Short-term Planning Optimization of Open Pit Mines with Monte-Carlo Haulage Simulation in Presence of Semi-Mobile IPCC[1]

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ABSTRACT

In-pit crushing and conveying (IPCC) is emerging as a viable alternative to traditional truck-shovel haulage in open-pit mines, driven by the rising fuel cost and concerns over greenhouse gas (GHG) emissions. Effective short-term planning in open-pit mines must account for operational and equipment uncertainties. However, optimizing short-term planning with IPCC integration is a relatively underexplored research area. This study addresses this gap by developing a novel simulation-optimization framework that combines mixed-integer linear programming (MILP) and Monte Carlo simulation (MCS) to simultaneously optimize short-term production schedules and evaluate haulage system performance under uncertainty. This framework explicitly incorporates IPCC operations and their failure-related uncertainties, an aspect largely overlooked in existing short-term planning models, into the planning process. The MILP minimizes haulage costs while generating schedules and meeting long-term production targets through optimal shovel allocation to mining cuts. These schedules are then input into a Monte Carlo haulage simulation model, which captures the uncertainties related to trucks, shovels, and IPCC operations. Additionally, the simulation estimates key performance indicators including maximum tonnes per gross operating hour (TPGOH) and the proximity to optimal production under uncertain conditions for both IPCC and truck-shovel scenarios. The model has been verified through a case study in an iron ore mine over a twelve-month planning horizon, yielding promising results that support the adoption of semi-mobile IPCC systems over traditional truck-shovel operations.

1. Introduction

Short-term planning in open-pit mining plays a critical role in ensuring the efficient execution of long-term production goals. As mining operations face increasing economic and environmental pressures, there is a growing need to improve the tactical planning of

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equipment, material movement, and production scheduling. Among various challenges, haulage remains one of the most significant cost drivers in open-pit mines, often accounting for over half of the operating expenses.

In recent years, the mining industry has explored alternatives to conventional truck-shovel systems to reduce costs, improve efficiency, and mitigate environmental impacts. One such alternative is in-pit crushing and conveying (IPCC), which has shown potential to streamline material handling. However, the integration of such systems into short-term mine planning presents several complexities due to operational variability and equipment interdependencies.

To better understand these challenges, it is essential to review the body of existing research in short-term mine planning and the application of IPCC systems. The following section provides a comprehensive overview of previous studies, highlighting their modeling approaches, objectives, and limitations.

1.1. Literature Review

In the context of short-term mine planning, several studies have focused on improving the efficiency of equipment utilization and reducing haulage costs. Efficient use of mining equipment is crucial, as haulage costs can account for over 50% of total operating expenses in a truck-shovel operation [34; 40]. Optimal equipment utilization can only be achieved by efficiently using all assets to meet the production targets set by the long-term plan. Therefore, the strategic allocation of shovels and trucks in short-term production scheduling is essential to ensure cost control and the achievement of long-term goals.

The majority of contemporary short-term planning models rely on MIP and incorporate explicit precedence constraints. Eivazy and Askari-Nasab [12] presented a short-term planning model using MIP that incorporates various mining directions and precedence constraints to reduce overall mining expenses, such as processing, haulage, rehandling, and rehabilitation costs. However, by utilizing aggregated mining blocks, the model may fall short in optimality, as it neglects specific ore type selection and real-world hauling dynamics. Additionally, the model focuses solely on cost reduction, omitting profit considerations. L'Heureux et al. [27] developed a comprehensive mathematical optimization model for short-term planning, covering operational details for up to three months. The primary goal is to reduce the operational costs of truck and shovel activities, as well as drilling and blasting. This model was successfully applied to scenarios involving up to 5 shovels, 90 periods, and 132 faces.

Kozan et al. [25] proposed a model to schedule drilling, blasting, and mining tasks with the goal of minimizing make-span. Later, Kozan and Liu [26] developed a throughput-maximizing model that also reduces equipment idle time, considering precedence and equipment constraints. In their latest work, Liu and Kozan [29] integrated pit design and equipment planning using job-shop scheduling to enhance efficiency.

