new way of mining will increase the tolerance on production uncertainty and equipment utilization. They further developed their work to integrate simulation and optimization to propose a new model of near-face stockpile for short-term planning. Their model is then validated by an oil-sand mine data (Gong, Moradi Afrapoli, et al., 2023).

When considering long-term planning for mining operations involving In-Pit Crushing and Conveying (IPCC) systems, the selection and development of a suitable mine scheduling model becomes pivotal. This model must possess both technical prowess and practical applicability to effectively accommodate the complexities of the operation. According to Noriega & Pourrahimian (2022) using the metaheuristic has become a prevalent approach to tackle the complex large-scale feature of the long-term and short-term production planning with emphasis on genetic algorithm and simulated annealing methods. The important concern of these metaheuristic approaches is creating a model relying too much on the case study and making the model hard to be generalized. To address this complexity, the concept of creating mining cut implications emerges as a prominent solution, offering a practical approach to streamline the mathematical model's complexity. Notably, this idea was first introduced by (Askari-Nasab et al., 2010). In their research, they proposed the utilization of fuzzy logic clustering as a means to generate mining cuts for individual benches. This approach aimed to enhance efficiency by partitioning the mining blocks into coherent groups. However, a limitation arose in their initial implementation, as the technique did not account for the spatial arrangement of mining pushbacks. Consequently, instances occurred where a single mining cut encompassed blocks from adjacent pushbacks, potentially leading to suboptimal results. To overcome this challenge, an evolution took place in the method for generating mining cuts. This transformation occurred when Tabesh & Askari-Nasab (2011) introduced an innovative approach, replacing fuzzy logic clustering with an unsupervised machine learning technique known as hierarchical clustering. This advancement enabled the creation of mining cuts not only within each individual pushback but also by leveraging similarity indices for crucial parameters such as ore grade, rock type, and more. As a result, the revised method fostered more accurate and coherent mining cut delineations, enhancing the precision of long-term mine scheduling. Then this notion of mining cut creation resonates widely across diverse mine planning endeavors. Whether the focus is on scheduling for operations involving oil sands extraction or addressing environmental considerations such as tailing storage facility management or using it to schedule an underground mine, the approach has found successful implementation. The adaptability and robustness of this approach have enabled it to transcend specific contexts, contributing to a broader understanding of how to optimize mining operations efficiently (Badiozamani et al., 2019; Eivazy & Askari-Nasab, 2012; Koushavand et al., 2014; Maremi et al., 2021; M Tabesh et al., 2015; Mohammad Tabesh et al., 2014; Farshad Nezhadshahmohammad & Yashar Pourrahimian, 2019; Seyed Hosseini et al., 2020). Subsequent to its initial development, this approach underwent further refinement to enhance its capabilities. Notably, the method was subjected to iterative enhancements that encompassed the automatic generation of mining polygons, as pioneered by (Tabesh & Askari-Nasab, 2013). Additionally, in a

subsequent advancement, the method was fortified to confront the complexities arising from geological uncertainty (Tabesh & Askari-Nasab, 2019).

Since the location of the IPCC will impact the extraction sequence of the successor blocks or mining cuts due to the relocation time span and the fact that a specific location/s must be kept unextracted during the mine life, the mine schedule needs to be reassessed for making it compatible with the new condition. The critical point in this subject is to find the best locations which minimizes the haulage costs while obtaining the optimum extraction sequence and maximizing the NPV. This type of optimization is what we call it the simultaneous optimization in this research. Regarding the simultaneous optimization literature, there are only a few studies that are solved either for hypothetical case studies or with heuristic approaches. For example, in a study prepared by Paricheh & Osanloo (2020) the Mixed Integer Linear Programming (MILP) is proposed for a simultaneous optimization scenario for a semi-mobile IPCC where both the mine scheduling and IPCC location and relocation times are considered at the same time. However, they used two hypothetical copper deposits to verify their model with either a very limited number of blocks or very large block sizes which does not represent a practical mine open pit mining operation. Another example is a model proposed by Samavati et al. (2020) to optimize the mine schedule and a mobile IPCC which accounts for the locations of the conveyor. They attempted to schedule the blocks looking at the different compartments of the conveyor for a fully mobile IPCC system suggesting 16 equations to honor the block precedence considering different locations of the conveyors which will simply multiply by the number of blocks meaning that the model could grow up exponentially . Liu & Pourrahimian (2021) proposed a method to identify the conveyor line by exploring the pit limit from different perspectives. In their approach, the shape of mining cuts, or aggregated mining blocks is determined based on the conveyor location which the extraction should follow. They evaluated eight different conveyor locations and compared the scenarios to identify the best mine schedules that maximize the net present value (NPV). Once the optimal scenarios are identified, the location of the crusher and the relocation time (an input parameter) can be determined. The methodology's optimization is at the mining cut level, but since the extraction decision variable is binary, the model may not satisfy capacity constraints. Additionally, their model will not result in an optimal solution since it investigates scenarios to find the best answer among specified scenarios rather than calculating the global optimal solution Shamsi et al. (2022). addressed a mathematical model comparing the truck-shovel and IPCC system as the transportation means aiming to select the highest NPV. According to their model, each haulage method, truck shovel or IPCC for each type of material being ore or waste is one binary decision variable creating four different decision variables. The results show that the IPCC system could improve the NPV by 69%. However, to verify their model, they solved it in a 2D section of a deposit case study with few blocks.Top of Form

The existing literature in both Long-term planning optimization and IPCC optimization models reveals significant gaps that hinder the practical integration of long-term models with IPCC considerations. Three main obstacles emerge: Firstly, cost estimation predominantly relies on a simplistic $/t metric. Secondly, the models overlook critical equipment demands, such as truck requirements over the mine's operational lifespan. Thirdly, the excessive simplification assumption within the models renders them infeasible for real-world case applications. In the realm of IPCC optimization, two distinct modeling approaches are evident: one focusing solely on optimizing in-pit crusher locations without considering the mine extraction sequence, and another that simultaneously optimizes both mine scheduling and crusher placements. Additionally, the process of identifying potential locations for crushers entails either algorithm-based automated results or parametric-based dispersed outcomes.

The study reveals a conspicuous absence of the use of road network alongside the optimization of IPCC locations in the mine planning literature. Although previous research attempted to estimate costs based on direct distances, such an approach fails to account for the actual travel distance, which could be accurately represented by incorporating the road network. To address the identified research

gaps, a novel approach is proposed, centered around integrating the road network into the optimization framework. This integration would transform the unit cost from the traditional $/tonne to $/tonne.Km, offering a more realistic cost estimation. Furthermore, leveraging the road network enables a straightforward calculation of equipment demand by considering both material tonnage transferred and the total distance to be covered. To mitigate the complexity imposed by numerous constraints and to enhance practicality, this study introduces the concept of creating practical extraction units or blast polygons through techniques like block aggregation or mining cut creation.

Furthermore, the study recognizes the need for meticulous preparations when implementing a semi-mobile IPCC system. This entails a series of assembly arrangements spanning from truck dump locations to crusher feeders or bridges, culminating in the crusher discharge point at the conveyor. The study introduces the concept of "crusher panels" to denote these key installation spots. Notably, the selection of crusher panel placement significantly influences the extraction sequence and precedence constraints. As such, the study emphasizes the importance of choosing appropriately scaled crusher panels that align with practical mining widths and the average differences between pushback sizes. Figure 2 visually illustrates the interplay between in-pit crusher placement, the road network, conveyors, and crusher panels, underscoring their interconnectedness.

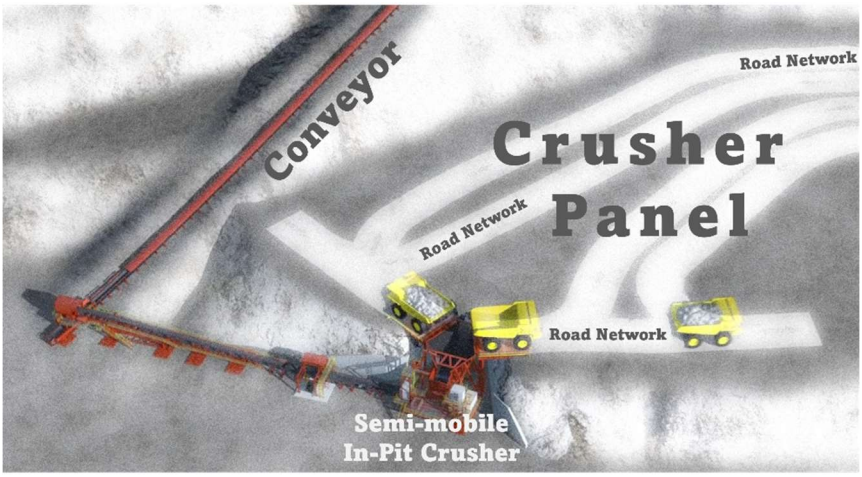


Figure 2. IPCC system position with the crusher panel and road network.

This paper introduces a pioneering simultaneous Mixed Integer Linear Programming optimization model designed to optimize the placement of in-pit crushers within a mine concurrently with the long-term mine schedule. The decision variables of this innovative approach operate at the mining-cut level, encompassing mine polygons or blast patterns formed through a hierarchical clustering algorithm. The methodology harnesses the mine's actual road network, inclusive of distinct roads and ramps, to optimize the positioning of the In-Pit Crushing and Conveying (IPCC) system. This optimization aims to minimize haulage costs through a nonlinear objective function, which is subsequently linearized by introducing an auxiliary variable. The primary objective of this model is to maximize the mine's Net Present Value (NPV) while simultaneously minimizing haulage costs. In essence, this proposed method presents a pragmatic avenue for enhancing in-pit crusher placement by factoring in the tangible road network within the mine, thereby enriching the decision-making process. The method further takes into meticulous consideration the precise geometry of mining cuts, a factor with considerable influence on extraction process efficiency and efficacy.

2. Methodology

In this research, we present a comprehensive methodology for optimizing the strategic placement and relocation timing of in-pit crushers within a mining operation. The primary goal is to maximize

the Net Present Value (NPV) of the mining project while minimizing haulage costs. This approach combines economic, operational, and geological considerations to facilitate well-informed decision-making in mining operations. The optimization problem is framed as a dual objective: maximizing NPV and minimizing haulage costs within one objective function, with a focus on haulage optimization influencing in-pit crusher placement and movement. This entails the compound task of determining the optimal locations for in-pit crushers, strategically forming crusher panels, delineating mining cuts, and establishing efficiently adopting the road networks. Moreover, factors such as the minimum mining width and pushback dimensions are taken into account to ensure the feasibility and practicality of the proposed solution. The following steps are mandatory for the proposed model application.

1. Pushback and Road Network Design:

The initial step involves delineating pushbacks, which serve as distinct mining areas. Within each pushback, the road network and ramps are extracted to establish a basis for subsequent analysis and optimization.

2. Crusher Panel Nomination via K-Medoid Clustering:

To identify potential in-pit crusher sites, we employ the k-medoid clustering algorithm. This technique allows us to cluster nominated crusher locations, referred to as "crusher panels," based on their alignment with the minimum mining width. These panels represent potential sites for in-pit crushers.

3. Crusher Panel Formation:

Building upon the nominated locations, we establish crusher panels within each pushback. The number of panels is influenced by both the dimensions of the pushback and the minimum mining width. These panels serve as fundamental units for subsequent stages of optimization.

4. Mining Cut Aggregation using Hierarchical Clustering:

Practical blasting polygons, or mining cuts, are formed within each crusher panel to streamline the mining process. Hierarchical clustering is employed to aggregate identified blocks into coherent mining cuts based on the similarity index of each of the blocks, enhancing operational efficiency.

5. Haulage Cost Calculation:

Calculating haulage costs is pivotal in optimizing the crusher locations and relocation times. By assessing transportation expenses from each mining cut to the respective crusher panel center, as well as from the panels to the processing plant, we obtain a comprehensive understanding of operational costs.

6. Simultaneous Optimization Model:

At the heart of our methodology lies the development of a simultaneous optimization model. The nonlinear formulation is transformed into a linear representation, which is then solved using the CPLEX solver connected to MATLAB. This model seeks to strike a balance between maximizing NPV and minimizing haulage costs, thereby guiding decision-making.

The results of the optimization process yield the optimal crusher panels that offer the lowest haulage costs. These panels, along with the most favorable relocation times, contribute to defining an optimized mine schedule that simultaneously maximizes NPV and minimizes operational expenses.

3. Clustering

The shape of a block model is rectangular and represents an orebody that is divided into uniform-sized shapes called blocks. Although the block model facilitates mine planning and extraction, it can make the problem size intractable for large deposits with millions of blocks, especially when

optimizing the extraction schedule over many time periods. Aggregation techniques are used to generate minable continuous mine plans that are achievable in practice and to reduce the problem size. To this end, block aggregation using a clustering algorithm is suggested. Blocks aggregate to mining cuts based on their similarity in rock type, ore grade, and distance.

Clustering is an unsupervised machine learning algorithm that distinguishes between data based on similarities or dissimilarities. Hierarchical and partitioning are two ways to cluster data. In this study, clustering algorithms are used to propose a new way of choosing candidate locations for the crusher and creating crusher panels inside each mining phase on every bench. Block aggregation has a long history in long-term open pit mine planning to reduce the problem size and computational time of such an optimization problem. The methods of block aggregation in their early use were based on the technical features of the blocks. However, more complicated clustering methods have been developed to comply with mine planning requirements, which require solving a linear programming mathematical optimization. The most common procedure is applying either hierarchical or partitioning clustering.

The clustering algorithm proposed in this paper creates crusher panels using the k-medoids algorithm, and then hierarchical clustering is used within the crusher panels. Similar to what was proposed by (M Tabesh & Askari-Nasab, 2011), the idea of distance hierarchy is applied to calculate the similarities between categorical variables. A penalty function is developed to calibrate the function in the distance hierarchy method. The similarity value between blocks i and j is estimated using Equation 1.

$$S_{ij} = \frac{R_{ij} C_{ij}}{\tilde{D}_{ij}^{w_D} \tilde{G}_{ij}^{w_G}} \tag{1}$$

where R_{ij} is the penalty assigned if blocks are from different rock types, C_{ij} is the penalty assigned to blocks not located above the same cluster, $\widetilde{D_{ij}}$ represents the normalized distance value between blocks i and j, $\widetilde{G_{ij}}$ represents the normalized grade difference between blocks i and j, and D_{ij} is the Euclidean distance between centers of blocks i and j.

The k-medoids algorithm is a type of partitioning clustering and is similar to the k-means algorithm in terms of performance function and iterative process. The general procedure of k-medoids clustering is summarized as follows (Kaufman & Rousseeuw, 2009):

1. Assume k arbitrary clusters where there are S_1, S_2, …, S_k representatives as medoids for each cluster c_1 to c_k.
2. Given S_1 to S_k medoids, update cluster c_k with the minimum distance rule applied to the performance function and call it c_k'.
3. Given cluster c_k, update the medoid S_k and check the stop condition.
4. Stop if the new c_k'= c_k, then make S_k = S'; otherwise, repeat steps 2 and 3.

