Evaluating Truck-Shovel and IPCC Scenarios through Discrete Event Simulation: An Iron Ore Mine Case

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ABSTRACT

In-Pit Crushing and Conveying (IPCC) systems represent a revolutionary approach to mineral extraction in open-pit mining. By integrating the crushing process with a conveyor system within the pit, these systems replace part of the haulage cycle that is done conventionally through the Truck-Shovel (TS) system, resulting in significant savings in haulage cost. This not only enhances operational efficiency and reduces costs significantly, but also streamlines material handling, reduces energy consumption, and minimizes environmental impact. In this study, a robust methodology is employed to analyze the cost-effectiveness and production efficiency of IPCC systems in a mature open-pit mine. First, statistical analysis and data wrangling are conducted to achieve valid operational data as input to distribution function fitting. Next, a full-scale Discrete Event Simulation (DES) model is developed using Simpy, an open-source Pythonic library for implementing DES. The model accounts for all in-pit operations, such as loading, haulage and dumping, refueling, shift changes, dispatching modes, equipment failures, and routine maintenance. The simulation model is validated by comparing its results against actual operational data. The model will be used as a decision support system for comprehensive scenario analysis to evaluate various scenarios of pure TS, IPCC, and Out-Pit Crushing and Conveying (OPCC) systems through a detailed assessment of the impact on operational costs, production rates, and overall timeline efficiency. The findings of this study offer valuable insights into the practical aspects of transitioning to IPCC systems in mature open-pit mines.

Keywords: *IPCC, Truck-Shovel system, Discrete Event Simulation, Mining Optimization, Continuous Haulage.*

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1. Introduction

In open-pit mining, the choice of mining method significantly influences production efficiency and schedule adherence. Continuous methods, such as In-Pit Crushing and Conveying (IPCC) and Out-pit Crushing and Conveying (OPCC), offer notable advantages over traditional Truck-Shovel (TS) systems. Continuous methods streamline the material handling process by integrating the extraction, crushing, and conveying stages into a seamless operation. This integration reduces the reliance on heavy truck fleets, which are prone to mechanical failures, high fuel consumption [1], and logistical bottlenecks.

While semi-mobile crushers in continuous methods applications still require trucks for feeding, this approach significantly reduces the distance trucks need to travel, thereby decreasing fuel consumption and maintenance requirements. This ensures a steadier flow of minerals from the pit to the processing plant, leading to consistent throughput and improved overall efficiency. Additionally, continuous systems are less susceptible to weather-related disruptions and provide greater operational predictability, aiding in more accurate schedule achievement.

On the other hand, traditional TS operations have their own set of advantages. They tend to be more cost-effective initially, requiring less capital investment compared to the extensive infrastructure needed for continuous methods. Additionally, TS systems offer greater flexibility and adaptability to varying mining conditions and ore body shapes. This flexibility allows for rapid adjustments in operations and is often more accessible worldwide due to the widespread availability of trucks and shovels. Thus, while continuous methods can markedly enhance production rates and ensure more reliable adherence to planned schedules, TS methods remain a viable and often preferable option in terms of initial investment cost and operational flexibility.

Due to the advantages of continuous mining methods, it is pretty common for large-scale open-pit mines to switch to continuous methods from the traditional TS approach. The decision to apply IPCC in a mature open-pit mine that has been under extraction using TS methods is more complex than implementing it in a new open-pit mine due to several factors inherent in the transition from an established system to a fresh one. These complexities arise from both operational and financial considerations, as well as the integration of new technologies into an existing workflow.

In a mature open-pit mine, significant investments have already been made in the TS infrastructure. This includes not only the purchase of trucks and shovels but also the establishment of maintenance facilities, fuel storage, and road networks optimized for truck movement. Switching to an IPCC system requires a reevaluation of these sunk costs and the potential for asset redundancy, leading to financial complexities that do not exist in a fresh mine where infrastructure is yet to be built.

Operationally, a mature mine has well-established workflows and production schedules that are finely tuned to the TS method. Introducing IPCC necessitates substantial changes to these workflows, which can disrupt production during the transition period. For instance, integrating semi-mobile crushers and conveyors requires redesigning parts of the pit, altering the haulage routes, and possibly reconfiguring processing plants and stockpiling areas. These changes can lead to temporary inefficiencies and potential production losses, making the transition more challenging compared to a fresh mine where systems can be designed around IPCC from the outset.

Another significant factor is the remaining life of the mature mine. The decision to invest in IPCC must consider the remaining mineral reserves and the expected operational lifespan. The financial justification for the high initial capital investment in IPCC infrastructure is more straightforward in a mine with a longer life. In contrast, for a mature mine with a limited remaining lifespan, the payback period might be insufficient to justify the switch unless there are substantial operational savings or productivity gains.

Additionally, mature mines often face spatial constraints that fresh mines do not. The layout of the pit, the location of waste dumps, and the proximity of infrastructure are already established, potentially limiting the optimal placement of IPCC components. This can lead to suboptimal system performance and increased operational costs, further complicating the decision. In contrast, fresh open-pit mines can be planned and developed with IPCC in mind from the early stages of mine design. This allows for the design of the entire operation around the strengths of the IPCC system, such as minimized truck haulage distances and optimized crusher and conveyor locations. The absence of legacy infrastructure and established workflows allows for a smoother and more efficient implementation, with fewer disruptions and a more transparent financial justification.

In evaluating whether to switch from a TS system to an IPCC system in a mature open-pit mine, modeling and analysis of operations are critical. Such a study must provide a detailed understanding of both current and potential future operations, enabling informed decision-making that balances operational efficiencies, costs, and strategic objectives. These include a detailed comparison of operational efficiencies, cost implications, financial viability, risk assessment, and environmental impact, enabling a comprehensive evaluation of the potential benefits and challenges associated with the transition. To achieve a comprehensive understanding of haulage methods, the literature offers diverse methods, including linear programming, queue theory, metaheuristic algorithms, and simulation modeling, among which the Discrete Event Simulation (DES) modeling has proven particularly effective. DES modeling allows for the creation of detailed dynamic models that simulate the sequence of operations and interactions within the mining process. By representing the mining system as a series of sequential discrete events, DES captures the complexities and variabilities inherent in mining operations, such as equipment breakdowns, maintenance schedules, and varying haulage velocities and distances. DES provides a robust and detailed approach for evaluating the feasibility and cost-effectiveness of adopting the IPCC method in a mature open-pit mine currently using the truck-shovel method. By capturing the complexities and variabilities of mining operations, DES enables informed decision-making, ensuring that the transition, if pursued, yields optimal operational and financial outcomes.

In the existing literature, much of the focus on the implementation of IPCC has been centered around new mine developments. This body of work predominantly assumes that IPCC systems are integrated from the onset of mining operations, overlooking the unique challenges and complexities associated with transitioning from established TS methods in mature open-pit mines. Consequently, there is a significant gap in the literature addressing the practical and operational difficulties inherent in such transitions.

This study aims to bridge this gap by leveraging the analytical power of DES to rigorously compare two primary scenarios: (1) transitioning to an IPCC system, including the optimization of the mine layout to minimize the distances trucks must travel to semi-mobile crushers, and (2) continuing with the TS system. By examining these scenarios through the lenses of economic viability and productivity metrics, this research provides a comprehensive analysis that enhances our understanding of the practical implications and potential benefits of IPCC implementation in mature mining operations. This study's contributions will offer valuable insights for decision-makers considering similar transitions in their mining practices, thereby addressing an important but often overlooked aspect of mining operations.

This study is organized as follows: Section 1 presents a brief introduction to the research problem. In the Background section, relevant literature is reviewed, and existing gaps in knowledge are elaborated. Section 3 explains the applied methodology, covering everything from data acquisition to DES modeling. Subsequently, Section 4 illustrates the obtained results and offers a detailed discussion of the insights retrieved. Finally, the manuscript concludes by highlighting key results and study limitations and suggesting avenues for future research.