Blom et al. [8; 6] formulated an MIP-based rolling horizon model to generate multiple short-term schedules that optimize shovel utilization while accounting for blending, availability, and processing path constraints. Blom et al. [7] provide a comprehensive review of short-term mine planning, with a more recent overview available in [21].

Thomas et al. [59; 60] focused on integrated coal supply chain scheduling, using Lagrangian relaxation to minimize earliness, tardiness, and cost under transportation constraints. Mousavi et al. [36] introduced a block sequencing model minimizing various cost components, solved via a hybrid of branch-and-bound and simulated annealing. A recent optimization model for short-term open pit planning has been proposed by Nelis and Morales [37] that generates cut configurations and production plans rapidly, completing in under 15 minutes for a real copper mine.

Manriquez et al. [31] proposed a deterministic short-term planning model for open-pit mining using goal programming to minimize deviations in ore tonnage, plant capacity, fines, and shovel movement. Both weighted sum and hierarchical methods yielded optimal schedules in a copper mine case study. Similarly, Upadhyay et al. [64] developed a goal programming-based short-term planning model focusing on optimal shovel allocation, aiming to maximize production and minimize mill grade deviation and shovel movement. Silva-Júnior et al. [55] introduced a MILP goal programming model for optimizing truck allocation and routing in an iron ore mine, minimizing deviations from production, grade, and particle size targets, while reducing truck requirements under varying operational conditions.

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

Bodon et al. [9] and Sandeman et al. [49] developed LP-based simulation-optimization models to maximize tonnage, meet blending and quality targets, and evaluate trade-offs in capital and maintenance decisions under equipment and port constraints. Shishvan and Benndorf [52; 53] introduced a stochastic simulation framework incorporating geological uncertainty through geostatistical realizations and DES, with a weighted objective balancing production deviation and equipment utilization. This methodology was later applied in industrial case studies by Shishvan and Benndorf [54].

Torkamani and Askari-Nasab [61] used an MIP-based truck-shovel allocation model integrated into a stochastic simulation to analyze haulage systems. Upadhyay and Askari-Nasab [62; 63] applied goal programming in a simulation-optimization model to align short-term plans with strategic goals, minimizing opportunity costs and enhancing utilization. Manriquez [32] proposed a similar framework using discrete event simulation to extract performance indicators, though limited by its sole focus on extraction value. Martins et al [33]. integrated a hierarchical MILP with DES to evaluate shift schedules across four scenarios, showing how different planning priorities affect production efficiency and plant performance.

Bernardi et al. [5] used ARENA to compare semi-mobile and fixed IPCC, finding 10% higher NPV and better target adherence with semi-mobile IPCC, though based on simplified assumptions. Abbaspour and Drebenstedt [1] used system dynamics to compare haulage systems, showing truck-shovel was generally preferred, but FMIPCC performed better in some periods.

Gong et al. [18] proposed a near-face stockpile (NFS) method integrating IPCC, achieving 9.3% higher NPV and 20% lower grade deviation. In a subsequent study, Gong et al. [17] further developed the NFS method, employing discrete event simulation and MILP optimization to assess its performance. Their case study in an oil sands mine confirms NFS's advantages, demonstrating increased production and reduced transportation costs.

IPCC can be a viable alternative to truck haulage in an era of constantly rising environmental concerns over mining. While IPCC is not a new concept, it is yet to be adopted widely in open pit mines across the world. Several life cycle assessment studies and environmental comparisons [38; 15; 13; 3] have found IPCC system to be more ecofriendly compared to pure truck-shovel haulage. Moreover, several economical comparative studies between IPCC and truck-shovel haulage systems found IPCC to be more cost effective [11; 39; 35]. Despite that, mine planning with IPCC has been underexplored. A comprehensive review of short-term mine planning and IPCC by Habib et al. [19] shows that mine planning, more specifically short-term mine planning considering IPCC is an almost unexplored area of research. This is a good read for those looking to get an insight on different IPCC configurations, their pros and cons and the challenges of integrating IPCC to mine planning. Majority of the IPCC literature, for example, Konak et al. [24], Taheri et al. [58], Rahmanpour et al. [46], Roumpos et al. [47], Paricheh and Osanloo [41; 44; 45; 43] have been concerned with finding an optimum crusher location and time to install IPCC systems without considering the fact that the optimality of an IPCC system needs to be integrated to the mine plan.