Using the k-medoids and categorizing each bench within its pushback would be the first step of this framework in which the blocks are clustered as crusher panels. The next step is to implement the blocks' cluster within the boundary of the crusher panel while preserving the precedence. The crusher location optimization process uses the medoids to calculate the related distance and cost for the crusher location problem.

4. Mine scheduling in presence of IPCC

In this section, the MILP formulation will be presented which will take care of the optimization for the IPCCs locations, relocation times and mine schedules while a crusher occupies multiple blocks,

thereby obstructing a specific crusher panel from being extracted for a predetermined period. However, the general MILP formulation in the long-term open pit mine planning premise can not handle the IPCC arrangement therefore needs to be reformulated to address all the objectives of this research. The objective function, as described in Equation 2, aims to maximize NPV by identifying the optimal extraction periods (T) for both the portion of the mining cut ($x_{k,p,t}$) sent to the mill and the portion of the panel ($d_{p,t}$)sent to the waste dump. In this equation, $v_{k,p,t}$ represents the discounted revenue minus the extra cost of mining ore in the mining cut $x_{k,p,t}$, whereas $q_{p,t}$ denotes the discounted cost of mining.

This model has six decision variables, three of which are continues from zero to one and the other three are binary. The first three continuous starts with the variable accounting for the amounts of ore must be sent to the mill (x) from each mining cut k in which period t and to which crusher panel p. The second one is the amounts of waste must be extracted (d) in which period t from each panel p, and the third one is an auxiliary variable w which is added to linearize the non-linear equation of $x \times l$. The other three binary decision variables are b which is to hold the precedence corresponding to the crusher panels extracted in period t and onwards equals to one and zero otherwise. The second binary variable is y', an auxiliary variable to guarantee that the crusher panel will remain unextracted for the assigned period/s. The last binary variable is l to decide the best locations of the IPCC by finding the best crusher panels p over time t and assigning mining cut k for transferring to them. The goal here is to minimize the haulage costs.

$$\max \sum_{t=1}^{T}\sum_{p=1}^{P}\left(\sum_{k=1}^{K}(v_{k,p,t}\times x_{k,p,t})-(q_{p,t}\times d_{p,t})\right) \quad (2)$$

subject to

$$ml^{t} \le \sum_{p=1}^{P}(o_p + w_p)\times d_{p,t} \le mu^{t} \quad \forall t \in \{1,...,T\} \quad (3)$$

$$pl^{t} \le \sum_{p=1}^{P}\sum_{k=1}^{K} o_k \times x_{k,p,t} \le pu^{t} \quad \forall t \in \{1,...,T\} \quad (4)$$

$$\sum_{k=1}^{K} o_k \times x_{k,p,t} \le (o_p + w_p)\times d_{p,t} \quad \forall t \in \{1,...,T\}, p \in \{1,...,P\} \quad (5)$$

$$0 \le \sum_{k=1}^{K}(g_k^{e} - gl^{t,e})\times o_k \times x_{k,p,t} \quad \forall t \in \{1,...,T\}, e \in \{1,...,E\} \quad (6)$$

$$\sum_{k=1}^{K}(g_k^{e} - gu^{t,e})\times o_k \times x_{k,p,t} \le 0 \quad \forall t \in \{1,...,T\}, e \in \{1,...,E\} \quad (7)$$

$$\sum_{t=1}^{T} d_{p,t} = 1 \quad \forall p \in \{1,...,P\} \quad (8)$$

$$b_p^{t} - \sum_{i=1}^{T} d_s^{i} \le 0 \quad \forall t \in \{1,...,T\}, p \in \{1,...,P\}, s \in C_p \quad (9)$$

$$\sum_{i=1}^{T} d_p^{i} - b_p^{t} \le 0 \quad \forall t \in \{1,...,T\}, p \in \{1,...,P\} \quad (10)$$

$$b_p^{t} - b_p^{t+1} \le 0 \quad \forall t \in \{1,...,T-1\}, p \in \{1,...,P\} \quad (11)$$

FORLOOP d_v = *the No. of Optimum Crusher Panels*

$$\sum_{h\in d_v}\sum_{t=1}^{tloop} d_h^{t} + M\, y_t^{'} \ge length(d_v) \quad \forall tloop \in \{1,...,T\} \quad (12)$$

$$\sum_{ny\in No.of\ Yrs} -b_{ny} - M\, y_{tloop}^{'} \le -ny \quad \forall tloop \in \{1,...,T\} \quad (13)$$

$$\sum_{t=1}^{tloop}\left(y_t^{'} + \sum_{i=t+1}^{tloop}\frac{y_i^{'}}{tloop - t}\right) \le 1 \qquad \forall tloop \in \{1,...,T\} \quad (14)$$

END of FOR LOOP

$$x_{k,p,t}, d_{p,t}, w_{k,p,t} \in [0,1] \ \forall t \in \{1,...,T\}, p \in \{1,...,P\}, k \in \{1,...,K\} \quad (15)$$

$$b_{k,t}, y_t', l_{k,p,t} \in \{0,1\} \ \forall t \in \{1,...,T\}, k \in \{1,...,K\}, p \in \{1,...,P\} \quad (16)$$

Knowing that $x_{k,p,t}$ and $d_{p,t}$ are the decision variables, $v_{k,p,t}$ and $q_{p,t}$ can be broken down to Equations 17 & 20 from which we can obtain the revenue of selling mining cut *k* being extracted in period *t* and sent to the crusher panel *p* as $Rev_{k,p,t}$. Similarly, the Total Mining Cost (TMC) of extracting mining cut *k* in period *t* and sending it to the crusher panel *p* is called $TMC_{k,p,t}$. From there, $TMC_{k,p,t}$ is equal to general cost of mining cut *k* extraction ($mc_{k,p,t}$) plus the haulage cost which constitutes the Equation 18 if there is an ore crusher in the pit and Equation 19 if the material is transferred to outside of the pit using truck shovel. It is worth noting that since there is no need to

optimize the crusher location when the material handling method is truck shovel, in Equation 19 we do not need to have subset *p* referring to the crusher panels.

$$v_{k,p,t} = \frac{\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T} \mathrm{Re}\, v_{k,p,t} - TMC_{k,p,t}}{(1+r)^t} \tag{17}$$

If there is an Ore Crusher in the pit :

$$TMC_{k,p,t} = mc_{k,p,t} + \left[\left((SPath_{k,p} \times o_k \times c_{k,p,t}) + (Pdist_p^{pl} \times o_k \times cn_p^{pl,t})\right) \times l_{k,p,t} - (SPath_k^{du} \times w_k \times c_k^{du,t})\right] \tag{18}$$

else, will be handled by Truck Shovel (*Shortest Path*):

$$TMC_{k,t} = mc_{k,t} + \left((SPath_k^{pl} \times o_k \times c_k^{pl,t}) - (SPath_k^{du} \times w_k \times c_k^{du,t})\right) \tag{19}$$

$$q_{p,t} = \frac{\sum_{p=1}^{P}\sum_{t=1}^{T} TMC_{p,t}}{(1+r)^t} \tag{20}$$

The Waste will be handled by Truck Shovel (*Shortest Path*) :

$$TMC_{p,t} = mc_{p,t} + (SPath_p^{du} \times w_p \times c_p^{du,t}) \tag{21}$$

Let's look further at the Equation 18 where we have general mining cost + haulage costs making it look like the following:

$$TMC_{k,p,t} = mc_{k,p,t} + \left\{\begin{bmatrix} To\ Ore\ InPit\ Crusher\ \left(By\ Truck\ \&\ ShortestPath\right) + \\ To\ Plant\ \left(By\ Conveyor\ \&\ MinimumDistance\right) \end{bmatrix} \times l_{k,p,t} - \right\} \tag{22}$$
$$\left\{ To\ Waste\ Dump\ \left(By\ Truck\ \&\ ShortestPath\right) \right\}$$

We can summarize Equation 22 into the following:

$$TMC_{k,p,t} = mc_{k,p,t} + (HC_{k,p,t} \times \ l_{k,p,t}) - Ext_{k,p,t} \tag{23}$$

Now we can change the objective function and make it compatible with the new condition of in-pit crusher location determination. Equation 24 is the new non-linear objective function having the $x_{k,p,t}$ and $l_{k,p,t}$ multiplied both are decision variables aiming for maximizing NPV. We will then linearize this objective function by introducing a new auxiliary variable *w* and a set of constraints relating *w* to *x* and *l*.

$$\max \sum_{t=1}^{T}\sum_{p=1}^{P}\left(\sum_{k=1}^{K}\left((Rev_{k,p,t} - mc_{k,p,t} + Ext_{k,p,t}) \times x_{k,p,t} - HC_{k,p,t} \times x_{k,p,t} \times l_{k,p,t}\right) - (q_{p,t} \times d_{p,t})\right) \tag{24}$$

Assuming that $x_{k,p,t} \times l_{k,p,t} = w_{k,p,t}$ $0 \le w \le 1$ we can rewrite the Equation 24 and add the relative constraints to linearize the objective function as follows.

$$\max \sum_{t=1}^{T}\sum_{p=1}^{P}\left(\sum_{k=1}^{K}\left((Rev_{k,p,t} - mc_{k,p,t} + Ext_{k,p,t})\times x_{k,p,t} - HC_{k,p,t}\times w_{k,p,t}\right) - (q_{p,t}\times d_{p,t})\right) \quad (25)$$

$$x_{k,p,t} - N(1-l_{k,p,t}) \le w_{k,p,t} \quad \forall N>1,\ k\in\{1,...,K\},\ p\in\{1,...,P\},\ t\in\{1,...,T\} \quad (26)$$

$$w_{k,p,t} \le l_{k,p,t} \quad \forall k\in\{1,...,K\},\ p\in\{1,...,P\},\ t\in\{1,...,T\} \quad (27)$$

$$w_{k,p,t} \le x_{k,p,t} \quad \forall k\in\{1,...,K\},\ p\in\{1,...,P\},\ t\in\{1,...,T\} \quad (28)$$

The rest of the constraints are for controlling the *l* and controlling how it should behave.

$$\sum_{t=1}^{T}\sum_{p=1}^{P} o_k \times x_{k,p,t} = do_k \ \ \forall\ k\in\{1,...,K\} \quad (29)$$

$$lM^p \times \sum_{t=1}^{T}\sum_{k=1}^{K} l_{k,p,t} \le \sum_{t=1}^{T}\sum_{k=1}^{K} o_k \times x_{k,p,t} \le uM^p \times \sum_{t=1}^{T}\sum_{k=1}^{K} l_{k,p,t} \ \ \forall\ p\in\{1,...,P\} \quad (30)$$

$$\sum_{t=1}^{T} o_k \times x_{k,p,t} \le do_k \times \sum_{t=1}^{T} l_{k,p,t} \ \ \forall\ k\in\{1,...,K\},\ p\in\{1,...,P\} \quad (31)$$

$$\sum_{p=1}^{P}\sum_{k=1}^{K} l_{k,p,t} = 1 \ \ \forall\ t\in\{1,...,T\} \quad (32)$$

$$\sum_{t=1}^{T}\sum_{p=1}^{P} l_{k,p,t} = 1 \ \ \forall\ k\in\{1,...,K\} \quad (33)$$

Indexes:

t: mining periods based on year. $t \in T$

k: mining cut. $k \in K$

p: crusher panel which are the candidate locations for the crusher. $p \in P$

ocp: optimum crusher panels. $ocp \subset P$

pl: processing plant/s

du: waste dump/s

Variables:

Rev_k^t: revenue as a result 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 and smelting and refining costs.

TMC_k^t: Total Mining Costs of extracting mining cut *k* in period *t*.

TMC_p^t: Total Mining Costs of extracting crusher panel *p* in period *t*.

mc_k^t: 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: mining cost of extracting crusher panel *p* minus the haulage cost of crusher panel *p* to the waste dump *du* in period *t.*

SPath: The shortest path in the road network which could be between either mining cut *k* or crusher panel *p* to the optimum crusher panel *ocp* or waste dump *du.*

$Pdist_{pl}^{ocp}$: The minimum distance between the processing plant *pl* and the optimum crusher panel *ocp*.

o_k : is the ore tonnage in the mining cut *k.*

w : is the waste tonnage in the mining cut k or crusher panel p.

r: is the discount factor.

c^t: is the dollar cost of hauling one tonnage of ore or waste per one kilometre with haul truck to their destination either the optimum crusher panel *ocp* or waste dump *du* or directly to the processing plant *pl* in period t (\$/ton.km).

$cn_{pl}^{ocp,t}$: is the dollar cost of transferring one tonnage of ore per one kilometre using the conveyor from the optimum crusher panel *ocp* to the processing plant *pl* in period t.

v_k^t: represents the discounted revenue minus the extra cost of mining ore in the mining cut x_k^t based on the Eq. 13 and 14.

q_p^t: denotes the discounted cost of mining based on the Eq. 15 and 16.

$x_k^t \in [0,1]$ is a continuous decision 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 decision variable, representing the portion of the crusher panel p to be mined in period t, fraction of y characterizes both ore and waste included in the panel.

$l_k^{p,t} \in \{0,1\}$ is a binary decision variable deciding which crusher panel should be the location of the in-pit crusher.

$b_p^t \in \{0,1\}$ is a binary integer decison 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.

C_p is the set of the panels that have to be extracted prior to panel p.

K_p is the set of mining-cuts within panel p.

g_k^e is the average grade of element e in ore portion of mining-cut k.

$gl^{t,e}$ and $gu^{t,e}$ are the upper bound and lower bound on acceptable average head grade of element e in period t in percent.

pl^t and pu^t are the upper and lower bounds on ore processing capacity in period t in tonnes.

ml^t and mu^t are the upper and the lower bounds on mining capacity in period t in tonnes.

In the proposed model, the objective function, as described in Equation 2, aims to maximize NPV by identifying the optimal extraction periods (T) for both the portion of the mining cut ($x_{k,p,t}$) sent to the mill and the portion of the panel ($d_{p,t}$) sent to the waste dump. Equations 3 and 4 are the mining and processing capacity constraints. Equation 5 modifies the relation between the extracted ore tonnage and the total extracted tonnage from the corresponding cuts and panels respectively. Equation 6 and 7 control the maximum and minimum grade of the material sent to the mill or waste dump. Equation 8 ensures that all the panels will be extracted during the mine life. Equations 9-11 provide the extraction precedence of the crusher panels, which are created within the mine phases and contain the mining cuts. Equation 9 is a precedence constraint which forces b_p to be 0 until all the predecessors crusher panels ($\sum d_s$) are extracted. Equation 10 is to ensure that the crusher panel p does not extract unless the subsequent $b_p^t$for that crusher panel in a period t becomes 1. Equation 11 makes all the b variables 1 for $t+1$ after it becomes 1 in period t. For instance, if crusher panel one should be extracted prior to crusher panel two, all the mining cuts within crusher panel one is the dependent clusters for the mining cuts within the crusher panel two.