2. Background and Literature Review

This section aims to review the relevant background and the available literature on IPCC and TS material haulage in open-pit mines and applications of DES in modeling and analyzing such systems to provide context, demonstrate the relevance of the research, identify gaps, and establish a foundation for the study's objectives.

2.1. Background

IPCC systems, first introduced in Germany at the Werk Hover mine in 1956 [2], have significantly innovated open-pit mining operations by relocating the primary crusher into the pit and extending the conveyor system deeper into the site. This method eliminates the need for many haul trucks, reducing extensive costs associated with truck haulage, which constitutes nearly half of mining operational expenses. Conveyors, compared to trucks, offer substantially lower operating costs over long distances [3], enhanced operational efficiency, and reduced environmental impact due to lower emissions and energy consumption. While IPCC systems require a high initial capital investment, they provide significant long-term savings through reduced truck usage, lower fuel consumption, and minimal maintenance, making them ideal for high-production, long-term projects.

In contrast, the TS system, predominant in over 80% of Greenfield mining operations, is favored for its flexibility and adaptability, particularly in the early stages of mining where haulage distances are short and fewer trucks are needed [2]. Trucks in the TS system can easily adjust to varying production rates by changing the number of trucks in operation. However, as mining operations progress and pits deepen, the efficiency of trucks diminishes due to increased travel distances, leading to higher fuel consumption, frequent maintenance, and a greater need for trucks, driving up operational costs. The TS system also generates higher emissions and causes more significant environmental impacts due to extensive fuel consumption and the requirement for larger road networks. Despite lower initial costs, the TS system's long-term sustainability decreases, making IPCC systems a more economically and environmentally viable option for long-term, stable mining operations.

2.2. Relevant Literature

2.2.1. TS Haulage System

This section reviews the most recent advancements in haulage systems. A thorough examination of the literature reveals a substantial body of work focused on enhancing dispatching and fleet management in TS haulage systems. Some of the notable studies are reviewed below. For instance, Moradi-Afrapoli et al. [4] applied Fuzzy Linear Programming (FLP) to achieve an interaction-aware dispatching plan. Their framework could address the significant operational cost associated with material handling in surface mines, which accounts for around 50% of the total cost. Traditional truck dispatching models in surface mining often overlook crucial interactions between truck fleets, shovel fleets, and processing plants, fail to incorporate strategic-level goals and disregard the uncertainty of input parameters. They introduced a new truck dispatching model that aims to overcome these limitations by employing FLP to handle the inherent uncertainty in mining operations. The proposed model was implemented in a surface mining operation, where it demonstrated a significant improvement in production and fleet utilization. Specifically, the FLP model increased the hourly ore delivery to processing plants by 21% and 15% for the two plants in the study and optimized shovel utilization by prioritizing ore shovels over waste shovels. Additionally, the truck fleet efficiency was enhanced, reducing the average queue time per truck by 15%.

While the majority of research initiatives have been focused on the operational dimensions of mining to utilize the available fleet efficiently, it is noteworthy that enhancing fleet performance can also be realized with respect to the strategic plan. Moradi-Afrapoli et al. [5] highlighted this point and developed a Nested Fleet Management System (NFMS) that bridges the gap between operational execution and strategic planning by integrating shovel allocation with plant feed optimization. Such an integration is crucial for ensuring that operational decisions are closely aligned with strategic production goals, thereby enhancing overall efficiency. By employing two nested multiple-objective Mixed-Integer Linear Goal Programming (MILGP) models, the NFMS can make more holistic and informed decisions. The developed framework led to a 14.6% enhancement in its required truck fleet capacity to meet the production target, compared to a traditional locked-in operation. This improvement underscores the potential of the NFMS to boost operational efficiency and resource utilization in open-pit mining.

Similarly, Mohtasham et al. [6] developed a framework to optimize truck and shovel scheduling in open-pit mines. This research addressed four main objectives: maximizing production, minimizing deviations in head grade, minimizing deviations in tonnage to ore destinations, and minimizing fuel consumption of mining trucks. The study utilized a MILGP to achieve these goals while examining how the prioritization of objectives affects the efficiency of the mining operation. Their approach involves the development of a mathematical optimization model that schedules the allocation of trucks and shovels, considering operational constraints such as equipment compatibility, ore quality, and stripping ratios. The model used Sequential Linear Goal Programming (SLGP), an interactive approach that optimizes goals in a sequence based on their priority levels. Their results underscore that different priorities can lead to vastly different operational outcomes, emphasizing the need for a flexible and adaptive approach to mine planning.

Mohtasham et al. [7] employed Mixed-Integer NonLinear Programming (MINLP) models to estimate the optimal number of trucks based on the match factor, with two distinct strategies: one addressing each loader type individually and the other considering all types of loaders simultaneously. The novelty of this research lies in the dual-strategy approach to optimizing truck fleet size, which includes both individual loader-focused optimization and a comprehensive model that addresses all loaders together. Additionally, the study integrated short-term production scheduling and traffic conditions into the match factor calculation. The study revealed that both MINLP models effectively improve fleet efficiency and productivity compared to the truck fleet size used in the case study.

Time complexity is one of the limitations in optimized dispatching, particularly in large-scale problems. This issue hinders their real-time applications. In this context, Noreiga et al. [8] harnessed Artificial Intelligence (AI) capabilities to achieve real-time dispatching systems. They developed a truck dispatching system based on deep reinforcement learning that optimizes the real-time assignment of trucks in open-pit mines, aiming to enhance the efficiency and utilization of mine equipment and achieve production and processing targets. They leveraged a Double Deep Q-Learning (DDQN) algorithm to handle the dynamic and uncertain environment of open-pit mining operations. Their methodology involved developing a DES model that replicates the TS environment in an open-pit mine. The DES model incorporates various uncertainties, such as equipment cycle times and road conditions, to create a stochastic training environment for the deep reinforcement learning agent. The DDQN algorithm is employed to train a centralized dispatching agent that makes real-time dispatch decisions based on the current state of the mining system.

Fuel consumption is one of the critical factors in the TS haulage system as it directly influences both the operational costs and environmental impact of mining operations. High fuel consumption not only increases the expenditure on diesel, which constitutes a significant portion of the overall mining costs, but also leads to higher emissions of greenhouse gases. Efficient fuel consumption can be achieved by optimizing truck sizes, load capacities, and haul road conditions, ultimately enhancing the cost-effectiveness and sustainability of mining operations. Therefore, minimizing fuel consumption not only aligns with economic objectives by lowering operating costs but also supports environmental goals by reducing emissions, making it a vital aspect of the haulage method decision in mining. In this regard, Vera-Burau et al. [9] aimed to analyze the impact of different production scenarios on fuel consumption and truck model performance in open-pit mining operations. Utilizing a comprehensive methodology that included Vulcan-Maptek tools for mine planning and design, the researchers developed a block model of a real uranium deposit to evaluate the economic feasibility, operational efficiency, and environmental implications of various production rates and equipment configurations. Critical parameters such as NPV, ramp widths, and slope gradients were assessed to determine their influence on mine design and profitability. The findings revealed that higher production scenarios significantly increased NPV and reduced the life of the mine, emphasizing the importance of optimizing production rates for economic viability. Additionally, while variations in ramp width affected waste removal and final slope angles, the overall pit geometry remained stable. The study highlighted the critical role of equipment selection in minimizing fuel consumption and CO_2 emissions, aligning with sustainable mining practices. However, the research was limited to the parameters and conditions of the specific case study, suggesting a need for further exploration across different mining contexts and the integration of advanced technologies to enhance environmental performance.