Several methodologies have been developed for simultaneous optimization of IPCC locations and long-term schedules. Key contributors include Paricheh and Osanloo [42], Samavati et al. [48], Shamsi et al. [51], Liu and Pourrahimian [28], Kamrani et al. [22; 23], Liam and Dimitrakapoulos [14] etc. The primary objective across these studies is to maximize the net present value of the production while leveraging IPCC as the primary mode of material transport. Shamsi and Nehring [50] analyzed scenarios to find the optimal depth for switching from truck-shovel haulage to Semi-Mobile In-Pit Crushing and Conveying (SMIPCC). Using a hypothetical cone-shaped mine with four pushbacks, they found the switch is most economically advantageous at 335 meters during the second phase. Gölbaşı and Demirel [16] developed a simulation algorithm aimed at optimizing inspection intervals for mining equipment, with a focus on reducing maintenance costs and maintaining operational efficiency. Using real data from two draglines in a coal mine, the study demonstrated significant cost savings by optimizing inspection schedules. The approach is relevant for complex mining operations, like those using IPCC systems, where equipment uptime and cost control are crucial. Table 1 summarizes the number of different types of recent (post 2010) short-term planning and IPCC related articles based on some key features.

Table 1. Short-term planning and IPCC related articles post 2010 based on key features.

Category	Key attributes	Number of papers
Short-term planning	Strictly Deterministic	16
	Stochastic	17
	Designed for Truck Haulage	30

	Designed for IPCC	1
IPCC	Crusher location/relocation time optimization	17
	Economic or environmental comparison	15
	Integration with long-term plan	6
	Integration with short-term plan	1
	Integration with short-term planning considering uncertainty	0

1.2. Research Gap and Innovation of the Study

The above discussion and Table 1 highlight that short-term planning optimization and capturing uncertainties using IPCC as a hauling method is a largely unexplored research area. Key decisions regarding IPCC, including optimal crusher location, crusher relocation timing, and conveyor design, are made during the strategic phase of mine planning. Short-term planning must adapt to the installation and movement of crushers and align with long-term strategies to achieve the desired NPV. Furthermore, the uncertainties associated with IPCC, truck and shovel operations add to the complexity of the short-term planning optimization. To address the issue, this paper presents an innovative approach that combines simulation and optimization to create near-optimal short-term schedules while accounting for haulage uncertainties. A MILP model generates monthly production schedules by optimally assigning shovels to mining faces or mining cuts. These schedules are then input into the Monte Carlo haulage simulation model, which incorporates probability distributions for shovel loading time, truck travel time, dumping time, and failure probabilities for trucks, shovels, and the IPCC system. While the MILP model excels in producing near-optimal short-term schedules for both IPCC and pure truck-shovel haulage, the Monte Carlo simulation ensures that all haulage uncertainties are thoroughly captured. The challenges encountered in this study involved capturing and realistically modeling the inherent uncertainties and variabilities in shovel loading times, truck travel times, dumping times, equipment failure rates, and other operational disruptions. Additionally, integrating the simulation model to efficiently receive and process input from the MILP presented practical implementation challenges specific to this case study. The framework builds upon and enhances the short-term planning methodology proposed by Habib et al. [20] by addressing operational uncertainties. Additionally, it can serve as a comparative tool to determine the performance of IPCC system in comparison with truck-shovel system in terms of haulage cost savings.