Equations 12-14 are within a loop which they repeat based on the number of optimum crusher panels coming from the decision of how many crusher relocations should occur during the mine life. This decision has been made l variable where it constrains to consider the lower bound and upper bound

of the total tonnage milled during the time that 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 which should be bigger than the maximum number of dependent panels on top of the optimized panel or the crusher panel. For instance, if we only have two crusher panels introduced by *l*, and if there are three crusher panels on top of the first optimized panel, and four panels on top of the second optimized panel, then the value of *"M"* must be greater or equal to 5. The variable *"d'$_h$"* is responsible to keep track of the extraction percentage of the dependent panels of an optimized panel and eventually the Equation 12 will determine when all the top panels are extracted. Only then the Equation 13 will bring to an action preventing the optimized panel from extraction for as long as the next *l* in the next crusher panel becomes one. Therefore, *"b_{ny}"*, which is a binary variable controlling the precedence of panels' extractions, is now being forced to become zero only for those certain years. Equation 14 is to control the *"y'$_t$"* by making sure that it does not change value from zero to one haphazardly.

The decision variable boundaries are Equation 15 and 16 which will make the whole formulation result in optimizing the extraction plan in the presence of an in-pit crusher with the explained method. Equation 17 shows the components of $v_{k,p,t}$ which the total mining cost component will be the result of Equation 18 for the case where there is a crusher in the pit and Equation 19 for the case where there is not any crusher in the pit. Similarly, Equation 20 shows the components of $q_{p,t}$ which the total mining cost component will be the result of equation 21. Equation 22 and 23 is the written form and another form of the Equation 18 respectively. Equation 24 is the objective function in its new form considering the changes occurred in Equation 18. Equation 25 is the final form of the objective function with the auxiliary variable *w* used for linearization and Equations 26-28 are the necessary constrains to build the dependency between *w* and *x*×*l*. Equation 29 ensures that every mining cut, along with its corresponding ore tonnage, is assigned to a crusher panel. Equation 30 establishes a lower and an upper limit on the total tonnage milled during the time that the crusher is located on panel *p*. To ensure the problem's solvability, Equation 31 sets an upper bound for variable *z*. Finally, Equations 32 and 33 certify that in each period *t* there is only one optimum crusher panel available, and each mining cut *k* is sent to one optimum crusher panel, respectively.

5. Case Study

For verifying the method, a data set from real iron ore is selected which contains two pushbacks and 10 benches. The primary element is magnetite, but the deposit has a small amount of phosphorus (P) and sulfur (S). In these two pushbacks, we have 9952 blocks with the following dimension 20m × 10 m × 15m in X, Y, and Z respectively. The mill and the waste dump are two destinations fed by five different rock types, only three of which would be processed. The case study is tested on a machine with Intel® CPU with seven cores with 1.8 GHz speed and 16 GB of RAM. It is worth mentioning that the run time for the proposed model with the explained case study was between 30 to 50 seconds implying that this model is capable of tackling much larger deposits. Figure 3 shows the layout of the iron ore mine which is planned to accommodate a crusher inside.

In the first step, the number of crusher panels is selected automatically based on the minimum mining width in a way that each pushback is divided based on its area to a different number of crusher panels which results in having not more than three crusher panels in each pushback. The k-medoid clustering algorithm is used to create the crusher panels. Through the medoids, one block represents the whole panel forming the candidate locations for the crusher in each selected panel. Then, the blocks are aggregated within the crusher panels by applying the hierarchical clustering algorithm developed by (Tabesh & Askari-Nasab, 2011) to obey the mining phase boundaries. It is important to note that since the mining extraction follows the phases in each bench, the extraction of the next bench starts just after the current phase is fully extracted. However, the next phase might start within the current bench but will be left for the next stage. Therefore, the mining phases must cover the mining cuts.

The mining phases will create the panels that intersect between the designed pushbacks and the benches and will be used as mining units in the proposed mine planning formulation.

Table 1 shows the clustering parameters for both methods used to create the crusher panels and mining cuts.

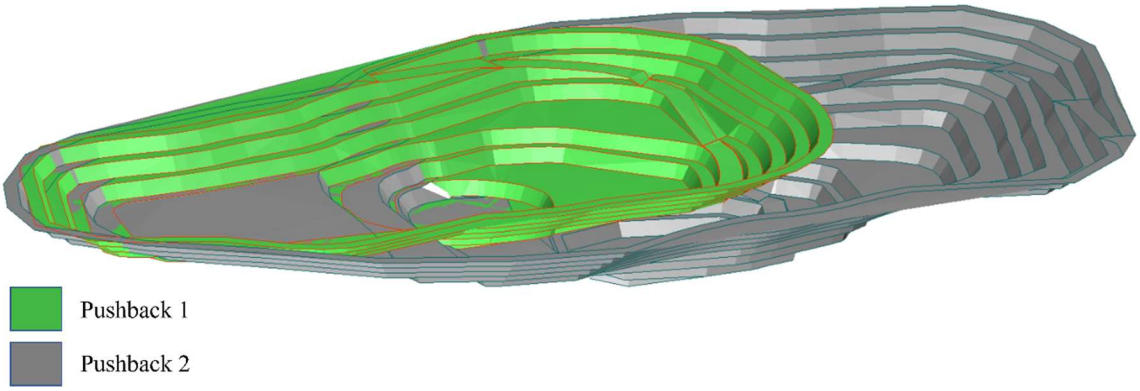


Figure 3. The iron mine layout with ramps and road network.

Table 1. Clustering Parameters.

Block Clustering Method	**Hierarchical**
Distance Weight	0.8
Grade Weight	0.2
Cluster Penalty	0.2
Rock Penalty	0.8
Approximate Block per Cut	30
Max Cluster Size	35
Crusher Panel Clustering Method	**k-medoids**
Algorithm to find medoids	Partitioning Around Medoids
Distance Minimization Method	Euclidean
Number of Replications	10

In this study, it assumed that the minimum diagonal distance of a crusher panel is 400m. This assumption improves the dimension of the crusher panels, especially when in the top or bottom benches, we have a small region encompassing blocks. Therefore, the current case has 16 bench-phase and 28 crusher panels in a total of 10 benches and 9 years of extraction. Figure 4 shows the plan view of the eighth bench with three features a) aggregating blocks to create mining cuts, b) clustering mining cuts to create the crusher panels, and c) mining panels or phases, respectively. In the next stage, distances are calculated from crusher panels to mining cuts, and the cost of material transportation is estimated. Existing mine roads are used for commuting. The cost of conveying materials using trucks and designed ramps is estimated to be $0.3 for hauling one tonne in one kilometer and $0.3 for transferring one tonne to the next level using the conveyor. The average travel distance between the ore mining cuts and the crusher is around 0.8 km, while the average travel distance for waste transportation and carrying ore to the mill is more than 4 km, assuming no in-pit crusher is in place. Figure 5 shows the road network for each of the pushbacks.

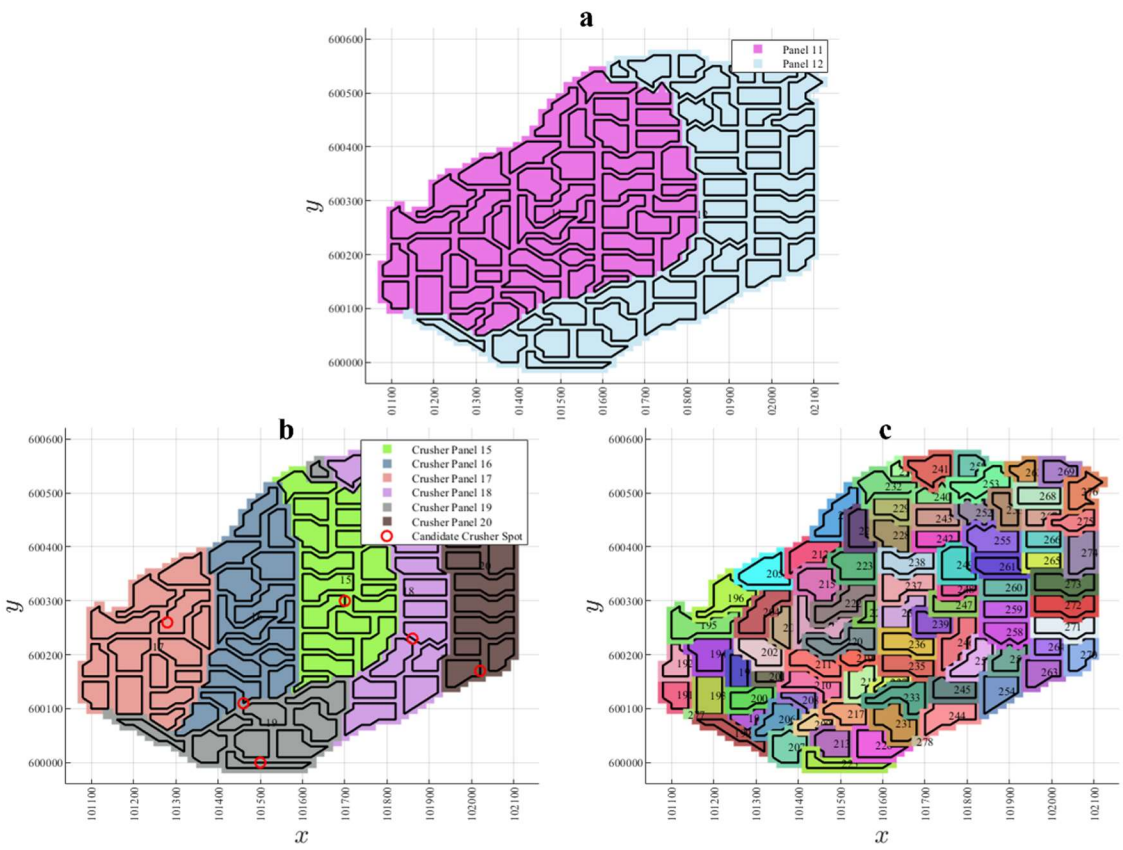


Figure 4. The plan view of bench number eight a) mining panels or phases, b) clustering blocks to create the crusher panels, and c) block aggregation to create mining cuts.

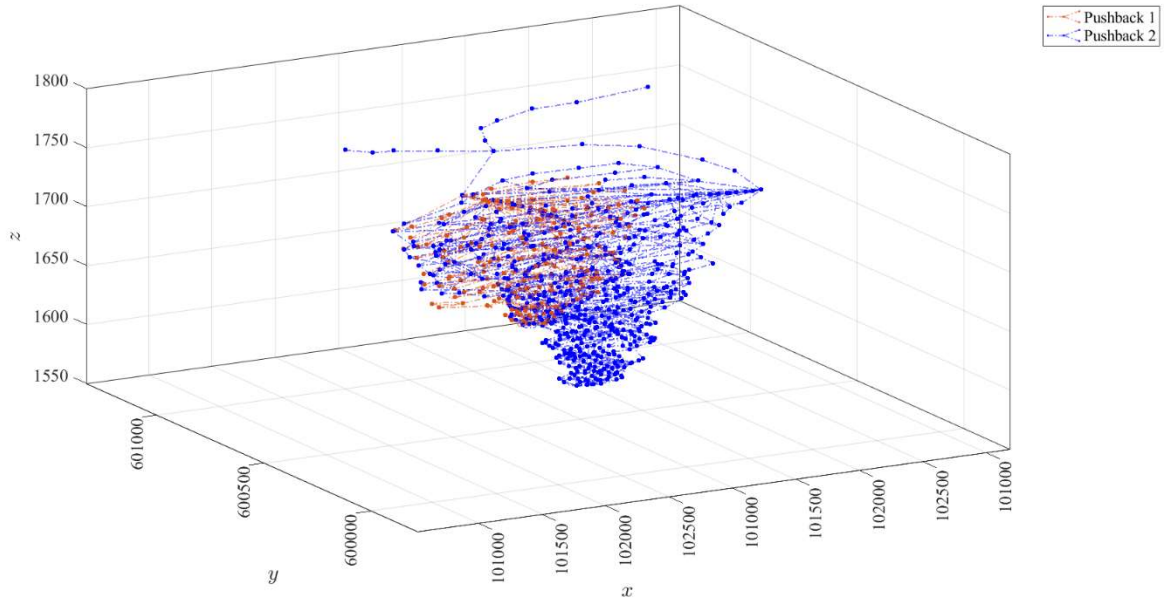


Figure 5. Schematic view of the road network.

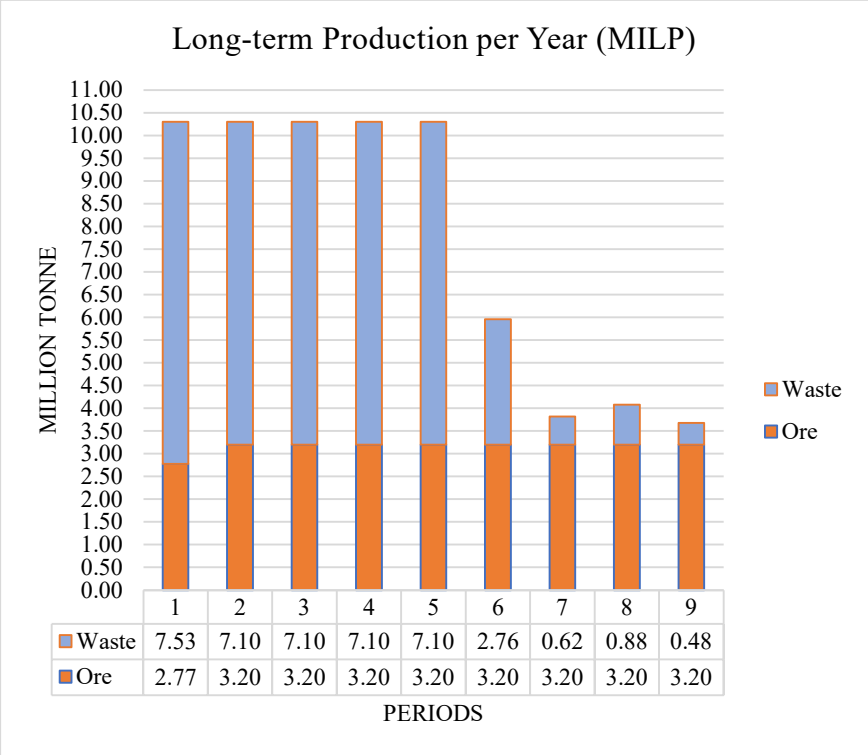
The total minable production is around 70 million tonnes (MT) within which 30 MT is ore. The yearly mining capacity and processing capacity are further assumed to be 10.3 MT and 3.2 MT respectively. It means that the operation will continue for 9 years. The MILP was formulated in

(MATLAB, 2023) and solved with the (IBM ILOG CPLEX Optimization Studio., 2011) solver. The model has two possible destinations: the in-pit crusher and the waste dump. The mill is no longer a destination in such models, but the capacity-related variable is still referred to as the processing capacity since it is the bottleneck variable in this formulation.

6. Discussion of Results

The case study was first carefully tested inside of the Whittle software so that through a trial-and-error process, a near-stable schedule could be generated. Hence the stripping ratio is relatively high, the mining capacity cannot be maintained from the 6th year although the processing capacity is nearly constant. Figure 6 shows the yearly schedule generated the proposed method. The new formulation which includes IPCC was able to increase the discounted cash flow from 560 to 606 M$, especially knowing that this schedule is disturbed due to the in-pit crusher location and its requirement to postpone the extraction of the optimized crusher panel. It is also observed that the designed MILP model sends around 2MT more material to waste dump. Figure 7 shows the yearly revenues versus cash flow graph for the proposed model.