2.2.2. IPCC material handling system

Recently, literature has witnessed massive efforts on different aspects of continuous haulage, particularly the IPCC method. IPCC affects pit-design requirements to accommodate semi-mobile crushers compared to traditional pit-shape constraints. In this regard, Hay et al. [3] investigated how to integrate the additional requirements of Semi-Mobile In-Pit Crushing and Conveying (SMIPCC) systems into the Ultimate Pit Limit (UPL) determination process, thereby altering the traditional pit shape requirements to accommodate the unique constraints of SMIPCC operations. By leveraging the mathematical principles of convex hulls, bounding boxes, and future value discounting, the study introduces a novel algorithm that extends the existing network flow method, ensuring both mathematical rigor and practical applicability. The developed algorithm efficiently incorporates the need for a straight conveyor wall, a constraint previously unaccounted for in traditional UPL determination methods, thus optimizing pit limits for metalliferous mining operations.

Key insights from the study reveal that despite SMIPCC pits being smaller than traditional TS pits, they can achieve higher Net Present Values (NPVs) due to reduced mining costs, underscoring their economic viability. The algorithm's efficiency, demonstrated through a detailed case study, highlights its applicability to a range of mining operations, proving its practicality for real-world implementation. However, One significant limitation is the complexity and computational intensity associated with accurately modeling the optimal pit limit in three dimensions. While the algorithm is designed to be mathematically rigorous and efficient for small case study block models, its performance and scalability for larger, more complex models remain uncertain. Additionally, the study highlights that the scheduling of SMIPCC systems is more constrained compared to traditional TS systems, which can negatively impact the NPV of mining operations. The economic viability of SMIPCC systems, despite higher upfront capital costs, depends heavily on accurate scheduling and operational consistency. Lastly, the developed algorithm assumes the final position of the crusher without accounting for progressive relocations over the mine's life, potentially limiting its adaptability to dynamic operational conditions.

Likewise, Al Habib et al. [10] delved into short-term mine plan updating under the IPCC system due to the semi-mobile crusher relocations. They focused on optimizing short-term production plans for open-pit mines utilizing SMIPCC systems. The primary objective is to generate an annual production schedule that minimizes material handling costs and maximizes revenue while meeting plant requirements and adhering to IPCC location constraints. The study proposes a mixed integer programming (MIP) model to achieve these goals, contrasting scenarios with and without IPCC systems. They revealed that incorporating SMIPCC can generate 0.66% higher profit compared to traditional TS systems, with a notable 30% reduction in truck requirements. The model effectively allocates shovels to mining faces, ensuring production targets align with long-term plans. However, the study's deterministic nature is a limitation, as it does not account for operational uncertainties such as equipment failures or maintenance. Additionally, the model does not consider ore blending requirements or the costs associated with shovel movements between benches, which could impact the realism and applicability of the results.

In a similar vein, Kamrani et al. [11] evaluated the long-term planning of open-pit mining operations in the presence of IPCC. The paper developed a two-step mathematical model that first determines optimal crusher locations and relocation times and then sequences the extraction process over the mine’s operational lifespan. The study investigated three distinct scenarios: no IPCC, IPCC for ore, and IPCC for both ore and waste. Their findings demonstrated that the third scenario, incorporating crushers for both ore and waste, significantly reduces ore and waste travel distances by 110 km and 395 km, respectively, compared to traditional truck haulage. Furthermore, the discounted cash flow analysis reveals a 15% improvement in the scenario with dual in-pit crushers, underscoring the cost-saving potential. While the study offers valuable insights, it has several limitations. Firstly, the model does not account for real-time operational uncertainties such as equipment failures and maintenance, which can impact overall efficiency. Additionally, the economic analysis does not fully consider capital investment variations under different scenarios.

As outlined in [12], choosing IPCC over TS is not a straightforward decision and can be a controversial issue. Consequently, a number of studies have focused on cross-comparisoning these two methods. Abbaspour and Drebenstedt [13] evaluated the effectiveness of various transportation systems in open-pit mining through the development and application of a technical index based on system dynamics modeling. The research addresses the need for a comprehensive assessment of the TS and IPCC systems, which include Fixed In-Pit Crushing and Conveying (FIPCC), Semi-Fixed In-Pit Crushing and Conveying (SFIPCC), SMIPCC, and Fully Mobile In-Pit Crushing and Conveying (FMIPCC). They developed a decision-making framework that incorporates system availability, utilization, and power consumption, thereby identifying the most effective transportation system at any point during the mine's operational lifespan.

Their findings indicate that the TS system generally emerges as the most preferred transportation method, except for two specific periods during the mine's operation. The results demonstrate the highest availability for the TS system (99.45% to 99.73%) and the highest utilization for FMIPCC (86.6%). One notable limitation of this study is its deterministic approach, which may not fully capture the stochastic nature of real-world mining operations. The research acknowledges that factors such as equipment failures, maintenance schedules, and operational delays can introduce significant variability. Future research should consider incorporating stochastic elements to enhance the model's robustness and reliability.

While the available literature mainly offers research initiatives aimed at enhancing the IPCC haulage system, a few studies focus on IPCC-driven novel extraction methods. In this regard, Gong et al. [14] proposed a new conceptual mining method known as the Near-Face Stockpile (NFS), combining IPCC systems with a pre-crusher stockpile. The primary objective of the study was to quantitatively evaluate the performance of the NFS method, which theoretically offers enhanced production efficiency, stability, and equipment utilization over traditional TS and IPCC methods. A MILP model was developed for short-term production scheduling, which optimized the mining schedule and integrated it into the simulation framework for comprehensive performance evaluation. A case study conducted on an oil sands mine validated the framework. Key insights from the study reveal that the NFS method increased overall production by 5.06%, reduced the transporting distance of minerals by 17.87%, and improved the utilization rates of shovels and crushers by 4.96% and 4.85%, respectively. The research confirmed that the NFS method effectively reduces truck cycle times and enhances operational stability by minimizing the impact of subsystem failures. However, the initial investment required for the NFS method is higher than that for traditional IPCC methods.

Additionally, while the operating cost of conveyors is relatively low, any damage to the conveyor system can have severe consequences. The NFS method also imposes higher requirements on the bottom size of the open pit and is more suitable for ore bodies with lower strip ratios. Furthermore, the added reclaim shovel introduces potential bottlenecks and additional risks.

From the economic perspective, Gong et al. [15] evaluated the NSF method's impact on plant throughput quality and NPV of the mining project. They introduced a novel approach by incorporating a stockpile near the mining face, which serves as a buffer to enhance the stability and efficiency of the mining operation. They employed a MILP model to optimize the short-term production schedule, ensuring an optimal mining sequence that maximizes NPV. The results indicated a 5.06% increase in overall production, a 17.87% reduction in truck transportation distance, and improvements in shovel and crusher utilization by 4.96% and 4.85%, respectively. However, the study also acknowledged certain limitations, such as the higher initial investment costs and the need for precise management of the stockpile to ensure consistent feed quality. Additionally, the study did not address the verification of quality blending and the impact of stockpile capacity and zoning on overall performance, which are areas suggested for further research.

2.2.3. DES applications in material haulage

DES can be highly effective in analyzing TS and IPCC scenarios by providing a detailed and dynamic representation of the mining operations. For TS scenarios, DES allows for the modeling of complex interactions between trucks, shovels, and other auxiliary equipment, capturing the variability in cycle times, travel distances, and operational delays. This level of detail enables the identification of bottlenecks and inefficiencies within the haulage system, facilitating the evaluation of different operational strategies and their impacts on productivity. By simulating various scenarios, DES can help optimize fleet size [16], equipment allocation [17], and scheduling [18], thereby improving the overall efficiency and cost-effectiveness of TS operations.

Fleet dispatching is one of the highly regarded use cases of DES in haulage systems. Empowering DES with the optimization algorithm makes a robust framework for finding optimal working scenarios. In this regard, Mohtasham et al. [17] presented an optimization framework that includes three sequential stages: fleet size selection, fleet allocation, and real-time truck dispatching. They integrated simulation and optimization to determine the optimal fleet size, which is coupled with a heuristic algorithm for operational decisions. This combination could address the stochastic nature of mining operations and incorporate real-time decision-making processes. The results demonstrated that the proposed framework significantly improves operational efficiency. This optimal sizing led to a balanced truck-shovel system with improved equipment utilization and a higher match factor.