2. Problem Definition

This study seeks to create a robust short-term planning methodology to enhance production schedules amidst uncertainties involving trucks, shovels, and/or IPCC systems. The approach utilizes a MILP model to allocate shovels to mining faces, aiming to achieve production targets and maximize profits. The optimized schedule, along with probability distributions for trucks, shovels, and IPCC systems, is used as input for a Monte Carlo haulage simulation model, ensuring accurate representation of operational uncertainties.

Although simulation optimization models have their limitations, such as difficulty modeling and high computational expenses, it demonstrates how effectively a mining operation can meet its production targets while considering the variability and uncertainties in haulage operations.

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

In addition to the general complexities of integrating IPCC into short-term mine planning, semi-mobile IPCC systems introduce unique planning challenges. One of the most critical factors is the need for periodic relocation of the in-pit crusher to align with the progression of mining faces. This relocation must be synchronized with production targets, haulage network adjustments, and shovel allocations to minimize disruptions and maintain efficiency. These added logistical considerations increase the complexity of planning and highlight the need for models that can accommodate dynamic infrastructure positioning over the short-term horizon.

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

While minimizing deviation from the strategic plan is a core purpose of short-term planning, this study assumes that long-term production targets have already been defined. In this context, the objective of minimizing haulage cost in the MILP model serves as a practical proxy for enhancing operational efficiency. These cost reductions are pursued within the constraints of meeting the strategic production targets, which are embedded into the model as fixed requirements. Therefore, the objective function does not replace the strategic plan but supports its execution by optimizing shovel allocation and haulage routes at the tactical level. This approach reflects the operational realities of mine planning, where short-term decisions are often made under fixed production targets, with efficiency being a key concern.

2.1. Scope and Assumptions of the Proposed Model

The methodology presented here is an improvement of the short-term planning model proposed by Habib et al. [20] to capture haulage uncertainties. The assumptions associated the MILP model and the simulation model are briefly summarized below.

2.1.1. MILP Assumptions

1. Semi-Mobile IPCC System: The IPCC system in this study is semi-mobile and is exclusively used for ore crushing and conveying. While it is acknowledged that

waste extraction and transportation are essential for accessing the ore and incur significant costs, the current model does not include a waste IPCC system. This decision is based on the high capital investment required and the inefficiencies associated with crushing waste material, which does not generate revenue. However, it is recognized that, in some real-world cases, the use of IPCC systems for waste material can help reduce costs and minimize environmental impacts, such as GHG emissions. Despite these potential benefits, the current state of the art of the model focuses solely on ore processing. The semi-mobile IPCC system was selected because it offers the most practical balance between flexibility and operational control among the three configurations. It is also one of the more commonly implemented IPCC systems in large-scale open-pit mines. This choice allows the model to accommodate dynamic crusher relocations throughout the planning horizon, which is consistent with the strategic inputs of the case study.

2. Crusher Locations, Relocations and Conveyor Ramp Design: The optimal locations and relocation times for the crusher and the conveyor ramp designs are predetermined based on strategic planning for the entire life of the mine. Pit and ramp design are beyond the scope of this study.
3. Ore and Waste Face Identification: Ore and waste faces are identified from long-term plans. Consequently, ore material is directed to the mill or crusher, while waste material is directed to the waste dump.
4. Shovel Allocation: Ore shovels are primarily assigned to ore faces, and waste shovels to waste faces. Reassignment across material types is allowed only if operational constraints, such as the depletion of available faces, necessitate it. However, this scenario did not arise in the case study.
5. No Stockpiling: The model assumes that there is no stockpiling of materials.
6. Mine Life Duration: The mine is expected to operate for more than 20 years.
7. Ore Blending: The current model does not incorporate ore blending.
8. Processing Destinations: The model does not consider multiple processing destinations for the ore.
9. Deterministic Model: The MILP operates under deterministic assumptions, without incorporating stochastic elements.