Given that some components such as queuing approach are zero when the required number of trucks is low, it is assumed that the waiting times in loading and dumping for both scenarios, with and without an in-pit crusher, are proportional. Based on the average travel time, the average number of trucks can be calculated. In this case study, the average travel distance for the in-pit crusher option is 837 m, compared to almost 4039m for trucks traveling directly to the mill. Loaded and empty trucks have a safe travel speed of 30 km/h and 60 km/h, respectively. Therefore, it takes around 2.5 minutes to travel to the in-pit crusher one way, compared to 12.1 minutes to travel to the mill one way. Installing a crusher in an optimal location reduces travel time by 4.8 times.



	1	2	3	4	5	6	7	8	9
Waste	7.53	7.10	7.10	7.10	7.10	2.76	0.62	0.88	0.48
Ore	2.77	3.20	3.20	3.20	3.20	3.20	3.20	3.20	3.20

Figure 6. Long-term yearly production generated using the proposed model for the in-pit crusher.

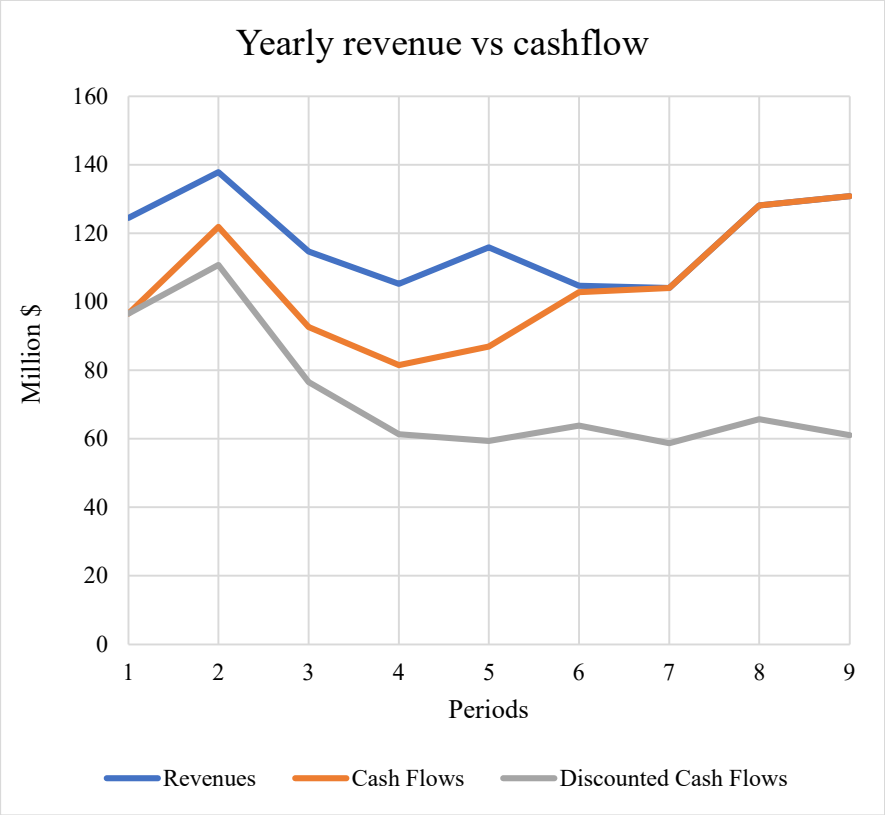


Figure 7. Revenue versus Cashflow based on each year from the proposed model for the in-pit crusher.

7. Conclusion

Due to the vast and broad use of IPCC in open pit mining operations, in this study, we tried to develop a mathematical model to not only consider the IPCC in the scheduling but provide the best locations for the crusher within the mine life at the same time. The idea was to create practical units for the crusher spots named crusher panels and employ the road network during the optimization. Additionally, the conventional MILP model should have been changed to accommodate a condition with which the optimized crusher panel remains undisturbed or unextracted when all the precedence blocks are extracted for a certain period of years. The proposed model implemented to an iron mine case study with two pushbacks, 10 benches with 9952 blocks gives 404 mining cuts, 28 crusher panels, and 2 optimized crusher panels with their associated crusher capacities of approximately 16 MT and 12 MT. We further discussed that the first optimized location was in the first bench, so it was considered an out-pit crusher location.

The simultaneous MILP model with the related IPCC constraints and the total mining capacity of 10.3 MT and processing capacity of 3.2 MT was solved using the CPLEX solver. The results show that the IPCC constraints can reinforce the in-pit crusher implementation. Furthermore, it increases the discounted cash flow by 8% compared with the best schedule without the in-pit crusher. As for one of the main reasons for the IPCC utilization which is to reduce the travel distance and truck number, the in-pit crusher could reduce truck travel time by 5 times considering the processing plant location and the optimized crusher panel.

8. References

[1] Al Habib, N., Ben-Awuah, E., & Askari-Nasab, H. (2023). Review of recent developments in short-term mine planning and IPCC with a research agenda. *Mining Technology*, 1–23. https://doi.org/10.1080/25726668.2023.2218170

[2] Askari-Nasab, H., Awuah-Offei, K., & Eivazy, H. (2010). Large-scale open pit production scheduling using Mixed Integer Linear Programming. *International Journal of Mining and Mineral Engineering*, *2*(3), 185–214. https://doi.org/10.1504/IJMME.2010.037624

[3] Badiozamani, M. M., Ben-Awuah, E., & Askari-Nasab, H. (2019). Mixed Integer Linear Programming for Oil Sands Production Planning and Tailings Management. *JOURNAL OF ENVIRONMENTAL INFORMATICS; Vol 33, Issue 2 (June 2019)*.

[4] Dos Santos, J. A., & Stanisic, Z. (1986). In-pit crushing and high angle conveying in a Yugoslavian copper mine. In *Mining Latin America/Minería Latinoamericana* (pp. 101–113). Springer.

[5] Eivazy, H., & Askari-Nasab, H. (2012). A hierarchical open-pit mine production scheduling optimisation model. *International Journal of Mining and Mineral Engineering*, *4*(2), 89–115. https://doi.org/10.1504/IJMME.2012.052436

[6] Farshad Nezhadshahmohammad, & Yashar Pourrahimian. (2019). A Clustering Algorithm for Block-Cave Production Scheduling. *Global Journal of Earth Science and Engineering*, *5*(1 SE-Articles), 45–53. https://doi.org/10.15377/2409-5710.2018.05.4

[7] Gong, H., Moradi Afrapoli, A., & Askari-Nasab, H. (2023). Integrated simulation and optimization framework for quantitative analysis of near-face stockpile mining. *Simulation Modelling Practice and Theory*, *128*, 102794. https://doi.org/https://doi.org/10.1016/j.simpat.2023.102794

[8] Gong, H., Tabesh, M., Moradi Afrapoli, A., & Askari-Nasab, H. (2023). Near-face stockpile open pit mining: a method to enhance NPV and quality of the plant throughput. *International Journal of Mining, Reclamation and Environment*, *37*(3), 200–215. https://doi.org/10.1080/17480930.2022.2160891

[9] IBM ILOG CPLEX Optimization Studio. (2011). *CPLEX User's Manual 12*. IBM Corporation.

[10] Kaufman, L., & Rousseeuw, P. J. (2009). *Finding groups in data: an introduction to cluster analysis*. John Wiley & Sons.

[11] Koushavand, B., Askari-Nasab, H., & Deutsch, C. V. (2014). A linear programming model for long-term mine planning in the presence of grade uncertainty and a stockpile. *International Journal of Mining Science and Technology*, *24*(4), 451–459. https://doi.org/https://doi.org/10.1016/j.ijmst.2014.05.006

[12] Liu, D., & Pourrahimian, Y. (2021). A Framework for Open-Pit Mine Production Scheduling under Semi-Mobile In-Pit Crushing and Conveying Systems with the High-Angle Conveyor. In *Mining* (Vol. 1, Issue 1, pp. 59–79). https://doi.org/10.3390/mining1010005

[13] Lonergan, J., & Barua, E. S. L. (1985). Computer-assisted layout of in-pit crushing/conveying systems. *SME-AIME Fall Meeting*, 1–6.

[14] Maremi, A., Ben-Awuah, E., & Askari-Nasab, H. (2021). Multi-objective Mathematical Programming Framework for Integrated Oil Sands Mine Planning and Tailings Disposal Optimization. *Mining, Metallurgy & Exploration*, *38*(3), 1355–1374. https://doi.org/10.1007/s42461-021-00418-7

[15] Matlab. (2023). *The MathWorks Inc*. The MathWorks Inc.

[16] Moradi-Afrapoli, A., & Askari-Nasab, H. (2022). *Advanced Analytics for Surface Extraction BT - Advanced Analytics in Mining Engineering: Leverage Advanced Analytics in Mining Industry to Make Better Business Decisions* (A. Soofastaei (ed.); pp. 181–203). Springer International Publishing. https://doi.org/10.1007/978-3-030-91589-6_8

[17] Noriega, R., & Pourrahimian, Y. (2022). A systematic review of artificial intelligence and data-driven approaches in strategic open-pit mine planning. *Resources Policy*, *77*, 102727. https://doi.org/https://doi.org/10.1016/j.resourpol.2022.102727

[18] Paricheh, M., & Osanloo, M. (2020). Concurrent open-pit mine production and in-pit crushing–conveying system planning. *Engineering Optimization*, *52*(10), 1780–1795. https://doi.org/10.1080/0305215X.2019.1678150

[19] Rahmanpour, M., Osanloo, M., & Adibi, N. (2014). An approach to determine the location of an in pit crusher in open pit mines. *International Journal of Engineering*, *27*(9), 1475–1484. https://www.researchgate.net/publication/287680691_An_approach_to_determine_the_location_of_an_in_pit_crusher_in_open_pit_mines#fullTextFileContent

[20] Roumpos, C., Partsinevelos, P., Agioutantis, Z., Makantasis, K., & Vlachou, A. (2014). The optimal location of the distribution point of the belt conveyor system in continuous surface mining operations. *Simulation Modelling Practice and Theory*, *47*, 19–27.

[21] Samavati, M., Essam, D., Nehring, M., & Sarker, R. (2020). Production planning and scheduling in mining scenarios under IPCC mining systems. *Computers & Operations Research*, *115*, 104714. https://doi.org/https://doi.org/10.1016/j.cor.2019.05.019

[22] Seyed Hosseini, N., Ben-Awuah, E., & Pourrahimian, Y. (2020). A two-step approach to incorporate cut-off grade and stockpiling in oil sands mine planning optimization framework. *Computers & Operations Research*, *115*, 104659. https://doi.org/https://doi.org/10.1016/j.cor.2019.03.005

[23] Shamsi, M., Pourrahimian, Y., & Rahmanpour, M. (2022). Optimisation of open-pit mine production scheduling considering optimum transportation system between truck haulage and semi-mobile in-pit crushing and conveying. *International Journal of Mining, Reclamation and Environment*, *36*(2), 142–158. https://doi.org/10.1080/17480930.2021.1996983

[24] Sturgul, J. R. (1987). How to determine the optimum location of in-pit movable crushers. *Geotechnical and Geological Engineering*, *5*(2), 143–148.

[25] Tabesh, M., & Askari-Nasab, H. (2011). Two-stage clustering algorithm for block aggregation in open pit mines. *Mining Technology*, *120*(3), 158–169. https://doi.org/10.1179/1743286311Y.0000000009

[26] Tabesh, M., & Askari-Nasab, H. (2013). Automatic creation of mining polygons using hierarchical clustering techniques. *Journal of Mining Science*, *49*(3), 426–440. https://doi.org/10.1134/S1062739149030106

[27] Tabesh, M., & Askari-Nasab, H. (2019). Clustering mining blocks in presence of geological uncertainty. *Mining Technology*, *128*(3), 162–176. https://doi.org/10.1080/25726668.2019.1596425

[28] Tabesh, M., Askari-Nasab, H., & Peroni, R. (2015). A Comprehensive Approach to Strategic Open Pit Mine Planning with Stockpile Consideration. *Applications of Computers and Operations Research in Mineral Industry - 37th APCOM*, 326–332.

[29] Tabesh, M., Mieth, C., & Askari–Nasab, H. (2014). A multi–step approach to long–term open–pit production planning. *International Journal of Mining and Mineral Engineering*, *5*(4), 273–298. https://doi.org/10.1504/IJMME.2014.066577

Comparative Analysis of Semi-Mobile In-Pit Crushing and Conveying System (SMIPCC) and Truck-Shovel System Using Python Programming: Case Study

Khaleeq Ahmed and Yashar Pourrahimian
Mining Optimization Laboratory (MOL)
University of Alberta, Edmonton, Canada

ABSTRACT

Semi-mobile in-pit crushers and conveying systems (SMIPCC) are a type of IPCC that attracted the miners due to their relocation nature as an alternative to conventional Truck-shovel (TS) haulage systems. Most of the cost of mining operations arises from purchasing and maintaining haulage trucks to transport material from the working face to the crushers located outside the mine. This study aims to understand the importance of SMIPCC and its comparison with the TS system and to use Python programming to develop a code for comparative analysis. This code is based on cost analysis and evaluating the environmental impacts of SMIPCC and TS. The code is run on real-time open-pit mine data to compare the feasibility of SMIPCC and TS in the early stages of a mining project.

1. Introduction

This article is intended to analyze the comparison between Truck-shovel (TS) and Semi-mobile In-pit crusher and conveying system (SMIPCC) based on capital expenditures (CAPEX) and operational expenditures (OPEX) for the life of an open-pit mine. Open-pit mining is a capital-intensive venture that involves huge capital expenses in the initial stages of the mine and operational expenses for the whole life of the mine. Therefore, deciding between alternatives for material handling and transport is critical. In this study, the alternatives are SMIPCC and TS operations for transporting and handling material from the mine to the processing plant. In large open pit mines, the in-pit crusher and conveying (IPCC) system gained momentum over conventional TS systems due to the increasing fuel cost and labor cost of the TS system and also less greenhouse gas emission in IPCC [1]. Most mining companies are still hesitant to adopt these systems (IPCC) despite their popularity [2].

About 50% of the OPEX in surface mining comes from truck-shovel operations to handle and haul the material as indicated in studies [3]-[6], etc. Also, the reason for the transformation from standard truck and shovel operations to IPCC is that as the mine becomes deeper and the haul roads get longer, conventional truck transportation expenses rise [7]. Therefore, it is the need of the hour to minimize this hauling cost with some other alternative. OPEX of TS comes from diesel, lubrication, tire, and labour costs. This study aims to compare this TS operation of surface mining to some other alternatives and decide between two alternatives. For this purpose, a Python code is developed that takes the inputs for both alternatives and calculates the cost associated with these two alternatives (TS and SMIPCC). Based on this cost analysis decision can be made to choose between alternatives.

ISBN: 978-1-55195-503-2

2. Methodology

The method is designed as a model that uses the data available from the early stages of the evaluation of mining projects, usually from the scoping studies, as an input parameter [8]. This study focuses on comparing two alternatives so the input parameters for both alternatives are discussed.