In the DES-based dispatching context, Mirzaei-Nasirabad et al. [19] developed a DES-based truck dispatching framework that addresses the real-time truck dispatching problem in open-pit mining operations. Their approach was built on a multi-stage dispatching approach to optimize TS material handling systems. This research is significant due to the critical role of efficient truck dispatching in enhancing operational efficiency and productivity in mining. The proposed methodology consists of two primary stages: allocation planning and dynamic allocation. Initially, a scenario-based method was employed to estimate the optimal number of trucks required for the mining operation, ensuring that the fleet size is well-suited to meet production demands. This model aimed to minimize fleet waiting times and deviations from the production paths established during the allocation planning stage. By incorporating multiple objectives, the model provides a comprehensive solution that balances various operational priorities, such as reducing idle times and ensuring consistent material flow. The results demonstrated that the model can achieve a better balance between minimizing waiting times and maintaining adherence to the planned production paths, thereby enhancing overall operational efficiency.

DES can also serve as a reliable tool for fleet estimation. Huayanca et al. [20] focused on estimating the required truck fleet size for an expanding open-pit copper mine in Peru using DES modeling. The DES model incorporated random variables such as fixed times and tonnages loaded to hauling equipment, allowing for a more realistic replication of the mine's yearly production plan. The study's methodology involved the development of a calibrated model that simulated daily operations, followed by the application of this model to a yearly plan under both stochastic and deterministic scenarios. The results demonstrated that the stochastic model required additional trucks and resulted in longer cycle times compared to the deterministic model. This finding indicates that the deterministic approach may underestimate the variability and operational challenges faced in real-world scenarios. The study provides valuable insights into the benefits of using DES for truck fleet estimation, highlighting its ability to anticipate potential issues such as longer queues and increased cycle times. However, the research is limited by its focus on a specific case study, suggesting that further studies are needed to generalize these findings to other mining operations.

In IPCC scenarios, DES offers a valuable tool for assessing the integration and performance of conveyor systems alongside traditional haulage methods. The simulation can model the continuous flow of material through crushers and conveyors, accounting for variations in material properties, equipment capacities, and maintenance schedules. This holistic view allows for the examination of how IPCC systems interact with and potentially enhance or disrupt existing TS operations. By analyzing different configurations and operational strategies, DES can help determine the optimal balance between truck haulage and conveyor transport, leading to more sustainable and efficient mining practices.

2.3. Gaps in Knowledge

Existing literature has extensively examined the implementation of various forms of IPCC systems, predominantly focusing on their integration into new mining operations. These studies typically assume the incorporation of IPCC systems from the initiation of mining activities, thus neglecting the unique challenges and complexities involved in transitioning from traditional TS methods to IPCC systems in mature open-pit mines. This oversight presents a substantial gap in current research, as the operational difficulties and practical implications of such transitions remain inadequately addressed.

This study seeks to address this critical gap by employing DES to conduct a rigorous comparative analysis of two primary scenarios: (1) the transition to an IPCC system, with an emphasis on optimizing the mine layout to minimize truck travel distances to semi-mobile crushers, and (2) the continuation of the conventional TS method. By focusing on the practical aspects of transitioning in established mines, this research aims to provide a comprehensive evaluation of the operational and economic impacts, thereby offering valuable insights for decision-makers in the mining industry.

3. Methodology

To evaluate the cost-effectiveness and production efficiency of transitioning to the IPCC/OPCC system in a mature open-pit mine, it is essential to develop a viable and accurate DES model that reflects the actual haulage operations. This section details the efforts undertaken to create and validate a comprehensive DES model replicating the activities of the open-pit ore mine used as a case study. The methodology applied encompasses several critical stages: data collection, data wrangling, DES model development, and model verification. Each of these stages is elaborated upon in the following sub-sections.

3.1. Data Collection

The initial phase of the study involved site visits and the collection of diverse input data essential for simulation input modeling. This data encompasses the following aspects:

- Pit design: The pit design data was used to extract road networks and understand the pit's shape at specific time sections, providing crucial information about the mine's layout and transportation routes. This detailed layout helps in creating an accurate representation of the operational environment within the simulation model.

- Short-term mine plan and production schedule: The production schedule was employed to determine mining polygons, blast patterns, and extraction sequences, offering insights into the mine's operational flow. This data, derived from the mine’s short-term (monthly) plans, specifies the quantity of material to be displaced from various benches by each contractor. Such information is vital for simulating the dynamic and sequential nature of mining operations.

- Operational data: Historical data regarding mining operations, such as load times, dump times, and full-haul and empty-haul velocities, are critical for understanding the efficiency of mining operations. These data points were collected using equipment-mounted GPS over the preceding year. This historical operational data provides a basis for modeling realistic operational behaviors and performance metrics.

- Available fleets and their maintenance Data: Given the fluctuating number of pieces of equipment employed throughout the project, accessing the exact number of equipment is essential for achieving dependable results. This includes information on the available equipment at any given time, as well as their associated downtimes and intervals. The study leverages Mean Time to Repair (MTTR) and Mean Time Between Failure (MTBF) data as the primary available data for modeling resource downtimes.

- Dispatching rules: This includes the criteria for allocating shovels to mining faces and assigning trucks to shovels. The pit design, mine topology, equipment functionality and capacity, and access restrictions influence these considerations. Understanding these dispatching rules is crucial for accurately modeling the decision-making processes involved in mine operations.

By analyzing this comprehensive set of data, the study aims to develop a robust DES model that accurately reflects the real-world operations of the open-pit ore mine.

3.2. Data analysis

Following data collection, rigorous data analysis was applied. This step is crucial in achieving valid operational data suitable for data preprocessing and input modeling. Since data analysis was conducted on different data types, a concise description for each data type is provided as follows.

3.2.1. Road Network

To begin with, it is crucial to establish a comprehensive road network to determine the distances between various dig and dump locations. This road network is derived based on the periodic pit profiles generated from aerial survey of the pit. By utilizing these pit designs and leveraging a semi-automated algorithm, an accurate representation of the mine's road profile is generated, ensuring that all routes between key points are accounted for. Furthermore, this road network undergoes validation through site visits, confirming that the extracted routes are aligned with actual road conditions and accessibility. This validation step is essential as it ensures the reliability and accuracy of the data, forming a solid foundation for further calculations and optimizations in the mining process.

3.2.2. Schedule

The short-term monthly plan serves as the cornerstone of the mine schedule. This plan delineates the areas (referred to as polygons) to be extracted, along with their corresponding priorities. The subsequent step involves extracting the mining schedule using polygon maps from these monthly plans. This schedule is vital for outlining the entire mining operation, detailing the locations of loading faces that represent different extraction points within each polygon. Each face includes specific information, such as the tonnage of material to be extracted and the load types involved. By meticulously mapping out these details, a structured and efficient schedule is developed to manage the mining process, ensuring that all necessary faces are mined out during the planned periods.

3.2.3. Distance Matrix

Following the analysis of the road network and mine schedule, Dijkstra's algorithm is employed to compute the matrix distances between various nodes on the road network. These nodes encompass dig points, dump points, crushers, fuel stations, maintenance shops, and parking areas. Dijkstra's algorithm is particularly effective for this purpose as it identifies the shortest paths between nodes in a graph, ensuring that the distance matrix is both accurate and optimized. This matrix serves as a critical tool for planning and logistics, allowing for precise calculation of travel times and routes.

3.2.4. Operational Data

Operational data encompasses several key metrics, including loading time, dumping time, full-haul, and empty-haul velocities. Each of these metrics is categorized based on influential factors such as equipment capacities, load types, and seasonal variations. It is noteworthy that these factors are not uniformly applicable across all metrics. For example, loading time is influenced by the capacity of the trucks and shovels, the type of load, and the season. In contrast, empty-haul velocity depends on the type of truck, load types, and the season.

The initial preprocessing of this operational data involves omitting null values and corrupt data entries, such as zero logging or aggregated time records, to ensure the integrity of the dataset.