2.1.2. Monte Carlo Simulation Assumptions

1. Probability Distributions: Full and empty haulage speeds, loading/dumping time, bucket capacity and other uncertain variables follow specific probability distributions (e.g., normal, lognormal, exponential). These distributions are based on recorded historical mining data and are modified for confidentiality reasons.
2. Fixed Operational Parameters: Certain parameters, such as route lengths, payload capacities, shovel cycle times and capacities, are assumed to be constant.
3. Working Conditions: The working conditions of the mine are assumed to be same for the scenario with IPCC and TS because of the lack of historical mining data with

IPCC. As a result, the parameter and variable distributions for trucks and shovels, such as truck speed, loading, and spotting times, are kept the same in both scenarios.

4. Failures and Downtime: Equipment failures and downtime are incorporated into the simulation and modeled using statistical distributions based on historical data.
5. Steady-State Conditions: The simulation assumes the system reaches steady-state conditions, where the effects of initial transient states are negligible.
6. Schedules: Production schedules and haulage demands are fixed across all simulated scenarios and extracted from the MILP model.
7. Mine Layout: The physical layout of the mine, including the road network and dumping locations, is predefined and does not change during the simulation.
8. Resource Allocations: The allocation of shovels to mining faces are determined by the MILP model. The ore and waste trucks are separate and locked to respective ore and waste shovels throughout the simulation.
9. Waiting time: In this simulation, trucks are not modeled as individual agents or entities. Instead, truck waiting times are generated randomly based on a predetermined distribution. Waiting time is considered for shovel loading only. The M/M/c queuing model, which assumes exponential arrival and service times, has been was used to estimate the waiting time distribution due to the lack of historical waiting time data. The parameters are chosen to reasonably reflect the operational realities.

3. Methodology

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

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

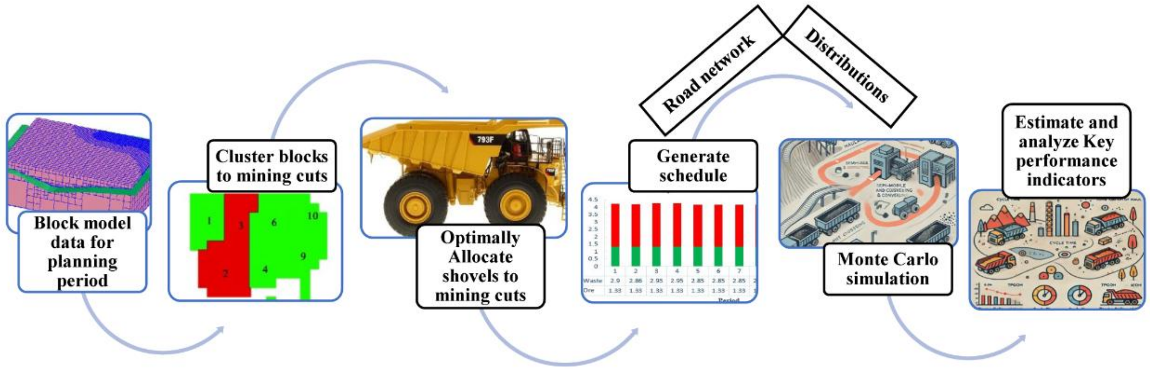


Figure 1. Outline of the proposed simulation-optimization framework.

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

3.1. Mathematical Model Formulation

The proposed optimization model is a MILP model. The objective is to maximize the overall profit derived from mining activities by minimizing mining, processing, haulage and shovel movement costs. This objective function comprises of six key components. Firstly, it calculates the mining costs associated with extracting the material. Secondly and thirdly, it computes the expenses for transporting ore to the crusher or the mill, and waste material to designated dumps, utilizing diesel trucks. The fourth component determines the costs involved in conveying ore material from the crusher to the processing plant. The fifth component calculates the cost of shovel movement between mining faces. Lastly, it evaluates the net revenue by subtracting processing costs from earnings generated by processed ore. The model and the parameter values used here are the same as Habib et al. [20] except for the shovel movement cost. Hence the model and the solution methodology will be briefly discussed here. Mathematically, the objective function can be represented as following,