2.1. Input Parameters

Input parameters for both alternatives are discussed below:

2.1.1. Material

Input parameters for the material are:

a. Density
b. Swell Factor
c. Moisture Content

2.1.2. Trucks Operating parameters

a. Haulage distance
b. Rolling and grade resistance
c. Speed limits (Empty and Full trucks)
d. Fixed time (load time, spot time, dump time)
e. Travel and wait time
f. Mechanical efficiency
g. Hourly efficiency

2.1.3. SMIPCC operating parameters

a. Primary crushing
b. Motor power
c. Length and height of conveyor

2.1.4. Economic parameters

a. CAPEX of trucks and SMIPCC
b. OPEX of trucks and SMIPCC
c. Discount and Exchange rate

The above following inputs are being used to calculate the fleet size for both TS and SMIPCC.

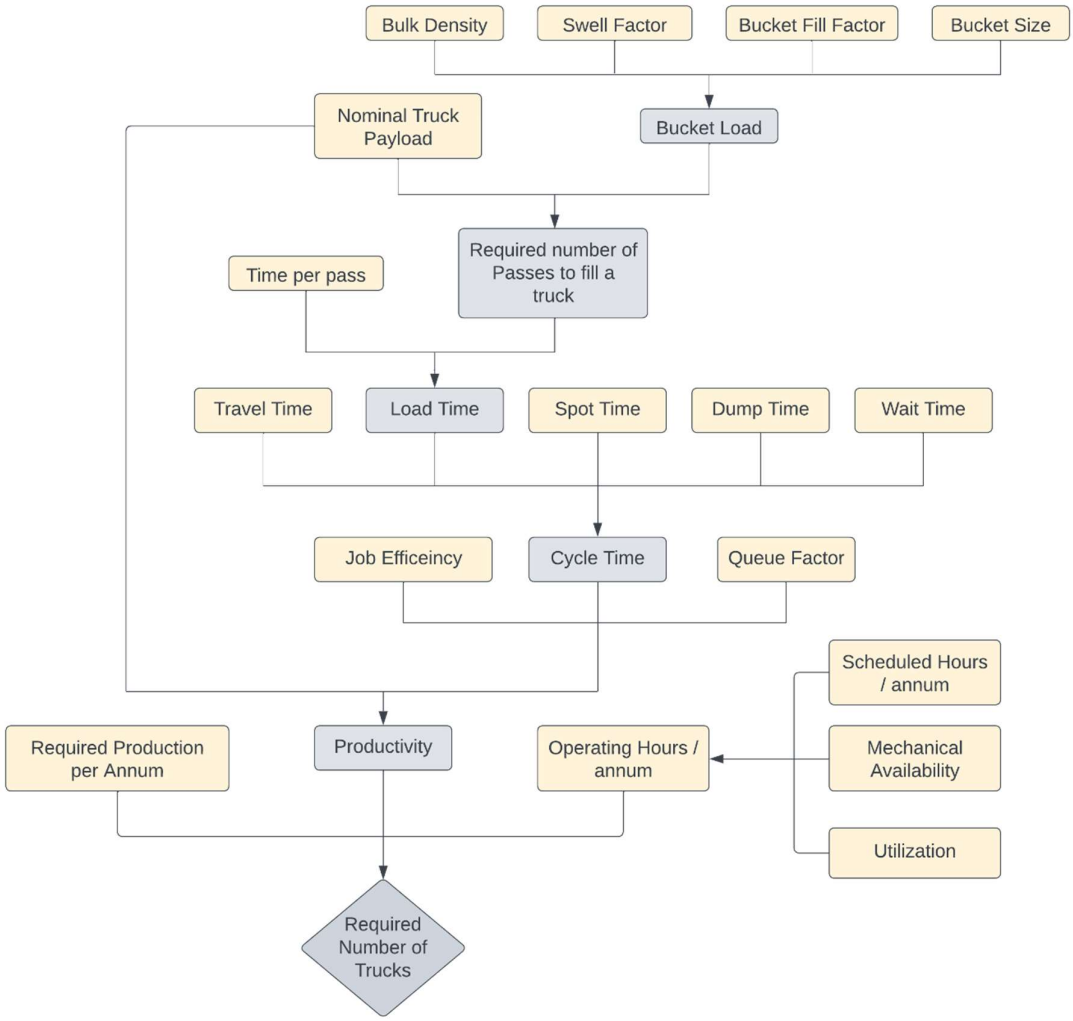
2.2. Fleet Sizing

Fleet sizing is calculated to find the number of trucks, excavators, and conveyors to handle and haulage the material being mined.

2.2.1. Truck Fleet Sizing

The following calculations are used to find the number of trucks required to handle and transport the material. Figure 1 illustrates the whole process for calculating the fleet sizing for trucks.

Figure 1. Fleet sizing for Trucks



a. Number of passes required to fill the trucks

The number of passes required to fill the trucks depends on the nominal payload of a truck and the bucket load. The nominal payload of a truck is the load that a truck can carry and is given by the manufacturer of the truck. Bucket load can be calculated using the density of the material being mined, bucket fill factor, and bucket size.

$$BL = \frac{BC \times BFF \times den}{SF} \tag{1}$$

Where BL is bucket load ($tonne$), BC is bucket capacity (m^3), BFF is bucket fill factor ($\%$), den is density of the material ($tonne/m^3$), and SF is swell factor of the material being mined.

After calculating the bucket load, the number of passes required to fill the truck can be calculated using Eq. (2):

$$\text{Number of passes} = \frac{\text{Nominal payload of truck (tonne)}}{\text{Bucket load (tonne)}} \quad (2)$$

b. Calculated truck payload

This payload is the average payload that the truck will carry after considering all of the above factors. It is calculated using Eq. (3):

$$\text{Calculated truck payload} = \frac{\text{Bucket load (tonne)}}{\text{Number of passes to fill truck}} \quad (3)$$

c. Load time

It is the time required to load a truck. It is calculated using Eq. (4):

$$\text{Load time (min)} = \text{time per pass (min)} \times \text{Number of passes to fill truck} \quad (4)$$

d. Fixed time

The time is essentially invariable for a truck and loading unit combination. It is the sum of load, spot, and dump time. Spot time depends on the nature of the spotting nature being used at the mine site and dump time depend on a truck's rear and bottom dump configuration. Fixed time can be calculated using Eq. (5):

$$\text{Fixed time (min)} = \text{Load time (min)} + \text{Spot time (min)} + \text{Dump time (min)} \quad (5)$$

e. Cycle time

It is the total time required for a truck to load, travel, and return for another trip. Travel time depends on the section length, maximum attainable speed, and speed factor. The speed factor for any truck can be found using a rimpull curve. The rimpull curve is the curve between the gross weight of the vehicle (GVW), the road's effective grade, and the truck's speed. Using Eq. (6), the travel time for any truck either it is empty or loaded with material can be calculated.

$$\text{Travel time (min)} = \frac{\text{Section length (m)} \times 0.06}{\text{Maximum attainable speed } (\frac{\text{km}}{\text{hr}}) \times \text{Speed factor}} \quad \textbf{(6)}$$

After calculating the travel time (for empty and full truck), total travel time can be calculated by adding empty and full truck travel time. The cycle time is calculated using Eq. (7).

$$\text{Cycle time (min)} = \text{Fixed time (min)} + \text{Travel time}_{\text{Full+Empty}}\text{(min)} + \text{Wait time (min)} \quad \textbf{(7)}$$

Wait time is the time a truck has to wait while the other truck is being loaded. This time depends on the excavator's configuration for loading the trucks.

f. Productivity

It is the amount of material being transported in a given time. It depends on efficiency, cycle time, calculated truck payload and queue factor. The queue factor is the time loss in queuing of

trucks. It ranges from 0.7 to 1.0 depending on the amount of time lost in placing the truck on a given position for loading. Productivity can be calculated using Eq. (8):

$$\text{Productivity}\left(\frac{\text{tonne}}{\text{hr}}\right) = \frac{\text{Efficiency (\%)}}{\text{Cycle time (min)}} \times \text{Queue factor} \times \text{Truck payload (tonne)} \quad (8)$$

Efficiency is basically the proportion of an hour as productive. It deducts the time being used in other operations like clean-up, fuelling, inspection etc.

g. Utilization

It is the measure of how much a mechanical unit can be utilized. It depends on mechanical availability and use of availability. It can be calculated using Eq. (9):

$$\text{Utilization (\%)} = \text{Mechanical availability (\%)} \times \text{Use of availability (\%)} \quad (9)$$

h. Operating hours

Operating hours per annum depend on the scheduled and utilization hours. It can be calculated using Eq. (10):

$$\text{Operating hours per annum} = \text{Scheduled hours per annum} \times \text{Utilization (\%)} \quad (10)$$

i. Production

Production (tonne/annum) depends on productivity (tonne/hr) and operating hours per annum. Production can be easily maximized by maximizing productivity.

$$\text{Production per annum (tonne)} = \text{Productivity}\left(\frac{\text{tonne}}{\text{hour}}\right) \times \text{Operating hours per annum} \quad (11)$$

j. Required units of trucks

Total number of units of trucks depends on the annual required production and the estimated annual production.

$$\text{Number of trucks} = \frac{\text{Annual required production (tonne)}}{\text{Estimated production per annum (tonne)}} \quad (12)$$

2.2.2. Excavator Fleet sizing

An excavator is used to mine and load the material into the trucks. Calculating the fleet size for the excavator is an important aspect to consider in feasibility studies. The process of finding the number of excavators required for a certain amount of production depends on productivity. It can be calculated using Eq. (13).

$$\text{Productivity}\left(\frac{\text{tonne}}{\text{Hour}}\right) = \frac{\text{Efficiency (\%)}}{\text{Load time + Sopt time}} \times \text{Calculated truck payload} \times \text{Propel factor} \times \text{Presentation factor} \quad (13)$$

Propel factor accounts for the time lost due to the movement of loading units around the mine. It depends on the loading unit type, pit size and the amount of movement required. It generally ranges from 0.95 to 1.0 for rope shovel and front-end loader, respectively. The presentation factor accounts for the time lost during waiting for a truck. It also generally ranges between 0.95 to 1.0. Rest of the process for calculating the number of excavators required is the same as for the number of trucks required, as explained before. Figure 2 shows the process for calculating the number of excavators required for a required annual production.

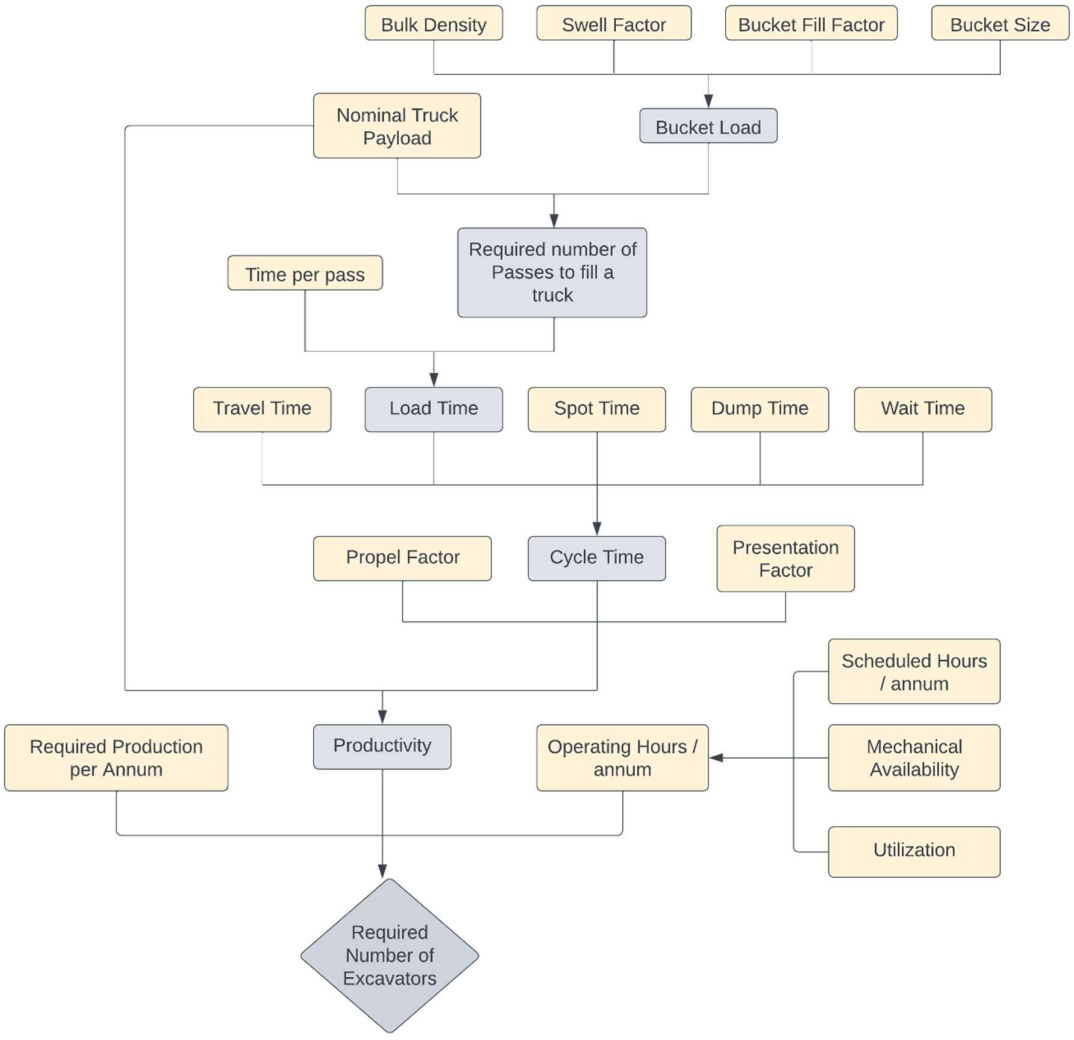


Figure 2. Fleet sizing for excavator

2.2.3. Conveyor Dimensions

As an alternative to truck shovel systems for material handling in mine, semi-mobile in-pit crushers and conveying (SMIPCC) systems are receiving more attention due to the rising cost of truck haulages, fuel price, and spare parts. SMIPCC is considered a low-operating-cost alternative due to its continuous operation, reduced labour, and lower energy consumption, but it requires high capital cost and has reduced flexibility (London et al. 2014).

In this study, SMIPCC aims to reduce the number of trucks and operation expenditures. In-pit crushers are being installed inside the pit at some location depending on the geotechnical properties and also to minimize the distance from the working face of the pit. Trucks haul the material from the face of the mine, and then IPCC crushes and conveys this material outside the pit using a conveyor. The cost of the following items is considered in the IPCC cost calculation.

- Conveyor belt
- Crusher
- Motors required to run the conveyor
- Head and tail assemblies
- Take up and Transfer towers
- Miscellaneous (20%)

The operational expenditures is related to the power required to run the motor. The power required to drive the conveyor belt is calculated using the following steps.

a. Power to drive empty belt

It is the power required to run the empty belt. It can be calculated using Eq. (14):

$$P_e = m_i \left(L + 45 \right) \times g \times \mu_e \times v \tag{14}$$

Where P_e is power to drive empty belt (Watt), m_i is the conveyor belt mass per unit length. It depends on the mass of the total conveyor belt length and the mass of the conveyor belt on idlers; taken from manufacturers' catalogues (kg/m). L is the conveyor length (m), g is acceleration, 9.81 m/s2, μ_e is the belt's friction coefficient on idlers, and v is velocity of the belt (m/s).

b. Power to convey the material

It is the power required to convey the material to the desired length. It is calculated using Eq. (15).

$$P_m = T \times L \times g \times \mu_e \tag{15}$$

Where T is carrying capacity of bulk solids in belt conveying system (kg/s).

c. Power to raise or lower the material

The power required to raise or lower the material to some height is calculated using Eq. (16).

$$P_r = T \times g \times h \tag{16}$$

Where h is the elevation change between the outlet and inlet (m).