Following this, an outlier-dropping procedure is conducted to remove data points that deviate significantly from the norm, further refining the dataset for analysis.

Subsequently, various statistical measures are calculated to gain a comprehensive understanding of the dataset. These measures include the count, mean, standard deviation, mode, median, percentiles (25th and 75th), and minimum and maximum values. This statistical analysis provides valuable insights into the distribution and variability of the data.

Multiple methods are employed to model the data distribution accurately, including Maximum Likelihood Estimation (MLE), moment matching, and least square methods. Additionally, empirical distribution fitting is conducted to capture the underlying patterns in the data. The goodness of fit for standard distributions is then evaluated using a combination of visual assessments, Kolmogorov-Smirnov (k-s) tests, and chi-square tests. These evaluations ensure that the chosen distributions accurately represent the operational data, providing a robust foundation for further analysis and decision-making in the mining process.

3.2.5. Dispatch Rules

By analyzing database records and multiple site visits, the general rules for fleet dispatching and shovel-to-face assignment have been extracted. Some of the paramount rules to be applied while dispatching in the DES model are cited in this section for the sake of brevity. This section explains the rules for allocating shovels to working faces and trucks to shovels, ensuring optimal resource utilization and operational efficiency.

Allocating shovels to workfaces involves several key factors: working face priority, shovel mobility, and load compatibility. In terms of workface priority, it should be noted that not all faces have the same priority. Larger shovels are assigned to higher-priority workfaces. For example, a workface with waste material above ore has a higher priority, necessitating the allocation of larger, more efficient shovels to expedite the removal process. Moreover, shovels move very slowly, which restricts their ability to be relocated frequently. To optimize operational efficiency, shovels are moved between nearby working faces, minimizing downtime and maximizing productive time at each face. Likewise, the efficiency of a shovel is significantly influenced by the load density it handles. Shovels with smaller buckets are more efficient with higher-density loads, such as ore, whereas larger shovels are better suited for lower-density loads, such as waste material. This compatibility ensures that each shovel operates at its optimal capacity, ensuring that equipment is working within its limits.

Similarly, allocating trucks to shovels involves several essential factors: workface priority, truck and shovel compatibility, and truck mobility. Due to resource constraints (i.e., the system works in under-truck conditions), it is essential to prioritize their allocation. Shovels operating at higher priority working faces, particularly those working on ore extraction, are given precedence for truck allocation. This prioritization ensures that critical material is transported efficiently, maintaining the continuity of mining operations. Furthermore, the fleet's heterogeneity necessitates careful matching of trucks and shovels. Larger trucks are assigned to shovels with larger buckets, ensuring that the loading process is efficient and that each truck can carry its maximum load capacity.

Conversely, smaller trucks are paired with excavators that have smaller buckets, maintaining operational harmony and preventing mismatched resource allocation. Lastly, it is noteworthy that larger trucks require wider paths for travel, influencing their allocation. These trucks must be assigned to shovels at working faces with adequate access and sufficient maneuvering space. This rule ensures that larger trucks can operate without hindrance, reducing the risk of delays and enhancing the overall safety and efficiency of material transport.

3.3. DES Model Development

A core component of the methodology is the development of a full-scale DES model. The DES model of an open-pit mine is structured around three primary components: resources (trucks, shovels, and crushers), locations (dig points and dump sites), and operational processes. According to the reality of the case study, the model employs a fixed allocation strategy, where resources are pre-assigned to specific locations based on a predetermined plan. This approach allows for the evaluation of different resource allocation strategies and their impact on overall mining efficiency. It is developed using the Simpy package in Python, creating a specialized module to simulate the entire process from extraction to material transportation. The model focuses on moving waste, ore, and tailing material to designated dump sites, utilizing essential resources such as trucks, shovels, and crushers. The developed model simulates real-world scenarios of open-pit mining operations, enabling the evaluation of different strategies for resource allocation and process optimization. Figure 1 visualizes different components of the developed DES model, which are described below.

A. Modeling and dig point schedule

The process begins with modeling objects and relationships, followed by running the simulation. The initiation of dig points is prioritized, and once ready, the dig point process is initiated. Trucks and shovels are requested to facilitate the excavation. A prerequisite waiting period occurs until the necessary dig points are prepared. If required, trucks are requested to support the operation. The sequence completes with trucks and shovels moving to their respective locations.

B. Shovel process

The shovel process is closely tied to the dig point schedule. After releasing the shovel from maintenance or failure checks, shovels proceed to serve trucks at the dig points. If a dig point is finished, the shovel is moved to a new dig point. In case of maintenance failure, the shovel undergoes necessary repairs before resuming operation. This process ensures that shovels continuously serve trucks until the extraction task is complete, after which they are released from the site.

C. Truck cycle

The truck cycle begins with trucks being dispatched to dig points where they request shovels for loading. Post-loading, trucks move to dump points. Depending on the presence of crushers at the dump point, trucks either dump material directly or queue for the crusher. After dumping, trucks determine if the previous mining face is finished, whether trucks require maintenance, refueling, or if the shift has ended. If the mining face is fully extracted, trucks follow alternative plans if available or are released from duty. Trucks needing maintenance or refueling are directed to maintenance shops or fuel stations. At the end of a shift, trucks are parked to await the next shift.

D. Truck decision-making

Decision-making for trucks is dynamic. Post dumping, trucks assess if the assigned dig point is completely mined out. If not, they check for maintenance needs, shift end conditions, and fuel status. Based on these checks, trucks either move to parking lots, fuel stations, or maintenance shops or return to the previous dig location to continue operations. This decision-making process ensures that trucks are always ready to serve the excavation needs efficiently.