Minimize, f =

$$\underbrace{\sum\nolimits_{p\in P,t\in T,f\in F} x_{p,f,t} \times RM_{p,f} \times TT \times M_c}_{\text{Mining costs}} + \underbrace{\sum\nolimits_{p\in P,t\in T,f\in F_{ore}} x_{p,f,t} \times RM_{p,f} \times TT \times D_{f,r} \times H_t}_{\text{Ore haulage costs}} +$$

$$\underbrace{\sum\nolimits_{p\in P,t\in T,f\in F_{waste}} x_{p,f,t} \times RM_{p,f} . TT \times D_{f,w} \times H_t}_{\text{Waste haulage cost}} + \underbrace{\sum\nolimits_{p\in P,t\in T,f\in F_{ore}} x_{p,f,t} \times RM_{p,f} \times TT \times C \times H_c}_{\text{Ore conveying cost}}$$

$$+ \underbrace{\sum\nolimits_{p\in P,t\in T} N_{p,t} \times D_{p,t} \times H_{sh}}_{\text{Shovel movement cost}} - \underbrace{\sum\nolimits_{p\in P,t\in T,f\in F_{ore}} x_{p,f,t} \times RM_{p,f} \times TT \times (R_k \text{-} PR_c)}_{\text{Revenue from selling ore}} \tag{1}$$

The variables, parameters and indexes are detailed below.

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

Parameter	**Unit**	**Description**
TT	Hr	Total time per period
$AV_{p,t}$	%	Availability of shovel p in period t
$RM_{p,f}$	t/h	Material throughput of shovel p in face f
TM_f	Tonnes	Total material in face f
$D_{f,w}$	km	Distance to waste dump from face f
TC	Tonnes	Mill capacity per period
C	Km	Conveyor length
SR	-	Stripping ratio
$D_{f,r}$	Km	Distance to crusher/mill from face f
$D_{p,t}$	Km	Distance traveled by shovel $p \in P$ in period $t \in T$
H_t	$/tonneKm	Transportation cost per unit; $1.2/tonneKm
H_c	$/tonneKm	Conveying cost per unit; $0.25/tonneKm
H_{sh}	$/Km	Shovel movement cost per kilometer; $0.4/km
M	-	A big number
R_k	$/tonne	Iron ore unit price; $151/tonne
M_c	$/tonne	Mining cost per unit; $3/tonne
PR_c	$/tonne	Processing cost per unit; $8.34/tonne
N^f	-	Number of precedences for face f
$c_{f,t} \in \{0,1\}$		Crusher location parameter, Equal to 1 if crusher is located on face $f \in F$ in period $t \in T$, 0 otherwise

Indexes	**Description**
p	Index for shovels

f	Index for faces
t	Index for periods

The model is subject to the following constants.

$$\textstyle\sum_{p\in P} s_{p,f,t} \le 1; \forall f \in F, \forall t \in T \tag{2}$$

$$\textstyle\sum_{f\in F} s_{p,f,t} \le 2; \forall p \ \in P, \forall t \in T \tag{3}$$

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

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

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

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

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

$$l_{f,t+1} = l_{f,t} - \textstyle\sum_{p\in P} x_{p,f,t} \times \ RM_{p,f} \times TT; \ \forall f \in F \ \& \ t=1 \dots T\text{-}1 \tag{7}$$

$$\mathrm{M}\times m_{f,t} <= \text{epsilon} - l_{f,t} \qquad ;\forall f \in F, t \in T \tag{8}$$

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

$$m_{f,t+1} \ge m_{f,t} \ ; ;\forall f \in F, t \in 1 \dots T\text{-}1 \tag{10}$$