The total power required to transport the material from one place to another can be calculated by summing all the powers calculated by Eqs. (14), (15), and (16) .

$$P_t = P_e + P_m + P_r \tag{17}$$

This is the total power required to convey the material from the pit to the outside. Based on this power required, the number of motors can be found and the cost associated with them, as shown in Figure 3.

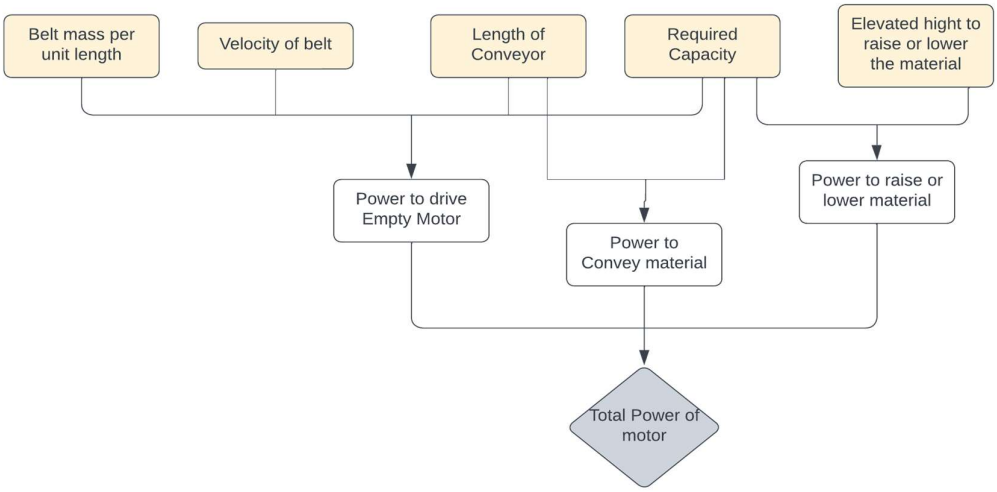


Figure 3. Fleet sizing for conveyor.

2.3. Economic evaluation

After calculating the fleet sizing for trucks, conveyors, and excavators, the next step is to evaluate the economics of these alternatives. The economic evaluation will take its CAPEX and OPEX, and based on these costs, the decision could be made.

2.3.1. Cost evaluation of trucks

In the TS haulage system, the CAPEX cost is purchasing the trucks, and its OPEX will be fuel, Lubrication, tires, and labour costs. Fuel cost for truck shovel alternative depends on the number of trucks required, fuel cost per litre, truck engine power, and fuel job factor (FJF). The FIF depends on machine and site-specific conditions. It usually ranges from 0.3 to 0.6. Fuel cost for trucks is calculated using Eq.(18).

$$\text{Fuel cost } (\frac{\$}{\text{hr}}) = \text{Engine power (kW)} \times 0.3\ (\frac{\text{L}}{\text{h}}\text{per kW}) \times \text{FJF} \times \text{Unit cost } (\frac{\$}{\text{L}}) \quad (18)$$

After calculating the fuel cost for a required number of trucks lubrication cost can be calculated using the fuel cost. Generally, the lubrication cost is 15 – 40 % of the fuel cost. So, the total OPEX for trucks can be calculated by summing the cost of fuel, lubrication cost, labor cost, and tires cost as shown in Figure 4.

$$\text{OPEX}_{\text{TRUCK}} = \text{Fuel cost (\$)} + \text{Lubrication cost (\$)} + \text{Labor cost (\$)} + \text{Tire cost (\$)} \quad (19)$$

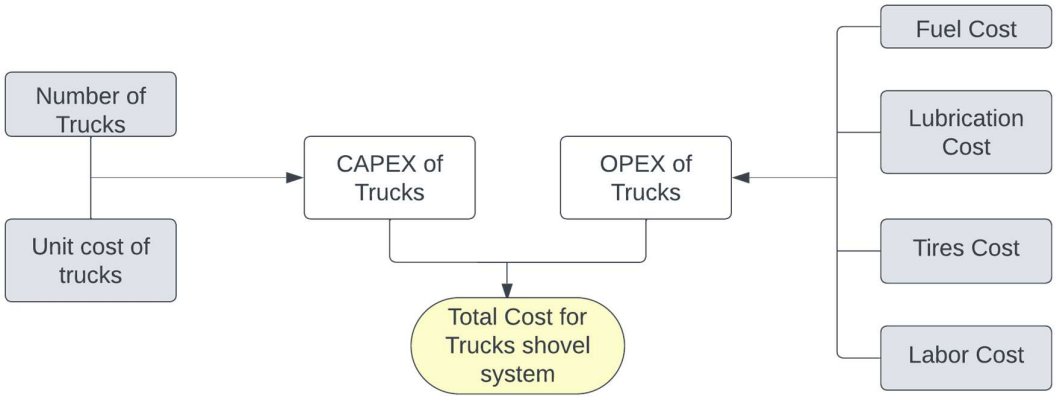


Figure 4. Cost evaluation for trucks.

2.3.2. Cost Evaluation for Conveyors

SMIPCC uses conveyors to transport the material from the pit to the outside. The cost associated with the conveyor design can be calculated after calculating the sizing for the conveyor design. The CAPEX associated with the conveyor is the installation of in-pit crusher, belt price, motor price, head and tail assemblies, take-up and transfer towers, and miscellaneous costs (20%). The OPEX related to the conveyor can be found as the total power consumption by the main motor and the additional motors, and power taken by the crusher to crush the material as shown in Figure 5.

2.4. Python GUI for Calculation

The main objective of this study is to develop the GUI for the calculation of fleet sizing and then cost evaluation of both the alternatives (Truck-shovel and SMIPCC). All of the coding is done by using Python 3.11.3. GUI has been developed to take the inputs from the user, and then based on these inputs system calculates the fleet sizing for trucks, conveyors, and excavators. All of the inputs and the calculation formulas have been discussed above. Users can choose between SMIPCC and Truck-shovel system as shown in Figure 6.

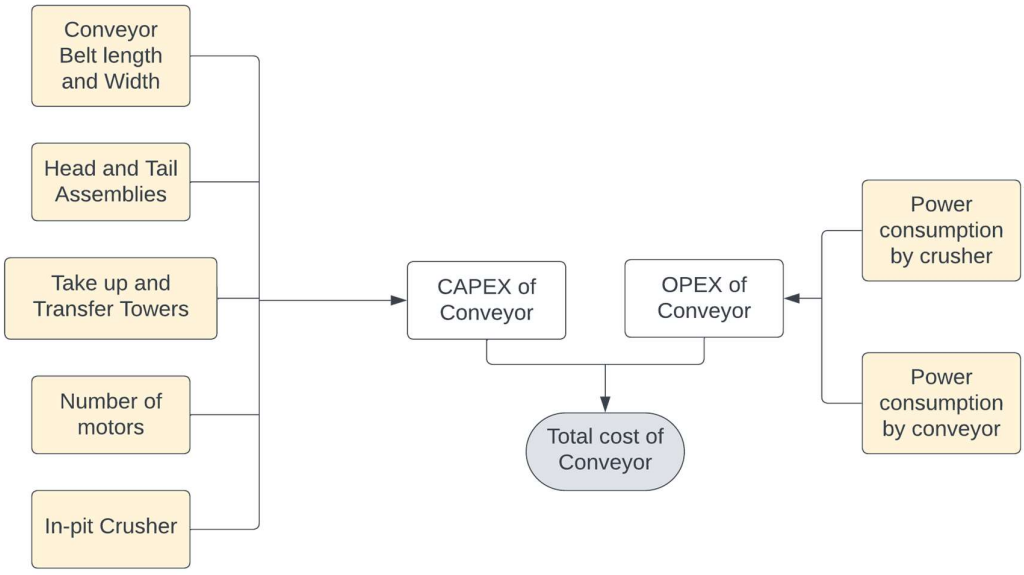


Figure 5. Cost Evaluation of IPCC.

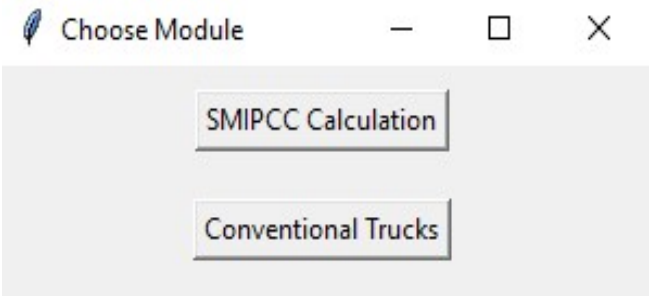


Figure 6. Starting GUI.

After selecting the choice by the user, the next window is to get input values from the user as shown in Figure 7. depicts the operational expenditures associated with the trucks. Similarly, the GUI for conveyor calculation and associated cost is developed as some part is shown in Figure 9.

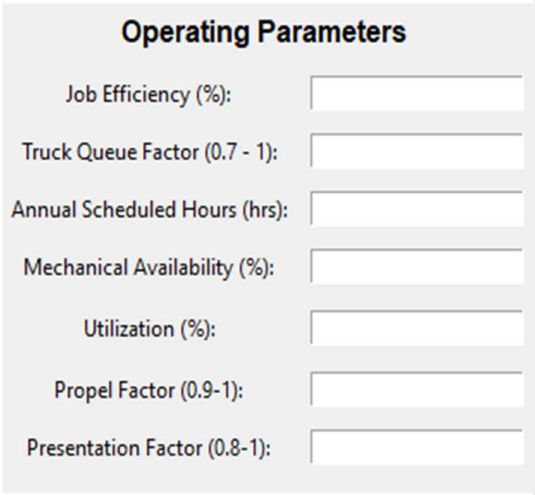


Figure 7. GUI for inputs of Trucks calculator.

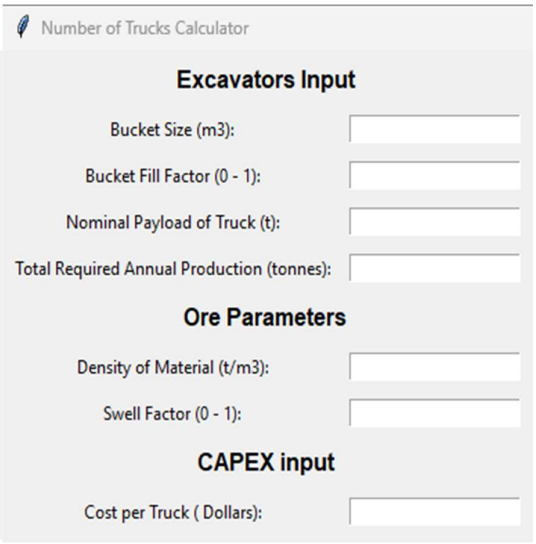


Figure 8. GUI for OPEX input for trucks.

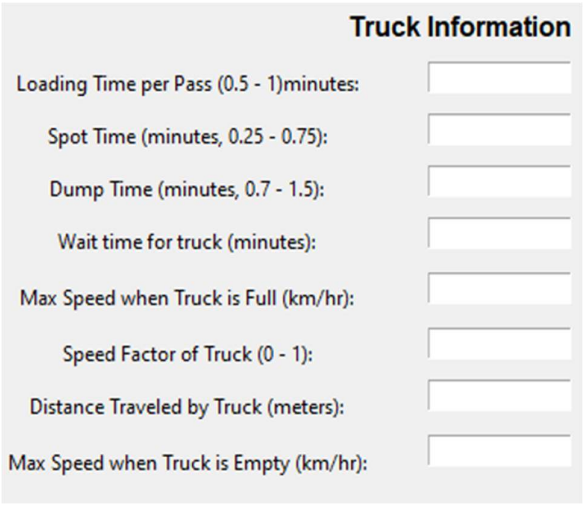
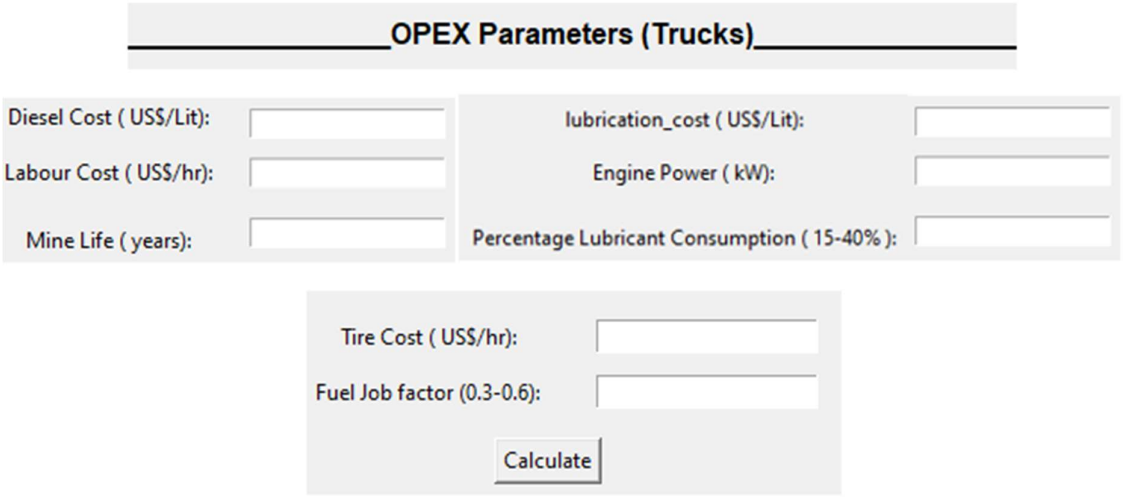


Figure 9. GUI for OPEX of Conveyor.



3. Case study and conclusion

Hypothetical data was input to this system to calculate the fleet sizing and was being cross verified with real-time data. The total distance from mine face to outside the crusher is 1600 meters. In the case of the truck shovel system, the material is mined and then transported to the outside crusher using only trucks. But using SMIPCC, the crusher is being installed at a distance of 500 meters from the face of the mine. So, the trucks deliver the material from the face of the pit to the crusher, which will then be crushed and transported to the outside of the pit by conveyor (1100 meters). Table 1 summarizes the rest of the data used in the evaluation.

Table 1. Hypothetical input data.

Equipment (Cat 789)			**OPEX truck data**		
Nominal payload	tonne	172	Electricity cost	US$/MWh	73.6
Material		Granite	Diesel cost	US$/l	0.7
Bulk density	tonne/m^3	2.65	Lubrication cost	US$/l	0.1
Swell factor		1.5	Tire cost	US$/h	68
Bucket load	tonne	38.87	Labour cost	US$/h	63.5
Time per pass	min	0.5	Engine power	kW	1082
Spot time	min	0.8	FJF	0.3-0.6	0.6
Dump time	min	1	Lubrication consumption	15%-40%	33.3
Travel time	min	12	**Time values**		
Waite time	min	0	Hours per year	hours	8760
Efficiency	min/hour	50	Effective hrs per year	hours	5887
Queue factor		1	LOM	yrs	20
Scheduled hrs/annum	hour	7580			
Availability	%	82			
Use of availability	%	85			

Required production	tonnes	1,000,0000	
Propel factor	%	0.9	
Presentation factor	%	0.8	

This input data comprises values required for both TS and SMIPCC.