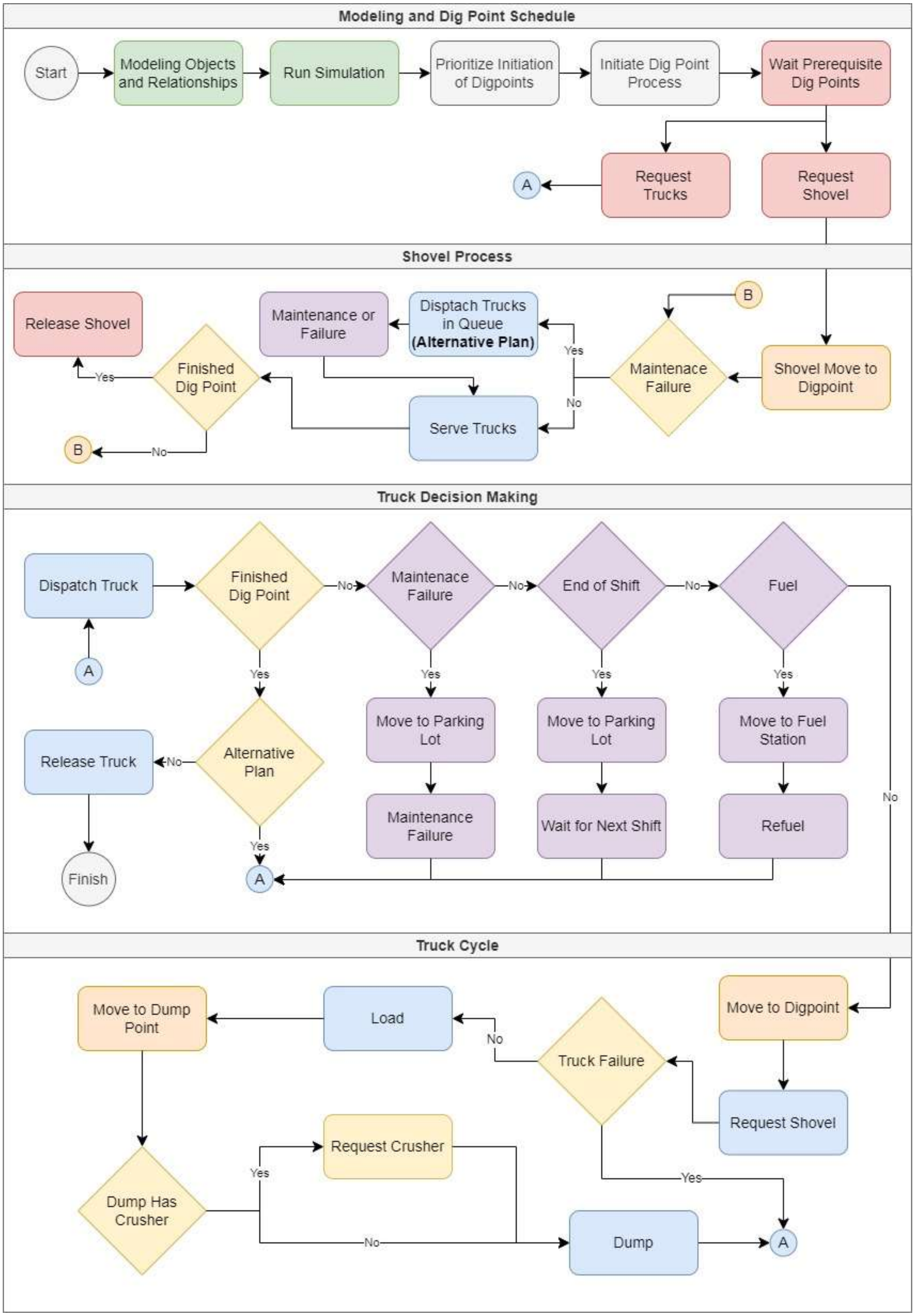


Figure 1. Overview of the developed DES model.

4. Case Study

This study focuses on an open-pit iron ore mine, being actively under extraction using a truck-shovel system for over two decades, facilitating continuous haulage operations 24/7 throughout the year. The mining operation employs a diverse fleet of trucks and shovels with varying capacities sourced from different manufacturers, reflecting a complex logistical and operational framework. The mine extracts three primary material types: ore, waste, and overburden. The ore reserve at this site is substantial and is projected to be sufficient for the next ten to twelve years, ensuring the mine's operational continuity and economic viability.

In addition to the current truck-shovel system, this study explores IPCC as an alternative scenario for the remaining work packages. The analysis will provide insights into the potential efficiency gains and operational benefits of IPCC compared to the traditional truck-shovel system, offering a comprehensive evaluation of both methodologies in the context of this specific open-pit mining operation.

4.1. Simulation Experiment Setup

The developed model is designed to interface seamlessly with a configuration file in Excel™ format, allowing for the manipulation of the majority of simulation behaviors. This approach provides extensive parameterization capabilities, enabling the adjustment of various operational aspects based on the configuration file. Key configurable parameters include allocation mode (fixed and floating), truck dispatch method (fixed and floating), simulation types (deterministic and stochastic), operational considerations (e.g., maintenance, failures, and refueling), general simulation settings (e.g., shift duration, daily shift count, and pit evacuation period), and replication length. Table 1 indicates the applied experiment setting in the configuration file.

Table 1. Simulation setup.

Item	Value
Allocation mode	Fixed
Dispatch method	Post-loading/post-dumping
Simulation type	Stochastic based on empirical distributions
Maintenance, Failure, Refueling	True
(# of shifts per day, shift duration)	(3, 480 minutes)
Evacuation period	30 minutes
Replication length	90 shifts

4.2. Input Data

The developed DES model can process both deterministic and stochastic data, as indicated in Table 1. With the exception of the distance matrix and schedule, the model primarily utilizes stochastic inputs to ensure more reliable results. By categorizing influential factors on operational data, multiple combinations were generated, some of which were deemed invalid. Categories with marginal data counts were considered invalid combinations, as they are unlikely to occur in reality. Table 2 presents the influential factors for each data set, along with the corresponding total and valid number of combinations.

Table 2, Operational data classification.

Data	Influential factors (# of instances)	Total combinations	Valid combinations
Loading	Truck capacity (4), Shovel capacity (3), Load types (3), Season (2)	72	40
Dumping	Truck capacity (4), Dumpsites (9), Load types (3), Season (2)	216	37
Full-haul velocity	Truck capacity (4), Load types (3), Season (2)	24	17
Full-haul velocity	Truck capacity (4), Load types (3), Season (2)	24	17

[1]:Truck capacities ranges from 35 to 135 tones.
[2]: Shovel capacity includes small, medium, and large (bucket capacities range from less than 5 m^3 to over 14 m^3).

Due to the high number of combinations, and for the sake of brevity, only a subset of the valid combinations is described statistically in Table 3.

Table 3, Combination data statistics (values are modified for the sake of confidentiality).

Data	Combo	Mean	Std	Fitted distribution	Fitting error
Loading (sec.)	100-Small-Waste-Wet	0.61	0.14	NORM(0.61, 0.15)	0.05%
Dumping (Sec.)	60-Waste-DWST2-Wet	0.5	0.17	0.12 + GAMM(0.08, 0.02)	0.2%
Full-haul velocity (Km/h)	35-Waste-Wet	0.66	0.14	0.28 + 0.75 * BETA(0.12, 0.11)	0.09%
Empty-haul velocity (Km/h)	35-Waste-Wet	0.69	0.12	TRIA(0.28, 0.77, 1)	0.46%

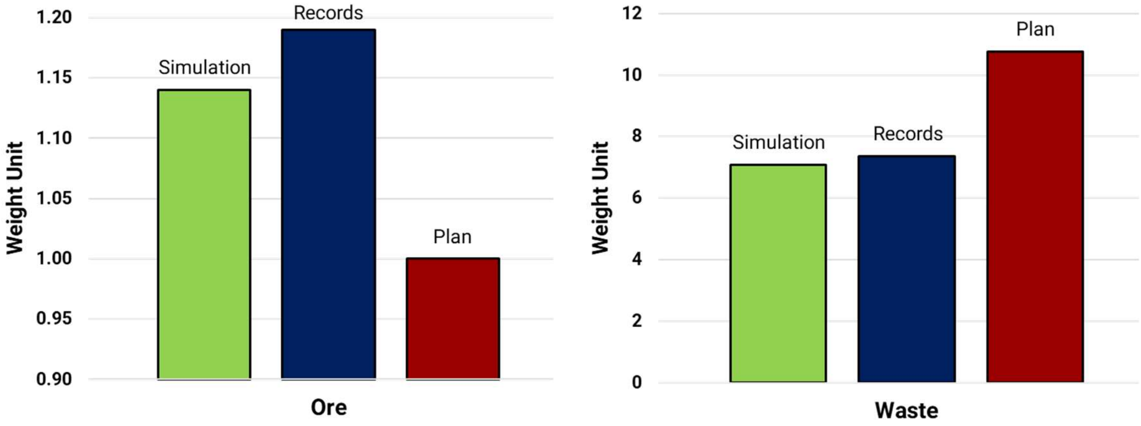
As shown in Table 3, distribution fitting was conducted rigorously, resulting in negligible fitting error. Moreover, all the analyzed data were subjected to empirical distribution fitting. Using an empirical distribution fitted on data in simulation modeling may be preferable to a standard distribution because it captures the actual observed behavior and nuances of the data, leading to more accurate and realistic simulation results. Empirical distributions do not assume a predefined shape, allowing them to better reflect the inherent variability and specific characteristics of the data set. This approach enhances the reliability of the simulation results by directly utilizing the empirical data's frequency and pattern, thereby improving decision-making and predictive accuracy in complex systems.

4.3. Results and Validation

Utilizing the adjustments detailed in Section 4.1, the simulation model was executed for a period equivalent to 90 working shifts, simulating one month of operations. In this section, the results retrieved from the simulation are validated against the actual data recorded in the database. Among the various simulation outputs, hauled tonnage is of paramount importance. Table 4 and Figure 2 compare the performance of the DES model against the actual operational data.

Table 4. Hauled tonnage comparison (values are modified for the sake of confidentiality).