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

$$\textstyle\sum_{f\in F} s_{p,f,t} \le s_{p,f,t} + m_{f,t} + (1 - s_{p,f,t-1}) + (1 - s_{p,f,t}\,) \times BM \ ;\forall f \in F, p \in P, t \in T \tag{11}$$

$$s_{p,f,t+1} \ge s_{p,f,t} - \ m_{f,t}; \ ;\forall f \in F, p \in P, t \in 1 \dots T\text{-}1 \tag{12}$$

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

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

$$\textstyle\sum_{p\in P, t\epsilon T} x_{p,f,t} \times \ RM_{p,f} \times TT \le TM_f; \forall f \in F \tag{14}$$

$$N^f \times \textstyle\sum_p s_{p,f,t} \ - \sum_{f'} m_{f',t} \le 0; \ \ \forall f \in F, p \in P, t \in T, f' \in precednece\ set \tag{15}$$

Eq. (14) ensures shovels' extraction do not exceed the material available in a face across periods. Eq. (15) enforces mining precedence, requiring a precedence face to be fully mined out before moving to its predecessor faces by making sure that assignment variable for a face cannot take a value of one unless all the faces in its precedence set are mined out completely.

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

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

Eq. (16) ensures shovel time allocation across faces does not exceed availability. Finally, Eq. (17) ensures that the number of movements made by a shovel within a specific period is one less than the number of faces it is assigned to in that period. This constraint prevents unrealistic or unnecessary movements that could inflate operational costs or cause infeasible allocations. Without it, the model might allow illogical shovel transitions, such as allocating a shovel to multiple faces without accounting for movement, or allowing movement when only one assignment is possible in a period. Eq. (17) therefore plays a key role in maintaining schedule feasibility and operational consistency. The model has been implemented and solved in MATLAB using a rolling planning horizon technique to reduce the runtime and computational expense

3.2. Monte Carlo Haulage Simulation

Mining haulage is a continuous process with variables that are typically continuous in nature. Monte Carlo simulation is particularly well-suited for this type of analysis because it handles continuous variables effectively by employing random sampling to generate a wide range of possible values for each variable. This approach allows for a comprehensive exploration of the entire probability distribution, making it ideal for modeling the inherent uncertainties and variability in mining operations, such as fluctuations in equipment performance and operational conditions. The goal of the simulation model is to evaluate total production across various scenarios, comparing IPCC and pure truck-shovel haulage under uncertain conditions. This comparison determines how each system aligns with the optimal production schedule generated by the MILP model, assessing performance in terms of production, reliability, and TPGOH.

Figure 2 illustrates the simulation flowchart for the mine haulage process. The simulation begins by reading the optimal schedules, road network, and probability distributions to ensure accurate data and realistic assumptions. These inputs reflect the variability and uncertainty in haulage operations. Once the data is set, the simulation proceeds and differentiates tasks based on whether they involve an ore face or a waste face. The flowchart is color coded with blue color representing ore haulage and green representing waste haulage. In both scenarios, ore is sent to the processing plant, but the haulage paths differ. The truck-shovel scenario uses direct truck transport, while the IPCC scenario delivers ore to an in-pit crusher, then conveys it to the plant. To ensure fair cost comparison, the MILP model includes the conveyor haul cost separately. In the simulation, conveyor movement is not explicitly tracked but modeled via failure and repair distributions, assuming a constant operating speed.