Based on the data, the model calculated the fleet sizing for both the TS system and SMIPCC.

Table 2 shows the fleet sizing for both conventional Truck shovel and SMIPCC. In conventional truck shovel the number of trucks is higher as compared to SMIPCC as in SMIPCC the section length is less than that of TS. Excavators, graders and bulldozer are same for both the alternatives. In SMIPCC there is conveyor to transfer the material from the mine to outside the pit.

After inputting the cost data, the TS system's CAPEX was low compared to the SMIPCC because a crusher and conveyor was installed in the pit as shown in Table 3. The prices are in thousands of dollars. But the OPEX of TS system is high as compared to the SMIPCC system because of the continuously fuel and maintenance cost involved in the trucks.

Table 2. Fleet sizing for TS and SMIPCC.

Fleet Sizing		
Equipment	Conventional	SMIPCC
Trucks	5	2
Excavator	1	1
Graders	1	1
Bulldozer	1	1
Conveyor	0	1

CAPEX of SMIPCC is almost 24% higher than that of the TS system as most of the capital is involved in installation of conveyor and crusher. This higher CAPEX of SMIPCC can be overcome if the life of the mine is more.

Table 3. Economic Results.

Thousands		**Conventional**	**SMIPCC**
Initial CAPEX	US $	$ 18,000	$ 22,350
OPEX	US $	$ 126,119	$ 76,694

But OPEX of trucks is about 37% more than that of the SMIPCC due to a smaller number of trucks involved in SMIPCC. Therefore, SMIPCC is getting more attention than the conventional truck shovel system, and the environmental concerns related to SMIPCC are less as in SMIPCC, few trucks are used compared to the truck shovel system. So, less fuel is burnt and less environmental hazard. The only problem that exists with the SMIPCC alternative is life of mine. Short mine life is not a feasible option because in SMIPCC, the CAPEX is high compared to the TS system and has a longer payback period.

4. References

[1] Al Habib, N., E. Ben-Awuah, and H. Askari-Nasab, Review of recent developments in short-term mine planning and IPCC with a research agenda. Mining Technology, 2023: p. 1-23.

[2] Shamsi, M., Y. Pourrahimian, and M. Rahmanpour, Optimisation of open-pit mine production scheduling considering optimum transportation system between truck haulage and semi-mobile in-pit crushing and conveying. International Journal of Mining, Reclamation and Environment, 2022. 36(2): p. 142-158.

[3] Afrapoli, A.M., M. Tabesh, and H. Askari-Nasab, An investigation into dispatch optimizers using truck-shovel simulation and a new multi objective truck dispatching technique. Mining Optimization Laboratory, 2017. 1(780): p. 100.

[4] Osanloo, M. and M. Paricheh, In-pit crushing and conveying technology in open-pit mining operations: a literature review and research agenda. International Journal of Mining, Reclamation and Environment, 2020. 34(6): p. 430-457.

[5] da Cunha Rodovalho, E., H.M. Lima, and G. de Tomi, New approach for reduction of diesel consumption by comparing different mining haulage configurations. Journal of environmental management, 2016. 172: p. 177-185.

[6] Bozorgebrahimi, E., R. Hall, and G. Blackwell, Sizing equipment for open pit mining–a review of critical parameters. Mining Technology, 2003. 112(3): p. 171-179.

[7] Moradi-Afrapoli, A. and H. Askari-Nasab, Advanced Analytics for Surface Extraction, in Advanced Analytics in Mining Engineering: Leverage Advanced Analytics in Mining Industry to Make Better Business Decisions. 2022, Springer. p. 181-203.

[8] Burt, K., C. McShane, and O. Fong, Monograph 27-Cost Estimation Handbook. Australia: 2nd ed. Australasian Institute of Mining and Metallurgy, 2020.

Decisive Factors and Constraints of In-Pit Crushing and Conveying (IPCC) Regarding Long-Term Mine Planning

Sandra Katharina Fahl and Hooman Askari-Nasab
Mining Optimization Laboratory (MOL)
University of Alberta, Edmonton, Canada

ABSTRACT

Different In Pit Crushing and Conveyor (IPCC) systems, their usage, benefits and functionality are outlined and compared. An overview is given on decision-making factors regarding the inauguration of IPCC in long-term mine planning. In addition, real world technical constraints of IPCC are identified through a comprehensive literature review. Suggestions are given for further research and the implementation of the decisive factors in decision making tools. An outlook on the implementation of decisive factors and constraints in current and future simulation and optimization tools regarding strategic mine planning is presented.

1. Introduction

The demand for sustainably mined raw materials is constantly rising. The world's population reached 8 billion people in 2022, and the demand for raw materials is growing with the world's population. Meeting this demand will represent a challenge, as the ore deposits are getting deeper and have lower grades. Thus, deposits are becoming more complex to mine. Moreover, the fuel and labor costs are continuously rising. To answer the climate crisis, more energy-efficient and sustainable mining solutions are required. Haulage is a major part of the mining costs, it represents approximately 50-60 %. Haulage also accounts for a lot of emissions.

In Pit Crushing and Conveyor (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, there is no coherent framework for the inauguration of IPCC. Which decision-making factors need to be analyzed when considering to implement IPCC? What are the constraints of the IPCC usage? Or in short, under which circumstances is it not feasible or thoughtful to use IPCC? Here, a comprehensive overview of decisive factors and constraints of IPCC usage found in the current literature is provided.

Currently decisive factors are only utilized based on case studies of single mining projects. These research data are therefore not in general representative for the entire surface mining industry. This paper aims to close this literature gap and to provide recommendations for further research on this topic. To achieve this, some general background information is given about different IPCC systems. Shortcomings and benefits of IPCC are compared. A structured, standardized review of the current literature is conducted to find out decisive factors and their relevance. All of the previously found decisive factors are listed and the usage is counted to evaluate the relevance of each factor. In a second step, constraints of IPCC usage are outlined and discussed. In conclusion an outlook on further research potential is given and the findings are summarized.

ISBN: 978-1-55195-503-2

2. General Information

Some background information about In-Pit Crushing and Conveyor (IPCC) systems is presented in the following. The three different types: Fully-mobile, Semi-mobile and Fixed IPCC are explained. A review of the current industry IPCC usage and current industry trends are referenced. The IPCC system is compared with truck haulage, the resulting benefits and shortcomings are listed.

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 of 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.

Figure 1 shows the process flow of the IPCC system, which is a bulk material handling system that includes a feed system, crusher stations(s), a conveyor belt and a discharge system. (Ritter, 2016) P.8

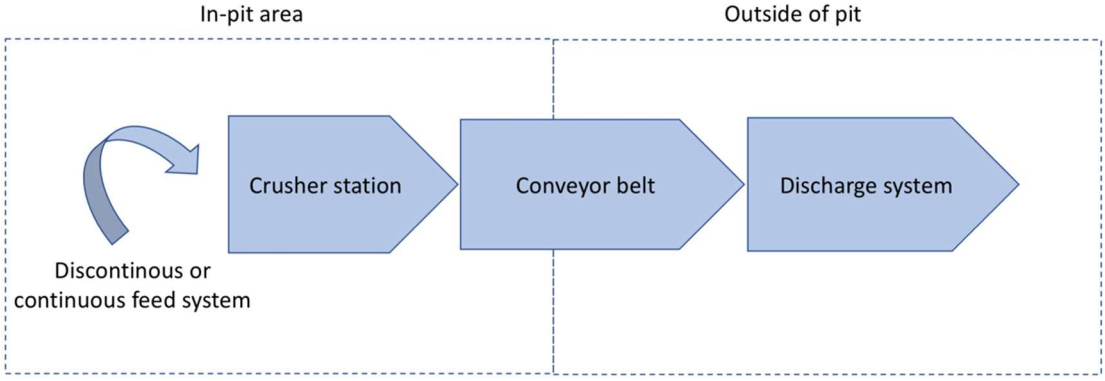


Figure 1 IPCC process flow chart based on (Ritter, 2016) P. 8

IPCC systems can be categorized based on their level of mobility into the three categories: Fixed, Semi-mobile and Fully mobile IPCC crusher systems. 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 are located at one specific position for several years. Fixed crusher stations are located inside the pit and do not change their position. (Ritter, 2016) P.8 et seq.

An industry overview is for example given by (Ritter, 2016). Other studies focused on specific countries or industry sections, for example (Braun, 2019) focused on quarries in Germany. To gain an overview of current trends in the IPCC usage, refer to current journal articles like (Leonida, 2019), (Al Habib et al., 2022), (Noriega & Pourrahimian, 2022) or (a Carter, 2010).

Benefits of IPCC include, but are not limited to:

- Less local emissions like dust, noise, NO_x emissions, CO_2 emissions
- Less deadweight transportation
- In most cases, reduced operating costs like labor costs, fuel costs
- Reduced safety risks
- Conveyor belts are able to cross obstructions
- Continuous and predictable operation due to continuous flow of material and long-term mine planning, process is easy to simulate which allows a flexible relocation analysis
- Notable reduction in road maintenance costs (Utley, 2011) P.909

There are some general, main shortcomings of IPCC compared to haul truck usage:

- The mine planning is not flexible. For instance, it is not possible to easily change the location of a conveyor belt or increase/decrease its capacity.
- High capital costs have to be paid beforehand
- Availability and reliability of the IPCC system is essential. There might be a shortage of repair parts in remote areas. Foresighted maintenance must be done. If only one component fails with unplanned downtime, the whole production stream is not utilizable. If these problems are not fixed, this might result in failure to meet the targeted production capacity.
- The material loaded must fulfill certain conditions to be crushable and transportable with the conveyor belt. Some properties are obvious, for example the lump size. Others like the clay content and the associated adhesive strength are not obvious.

  (Utley, 2011) P.909
- Few benchmarks of IPCC projects exist, especially for smaller operations it is difficult to obtain reference data
- IPCC systems are difficult to test before an inauguration decision is made

  (Braun, 2019) P.3 (Leonida, 2019)

Through this, some general information about IPCC was presented. Additional information sources for an industry overview, which is not scope of this work were given. Lastly, IPCC system usage was compared to the truck and shovel usage.

3. Decisive Factors

Considering the shortcomings and benefits of IPCC usage, it is not possible to draw a general conclusion about the usage of IPCC at a specific mine site or not. Therefore, other decisive factors need to be considered. To find out which factors are relevant, current books, dissertations, journal articles and conference proceedings were reviewed. Each decisive factor was listed in a table together with the reference to the source in the appendix. The relevance of each factor was evaluated.

The results are presented in Table 1. The most common and thus most relevant factors are explained below. Some factors were considered as neglected because of the number of occurrences in literature but considered important for the decision-making process. These factors are outlined without a relevance statement and discussed further along with the other results.

Table 1 Resulting overview of decisive factors found in current literature

Category	Decisive factor	Count	Relevance
Economic	Operating Cost (OPEX)	4	Medium
	Capital Cost (CAPEX)	4	Medium
	Economic Index (EcI)	1	Low
	Net Present Value (NPV)	7	High
Category	Decisive factor	Count	Relevance

	Other economic analysis, cost analysis, sensitivity analysis	5	High
Performance	Mine Life	3	-
	Mining Capacity	3	-
	Utilization	1	-
	Availability	3	-
	Productivity	1	-
	Mine Productivity Index (MPI)	2	-
	Resource Recovery	1	-
	Major shortcomings of truck usage*	1	-
Environmental	Pollutants	3	-
	Life Cycle Assessment (LCA)	2	-
	Other environmental study	1	-
Social	Safety	1	-
	Other social concerns	1	-

*Major mine specific shortcoming of truck usage for instance insufficient climatic conditions for road conditions, dust, wash holes etc.

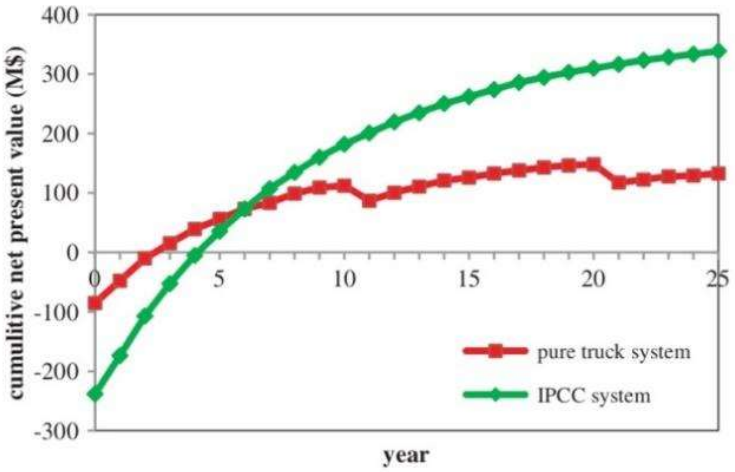


Figure 2 Graph showing the comparison of NPV for IPCC system and truck and shovel adopted from (Osanloo & Paricheh, 2019) P. 436

Figure 2 is a graph showing the typical comparison of NPV, or discounted cumulative yearly cash flow for both the operation of the IPCC system and the truck and shovel system. The IPCC system

must be replaced after 20 – 25 years whereas trucks require major replacement and maintenance after approximately seven to ten years of operation. This is a common example of the usage of decisive factors to evaluate IPCC systems in long-term mine planning. In practice, the long-term mine plan needs to include an optimal IPCC location and relocation plan in addition to the financial analysis. (Osanloo & Paricheh, 2019) P. 436, (Moradi-Afrapoli & Askari-Nasab, 2022) P.199

This section gave a coherent overview about decision-making factors regarding long-term mine planning. The major result, the importance of the NPV was analyzed and explained with an example.

4. Constraints of IPCC Usage

While constraints of IPCC usage seem to be similar to IPCC shortcomings and there might be some overlaps, the two topics are not totally similar. In this section it is asked under which circumstances it is not feasible or useful to inaugurate IPCC into a new or running operation. It is important to distinguish between technical and economical IPCC usage constraints, while each of them can be equally important. Both categories are presented here. The mentioned constraints are analyzed and discussed.