Ore Monthly plan: 1 unit			**Waste** Monthly plan: 10.77 unit		
Simulation	**Record**	**Difference**	**Simulation**	**Record**	**Difference**
1.14	1.19	-4.27%	7.09	7.37	-3.67%



a. hauled ore tonnage b. hauled waste tonnage

Figure 2. Hauled tonnage in plan, simulation, and reality.

Figure 2 demonstrates that the DES model can accurately replicate real-world conditions. The difference between the simulation results and actual data is less than five percent for both ore and waste, which is considered highly acceptable. Since the validation process was completed for all input parameters, this minor difference can be attributed to discrepancies between the actual fixed assignments and the simulated assignments. Although the applied assignments adhered to the established dispatching rules, they may not precisely replicate the exact conditions and decisions made in reality.

To better understand the hauled tonnage breakdown structure, a Sankey diagram is plotted in Figure 3 to visually illustrate the portion of extracted material from each bench and their corresponding dump destination.

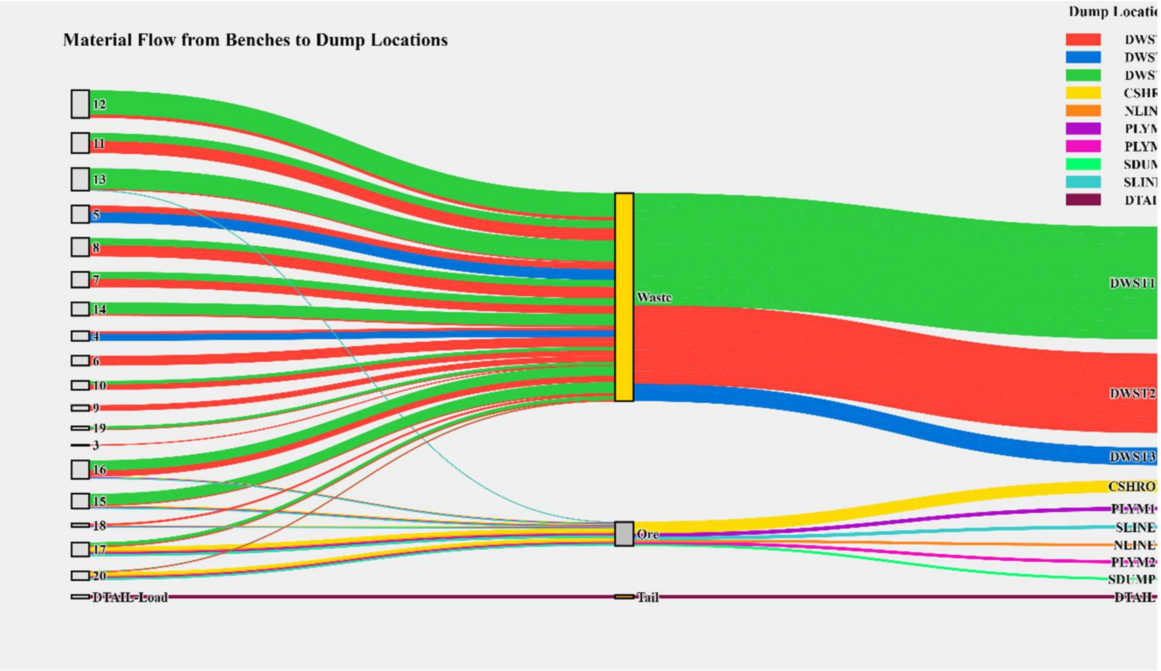
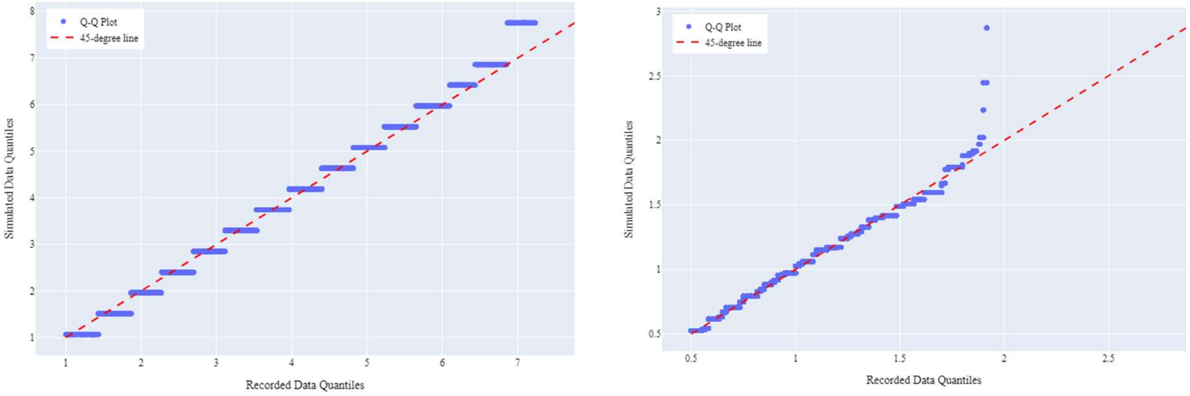


Figure 3. Hauled tonnage from each bench to dump locations.

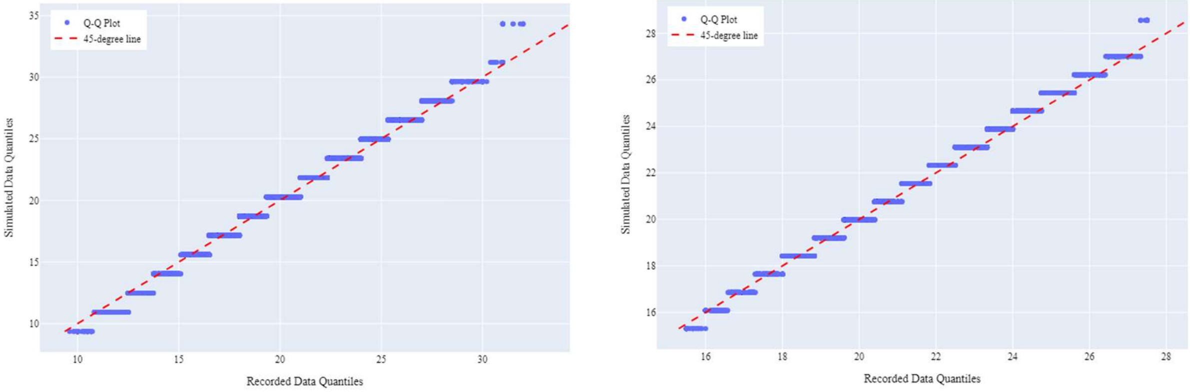
The Sankey diagram presented shows the flow of material from various benches to their respective dump locations. Each bench is represented on the left side of the diagram, with lines extending to the right, indicating the destination of the material. The width of each line corresponds to the volume of material being hauled, providing a clear visual representation of the haulage pattern. Figure 3 indicates that the majority of waste from the upper benches is directed to DWST2, while DWST1 primarily receives waste from the lower benches. Similarly, most benches produce a single load type, which is then transported to various dump locations.

In addition to cumulative material tonnage, Quantile-Quantile (Q-Q) plots were employed to illustrate the alignment between the simulation input data and the actual data distributions. These plots provide a visual representation of how well the sampled simulation data matches the statistical properties of the actual data. Specifically, Figure 4 presents Q-Q plots for selected combinations of input data, demonstrating the degree of conformity between the empirical and theoretical distributions. This analysis further validates the robustness of the simulation model in replicating real-world conditions by ensuring that the input data used in the model closely mirrors the actual operational data.



a. Q-Q plot for loading duration

b. Q-Q plot for dumping duration



c. Q-Q plot for empty-haul velocity

d. Q-Q plot for full-haul velocity

Figure 4. Q-Q plots for a sample of loading, dumping, full/empty-haul velocities.

The Q-Q plots presented in Figure 4 provide a visual comparison between the simulated data and the recorded data for various input data. The usage of empirical distribution in the depicted Q-Q plots is evident from the alignment of the data points. The diagonal form of the plot, represented by the close alignment of the data points along the 45-degree reference line, confirms that the simulated data and recorded data are drawn from similar distributions. This alignment indicates a substantial similarity between the quantiles of the two data sets, further validating the accuracy and reliability of the simulation model in replicating real-world conditions. The close fit along the diagonal suggests that the simulation model effectively captures the statistical properties of the actual data, ensuring that the empirical distribution used in the model accurately represents the recorded data distributions.

5. Conclusion and Future Works

This study presents a comprehensive analysis of the idea of In-Pit Crushing and Conveying (IPCC) systems as a transformative alternative to the conventional Truck-Shovel (TS) system in mature open-pit mining operations. By integrating a conveyor system with the crushing process within the pit, IPCC systems offer a significant reduction in haulage costs, enhance operational efficiency, streamline material handling, reduce energy consumption, and minimize environmental impact.

Utilizing a robust methodology, the research involved statistical analysis and data wrangling to generate valid operational data for distribution function fitting. A full-scale Discrete Event Simulation (DES) model was developed using Simpy, an open-source Python library, to accurately represent all in-pit operations. The developed model was validated against actual operational data, ensuring its reliability and accuracy.

This model accurately simulates in-pit operations, providing insights into resource allocation, equipment maintenance, shift management, and haulage efficiency under the TS system. The findings from this analysis serve as a crucial baseline for future comparisons with the IPCC system. Although a conveyor simulation model has been developed, it has not yet been integrated with the TS model. Consequently, the analysis of the IPCC scenario, including the site layout optimization and the comparison of economic consequences between IPCC and TS systems, remains under development.

Future work by the authors will integrate the conveyor simulation model with the existing TS model to enable a comprehensive analysis of the IPCC scenario. This integration will facilitate a detailed evaluation of site layout optimizations aimed at minimizing truck travel distances to semi-mobile crushers and assessing the economic viability and productivity benefits of transitioning to an IPCC system. The forthcoming research will thus provide a holistic comparison of the two systems, offering robust recommendations for mining operations considering a transition from TS to IPCC.

The contributions of this study address a significant gap in the literature by focusing on the practical and operational challenges associated with transitioning from established TS methods to IPCC systems in mature mining operations. By leveraging the analytical power of DES, this research provides valuable insights into the economic viability and productivity metrics of IPCC implementation, offering a practical framework for decision-makers considering similar transitions in their mining practices.

In conclusion, while this study lays the groundwork by thoroughly analyzing the TS system, the full potential of IPCC systems and their comparative benefits are subjects of ongoing research. The insights gained from this study will inform future efforts, ultimately contributing to more efficient and cost-effective mining operations.

6. References

[1] Tadubana, G., B., Sigweni, and D.A., Ayoung, *Systematic review on prediction of haulage truck fuel consumption in open-pit mines.* International Journal of Mining, Reclamation and Environment, 2024. pp. 1-18. https://doi.org/10.1080/17480930.2024.2357509.

[2] 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), pp. 430-457. https://doi.org/10.1080/17480930.2019.1565054.

[3] Hay, E., M., Nehring, P., Knights, and M.S., Kizil, *Ultimate pit limit determination for semi mobile in-pit crushing and conveying system: a case study*. International Journal of Mining, Reclamation and Environment, 2020. **34**(7), pp. 498-518. https://doi.org/10.1080/17480930.2019.1639006.

[4] Moradi-Afrapoli, A., 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, 2021. **121**, pp. 505-512. http://dx.doi.org/10.17159/2411-9717/522/2021.

[5] Moradi Afrapoli, A., S.P., Upadhyay, and H., Askari-Nasab, *A nested multiple-objective optimization algorithm for managing production fleets in surface mines*. Engineering Optimization, 2023. **56**(3), pp. 378-391. https://doi.org/10.1080/0305215X.2022.2153840.

[6] Mohtasham, M., H., Mirzaei-Nasirabad, H., Askari-Nasab, and B., Alizadeh, *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, 2021. **35**(10), pp. 709-727. https://doi.org/10.1080/17480930.2021.1949861.

[7] Mohtasham, M., H., Mirzaei-Nasirabad, H., Askari-Nasab, and B., Alizadeh, *Truck fleet size selection in open-pit mines based on the match factor using a MINLP model*. Mining Technology, 2021. **130**(3), pp. 159-175. https://doi.org/10.1080/25726668.2021.1919374.

[8] Noriega, R., Y., Pourrahimian, and H., Askari-Nasab, *Deep Reinforcement Learning Based Real-Time Open-Pit Truck Dispatching System*. http://dx.doi.org/10.2139/ssrn.4408257.

[9] Vera-Burau, A., D., Álvarez-Ramírez, L., Sanmiquel, and M., Bascompta, *A Comparison of the Fuel Consumption and Truck Models in Different Production Scenarios*. Applied Sciences, 2023. **13**(9), p. 5769. https://doi.org/10.3390/app13095769.

[10] Al Habib, N., E., Ben-Awuah, and H., Askari-Nasab, *Short-term planning of open pit mines with Semi-Mobile IPCC: a shovel allocation model*. International Journal of Mining, Reclamation and Environment, 2024. **38**(3), pp. 236-266. https://doi.org/10.1080/17480930.2023.2262823.

[11] Kamrani, A., M.M., Badiozamani, Y., Pourrahimian, and H., Askari-Nasab, *Evaluating the semi-mobile in-pit crusher option through a two-step mathematical model*. Resources Policy, 2024. **95**, p. 105113. https://doi.org/10.1016/j.resourpol.2024.105113.

[12] 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. **132**(3), pp. 179-201. https://doi.org/10.1080/25726668.2023.2218170.

[13] Abbaspour, H., and C., Drebenstedt, *Truck–shovel vs. in-pit crushing and conveying systems in open pit mines: A technical evaluation for selecting the most effective transportation system by system dynamics modeling*. Logistics, 2023. **7**(4), p. 92. https://doi.org/10.3390/logistics7040092.

[14] Gong, H., A., Moradi Afrapoli, and H., Askari-Nasab, *Integrated simulation and optimization framework for quantitative analysis of near-face stockpile mining.* Simulation Modelling Practice and Theory, 2023. **128**, p. 102794. https://doi.org/10.1016/j.simpat.2023.102794.

[15] Gong, H., M., Tabesh, A., Moradi Afrapoli, and H. Askari-Nasab, *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), pp. 200-215. https://doi.org/10.1080/17480930.2022.2160891.

[16] Zamani, V., H., Taghaddos, and Y., Gholipour, *Sensor-fused simulation-based decision support system for earthmoving projects*. Automation in Construction, 2023. **156,** p. 105117. https://doi.org/10.1016/j.autcon.2023.105117.

[17] Mohtasham, M., 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*. International Journal of Mining, Reclamation and Environment, 2022. **36**(7), pp. 461-491. https://doi.org/10.1080/17480930.2022.2067709.

[18] Ben-Awuah, E., S., Kalantari, Y., Pourrahimian, and H., Askari-Nasab, *Hierarchical mine production scheduling using discrete-event simulation*. International Journal of Mining and

Mineral Engineering, 2010. **2**(2), pp. 137-158. https://doi.org/10.1504/IJMME.2010.035314.

[19] Mirzaei-Nasirabad, H., M., Mohtasham, H. Askari-Nasab, and B., Alizadeh, *An optimization model for the real-time truck dispatching problem in open-pit mining operations*. Optimization and Engineering, 2023. **24**(4), pp. 2449-2473. https://doi.org/10.1007/s11081-022-09780-x.

[20] Huayanca, D., G., Bujaico, and A., Delgado, *Application of discrete-event simulation for truck fleet estimation at an open-pit copper mine in Peru*. Applied Sciences, 2023. **13**(7), p. 4093. https://doi.org/10.3390/app13074093.