Some major economic constraints are presented here:

- One of the major economic constraints is the necessity to invest a high amount of **upfront capital costs**. (Utley, 2011) P.943
- The **flexibility** of the operation has decreased drastically**.** For example, it is not feasible to increase or decrease the capacity of the IPCC system whereas an additional truck is easily bought. (Osanloo & Paricheh, 2019) P. 452
- IPCC is most effective if used for **long haulage distances**, to transport **high tonnage** and used over a **long mine life**. Smaller operations are mostly unable to meet these constraints. (Mohammadi & Moosakazemi, 2011) P.11
- Predictive maintenance is necessary to overcome unplanned downtime. Maintenance and other **downtime** limit the production time and economic viability of the operation. (Morrison, 2017)
- **Limited knowledge** and the non-availability of benchmarks of similar projects makes it difficult to assess the performance of IPCC systems before implementing them. There is a high economic risk when implementing IPCC especially for smaller operations mainly because the system cannot be tested easily and of these lacks of information. (Braun, 2019) P.2

Some major technical constraints are listed below:

- The availability of a **stable electric grid** is a requirement for the successful implementation of an IPCC system. (Braun, 2019) P.2
- Often not considered but important is the **configuration of the loaded material**. Its coarseness, load ability, water content, abrasiveness or the content of sticky clays etc. can determine the success of an IPCC operation. (Utley, 2011) P. 944
- The **angle of the conveyor belt** is a limitation if a traditional conveyor belt is used. For high angle conveyors the additional cost of these alternative conveyor systems and eventual throughput limitations must be considered. (Osanloo & Paricheh, 2019) P.452
- Ideally **unconsolidated** or easy to extract **rock** makes an IPCC inauguration feasible (Braun, 2019) P.2

These constraints have changed in recent years with the technical progress. While technical restrictions are overcome, precise planning is still essential for the operation. (b Carter, 2015) P.42

For example the usage of high angle conveyors has become more common. A case study about the usage of a high angle conveyor can be found from (dos Santos & Stanisic, 1986).

5. Discussion of Results

The results obtained from the systematic review of the current literature and the search for decisive factors are discussed here. The relevance of the economic decisive factors are significant. Other factors like social life cycle analysis can be considered neglected, when considering how seldom they were mentioned in the latest literature. Economic factors are definitely important for the success of the IPCC inauguration but other factors like performance, environmental and social factors should not be neglected when making a decision.

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. This is the major shortcoming of the state-of-the-art approaches to decision-making and IPCC planning.

6. Conclusion

This review has covered a wide range of thirty studies to determine the major decisive factors of IPCC systems regarding long-term mine planning. In addition to the analysis of decisive factors, technical and economical constraints are categorized and summarized. The discussion of the results shows that many important decisive factors are neglected in the latest literature. It also shows the importance of economic factors such as the NPV. While this economic factor is without question important, other performance, economic, environmental and social factors are sparsely found in literature.

Some recommendations for further research are the systematic reporting of benchmarking parameters of existing IPCC operations to provide more data for the decision-making process in long-term mine planning. In addition, more modeling and subsequent simulations should be conducted, which overcomes the shortcoming of the lack of testability of IPCC systems.

Economic, performance, environmental and social decisive factors should be analyzed before deciding about the implementation of an IPCC system in a long-term mine plan. There are technical and economical constraints for the IPCC usage. Some of these constraints are often overlooked in long-term mine planning while others like the high upfront capital costs are more obvious. The technical constraints range from the configuration of the loaded material among others to the stability of the electric grid. The technical constraints can be overcome with technical progress, whereas precise planning stays crucial to overcome the economic constraints.

7. Suggestions and Future Research

An outlook on the implementation of decisive factors and constraints of the currently existing and future simulation and optimization tools regarding strategic mine planning is presented. Some approaches model the IPCC system mathematically for example with a system dynamics model (Abbaspour & Drebenstedt, 2019). Such models can be used to model the transition time from a truck and shovel operation to an IPCC operation. Other innovative approaches focus on simulation techniques such as discrete-event simulation. Unlike mathematical modeling discrete event simulation can be used to model dynamic processes. These tools can be used to study models that are discrete, dynamic and stochastic. The accessed decisive factors can be input parameters for future discrete event simulation models. With the help of such models, what-if scenarios can be created, to decide about the best possible IPCC operation. State of the art studies of comparison of truck and shovel operations with IPCC operations through discrete-event simulation were for instance

conducted by (Bernardi, Kumral, & Renaud, 2020) and (Villeneuve, Ben-awuah, & Vasquez-Coronado, 2020).

Further research should focus on the systematic reporting of benchmarking parameters of IPCC operations and the implementation of the accessed decisive factors into calculation or simulation models. Data of smaller IPCC operations is especially relevant for the future, successful implementation of the technique in the industry.

8. References

[1] Abbaspour, H., Drebenstedt, C., & Dindarloo, S. (2018). Evaluation of safety and social indexes in the selection of transportation system alternatives (Truck-Shovel and IPCCs) in open pit mines. *Safety Science, 1-12.*

[2] Abbaspour, H., & Drebenstedt, C. (2019). Determination of Transition Time from Truck-Shovel to an IPCC System Considering Economic Viewpoint by System Dynamics Modelling. *Proceedings of the 28th International Symposium on Mine Planning and Equipment*

[3] Abdollahi, S., Aghayarloo, R., Afrapoli-Moradi, A., & Askari-Nasab, H. (2020). An LCA-LCCA Decision Making Framework for Selecting the Most Sustainable Material Transportation System in Surface Mines. *International conference Economic Management in Mineral Activities - EMMA 5 (pp. 25-39). Hanoi: Publishing house for science and technology.*

[4] a Carter, R. (2010). Latest IPCC Systems Provide Improved Operational Flexibility, Higher Capacity. *Coal Age.*

[5] Al Habib, N., Ben-Awuah, E. & Askari-Nasab H. (2022). Review of Recent Developments in Short-Term Mine Planning and IPCC. *MOL Report Ten.*

[6] b Carter, R. (2015). Precise Planning is Paramount for IPCC success. *Engineering & Mining Journal, 42-46.*

[7] Bernardi, L., Kumral, M., & Renaud, M. (2020). Comparison of fixed and mobile in-pit crushing and conveying and truck-shovel systems used in mineral industries through discrete- event simulation. *Simulation Modelling Practice and Theory, 1-12.*

[8] Braun, T. (2019). Clusteranalytischer Technologievergleich zur Quantifizierung von ökonomischen Einsatzpotentialen alternativer Transporttechniken in Natursteintagebauen mit dem Ziel der Energieeffizienzerhöhung. Koblenz: *Fakultät für Georessourcen und Materialtechnik der Rheinisch-Westfälischen Technischen Hochschule Aachen.*

[9] c Carter, R. (2022). Taking a closer look at IPCC. *Engineering and Mining Journal, 16-19.*

[10] dos Santos, J., & Stanisic, Z. (1986). In-pit crushing and high angle conveying in a Yugoslavian copper mine. In K. Smale-Adams, *Mining Latin America/ Mineria Latinoamericana (pp. 101- 113)*. Dordrecht: Springer.

[11] Leonida, C. (2019). IPCC steadily gains traction. *Engineering and Mining Journal, 68-73.*

[12] Liu, Dingbang, & Pourrahimian, Y. (2021). A Framework for Open-Pit Mine Production Scheduling under Semi-Mobile In-Pit Crushing and Conveying Systems with the High-Angle Conveyor. *Mining, 59-79.*

[13] Mikhailov, A., Garmaev, O., Garifullin, D., & Kazakov, Y. (2019). A potential application of in-pit crushing-conveying and dewatering system in peat mining. *IOP Conference Series: Earth and Environmental Science, (pp. 2-5)*. St. Petersburg.

[14] Mohammadi, M., & Moosakazemi, F. (2011). Review of the in-pit crushing and conveying (IPCC) system and its case study in copper industry. *The 1st World Copper Congress, (pp. 1-15)*. Santiago.

[15] Moradi-Afrapoli, A., & Askari-Nasab, H., (2022). Advanced Analytics for Surface Extraction. *Advanced Analytics in Mining Engineering. Leverage Advanced Analytics in Mining Industry to Make Better Business Decisions.* Edited by Soofastaei A., Springer.

[16] Morrison, D. (2017). The full picture of IPCC system implementation; The reason why so many fail. *Mining Engineering Magazine, 15-19.*

[17] Nehring, Knights, Kizil, & Hay. (2018). A comparison of strategic mine planning approaches for in-pit crushing and conveying, and truck/shovel systems. *International Journal of Mining Science and Technology, 205–214.*

[18] Norgate, T., & Haque, N. (2013). The greenhouse gas impact of IPCC and ore-sorting technologies. *Minerals Engineering, 13-21.*

[19] Noriega, R., & Pourrahimian, Y. (2022). A systematic review of artificial intelligence and data-driven approaches in strategic open-pit mine planning. *Resources Policy, 1-13.*

[20] Nunes, R., Delboni, H., de Tomi, G., Infante, C., & Allan, B. (2019). A decision-making method to assess the benefits of a semi-mobile in-pit crushing and conveying alternative during the early stages of a mining project. *Mining REM Int. Eng. Journal, 285-291.*

[21] Osanloo, M., & Paricheh, M. (2019). In-pit crushing and conveying technology in open- pit mining operations: a literature review and research agenda . *International Journal of Mining, Reclamation and Environment, 430-457.*

[22] Paricheh, M., & Osanloo, M. (2020). Concurrent open-pit mine production and in-pit crushing–conveying system planning. *Engineering Optimization , 1780-1795.*

[23] Radlowski, J. (1988). In-Pit Crushing and Conveying as an alternative to an all truck system in open pit mines Master Thesis. Vancouver: *The University of British Columbia.*

[24] Ritter, R. (2016). Contribution to the Capacity Determination of Semi-Mobile In-Pit Crushing and Conveying Systems. Freiberg: *Faculty of Geosciences, Geoengineering and Mining of the Technische Universität Bergakademie Freiberg.*

[25] Samavati, M., Essam, D., Nehring, M., & Sarker, R. (2020). Production planning and scheduling in mining scenarios under IPCC mining systems. *Computers and Operations Research , 1-17.*

[26] Shamsi, M., Pourrahimian, Y., & Rahmanpour, M. (2022). Optimisation of open-pit mine production scheduling considering optimum transportation system between truck haulage and semi-mobile in-pit crushing and conveying. *International Journal of Mining, Reclamation and Environment, 142-158.*

[27] Sousa, J., Fernandes, R., Luz, R., dos Santos, I., da Silva, B., & Neto, I. (2022, January 31). Description of the IPCC mining process and analysis of the profile of productivity losses applied by a mining company in northern Brazil. *Retrieved from Researchsquare:* https://assets.researchsquare.com/files/rs-1308199/v1/6b573817-51ff-482d-90af-b17e17ab05d2.pdf?c=1643643722

[28] Topf, A. (2017, February 16). In-pit crushing and conveying systems changing the way ore is moved. *Retrieved from Mining.com:* https://www.mining.com/in-pit-crushing-systems-changing-the-way-ore-is-moved/

[29] Utley, R. (2011). In-Pit Crushing. In P. Darling, SME Mining Engineering Handbook (pp. 941-956). Littelton: SME.

[30] Villeneuve, J., Ben-awuah, E., & Vasquez-Coronado, P. (2020). Hierarchical Mine Planning for a Semi-Mobile In-Pit Crushing and Conveying System Using Discrete-Event Simulation. *Proceedings of 6th UMaT Biennial International Mining and Mineral Conference, (pp. 21-32). Tarkwa.*

[31] Wachira, D. (2022). Evaluation of In-Pit Crushing and Conveying (IPCC) Systems Productivity in Open Pit Mines. Voi: *Department of Mining and Mineral Processing Engineering of Taita Taveta University.*

[32] Wachira, D., Githiria, J., Onifade, Moshood, & Mauti, D. (2021). Determination of semi-mobile in-pit crushing and conveying (SMIPCC) system performance. *Arabian Journal of Geosciences, 1-13.*

9. Appendix

9.1. List of Abbreviations

Table 2 List of abbreviations used in the paper.

Term	Abbreviation
Capital Costs	CAPEX
Economic Index	EcI
In-pit crushing and conveying	IPCC
Life cycle assessment	LCA
Mine Productivity Index	MPI
Net present value	NPV
Operating Costs	OPEX

9.2. Detailed overview of results

Table 3 Resulting overview of decisive factors found in current literature.

References	Method of IPCC	Category	Decisive factor	Mentioned in number of papers
(Nunes, Delboni, de Tomi, Infante, & Allan, 2019), (Abbaspour & Drebenstedt, 2019) (Leonida, 2019) (Mohammadi & Moosakazemi, 2011) (b Carter, 2015) (c Carter, 2022) (Radlowski, 1988)		Economic	OPEX	7
(Nunes, Delboni, de Tomi, Infante, & Allan, 2019), (Abbaspour & Drebenstedt, 2019) (Leonida, 2019) (Mohammadi & Moosakazemi, 2011)			CAPEX	4
(Abbaspour & Drebenstedt, 2019)			EcI	1
References	Method of IPCC	Category	Decisive factor	Mentioned in number of papers

(Nehring, Knights, Kizil, & Hay, 2018), (Samavati, Essam, Nehring, & Sarker, 2020), (Nunes, Delboni, de Tomi, Infante, & Allan, 2019) (Liu, Dingbang, & Pourrahimian, 2021) (Paricheh & Osanloo, 2020) (Villeneuve, Ben-awuah, & Vasquez-Coronado, 2020) (Leonida, 2019) (Shamsi, Pourrahimian, & Rahmanpour, 2022) (Radlowski, 1988)	Semi-mobile, Fully mobile		NPV	9
(Bernardi, Kumral, & Renaud, 2020) (Osanloo & Paricheh, 2019) (Topf, 2017) (Mohammadi & Moosakazemi, 2011) (Mikhailov, Garmaev, Garifullin, & Kazakov, 2019) (Morrison, 2017)	Fixed/mobile Fully mobile		Other economic analysis, cost analysis, sensitivity analysis	6
(Abbaspour & Drebenstedt, 2019) (Villeneuve, Ben-awuah, & Vasquez-Coronado, 2020) (Mohammadi & Moosakazemi, 2011)	Semi-mobile	Performance	Mine Life	3
References	Method of IPCC	Category	Decisive factor	Mentioned in number of papers
(Samavati, Essam, Nehring, & Sarker, 2020)			Mining Capacity	3

(Norgate & Haque, 2013), (Ritter, 2016)				
(Ritter, 2016) (Morrison, 2017)			Utilization	2
(Sousa, et al., 2022), (Ritter, 2016) (Villeneuve, Ben-awuah, & Vasquez-Coronado, 2020) (Morrison, 2017)			Availability	4
(Sousa, et al., 2022) (Morrison, 2017)			Productivity	2
(Wachira, 2022) (Wachira, Githiria, Onifade, Moshood, & Mauti, 2021)			Mine Productivity Index (MPI)	2
(Nehring, Knights, Kizil, & Hay, 2018)	Semi-mobile,Fully mobile		Resource Recovery	1
(Mohammadi & Moosakazemi, 2011)			Major shortcomings of truck usage*	1
References	Method of IPCC	Category	Decisive factor	Mentioned in number of papers
(Norgate & Haque, 2013) (Sousa, et al., 2022), (Nunes, Delboni, de Tomi, Infante, & Allan, 2019)		Environmental	Pollutants	3

(Norgate & Haque, 2013) (Abdollahi, Aghayarloo, Afrapoli-Moradi, & Askari-Nasab, 2020)			LCA	2
(Braun, 2019) (b Carter, 2015)			Other environmental study	2
(Abbaspour, Drebenstedt, & Dindarloo, 2018) (Leonida, 2019) (b Carter, 2015)		Social	Safety	3
(Abbaspour, Drebenstedt, & Dindarloo, 2018)	Fixed, Semi, Fully		Other social concerns	1