3.2.1. Simulation Logic Flow

Ore Haulage

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

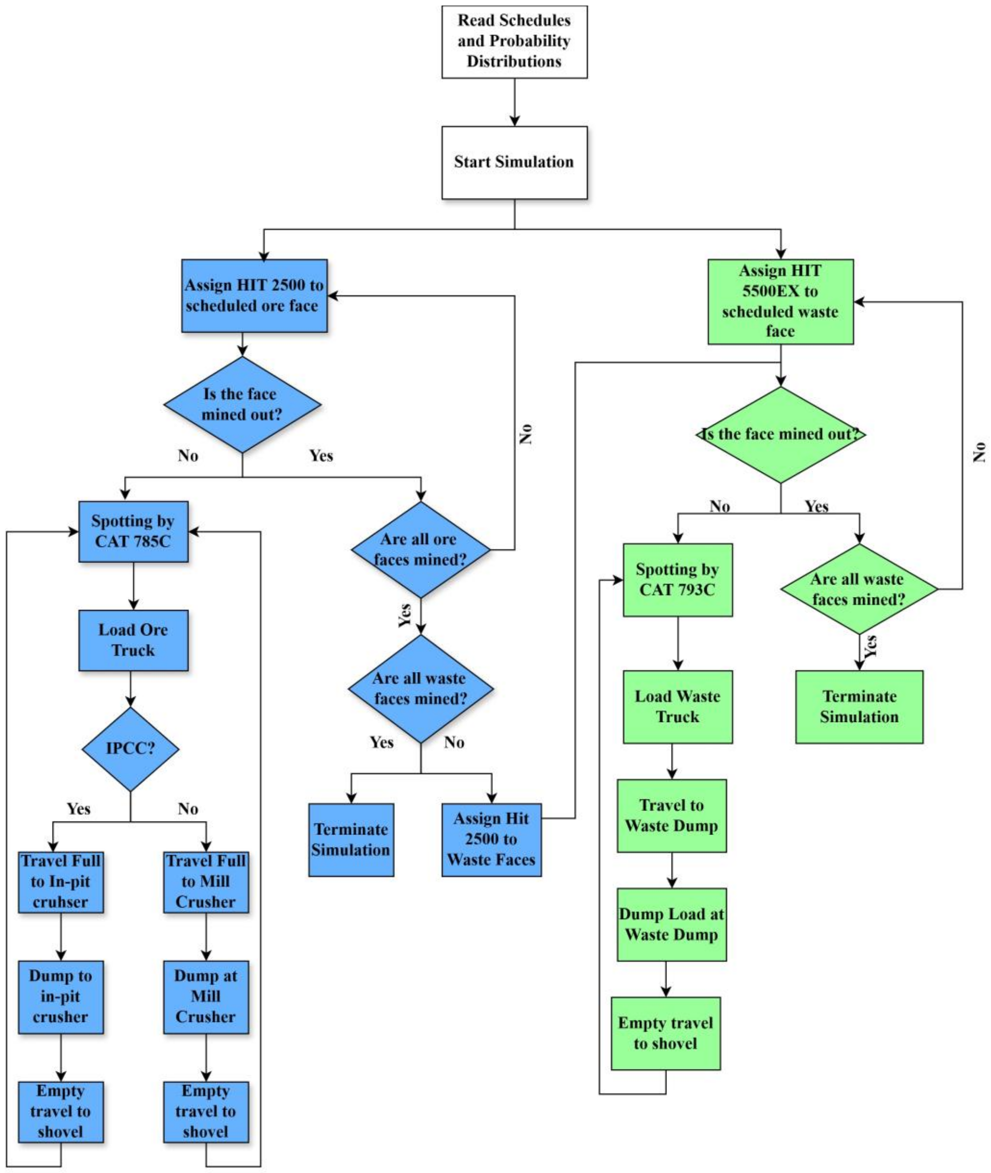


Figure 2. Haulage Simulation flowchart.

Waste Haulage

1. **Excavator Assignment:** Waste excavators are assigned to scheduled waste faces.
2. **Mining Status Check:** The simulation checks if the waste face is mined out.
3. **Loading Process:**
    - If not mined out, a waste truck positions itself to be loaded by the shovel.
4. **Haulage Path:**
    - The loaded waste truck travels to the waste dump, dumps its load, and returns empty to the shovel.
5. **Face Reassignment:**
    - If the current face is mined out, the system checks if all waste faces have been mined.

  - If not, the waste shovel is reassigned to the next waste face.

6. **Termination Check:**
  - If all waste faces are mined out, the simulation terminates.

This simulation framework ensures efficient and continuous haulage operations, reflecting the complexities and uncertainties of real mining activities.

4. Case Study

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

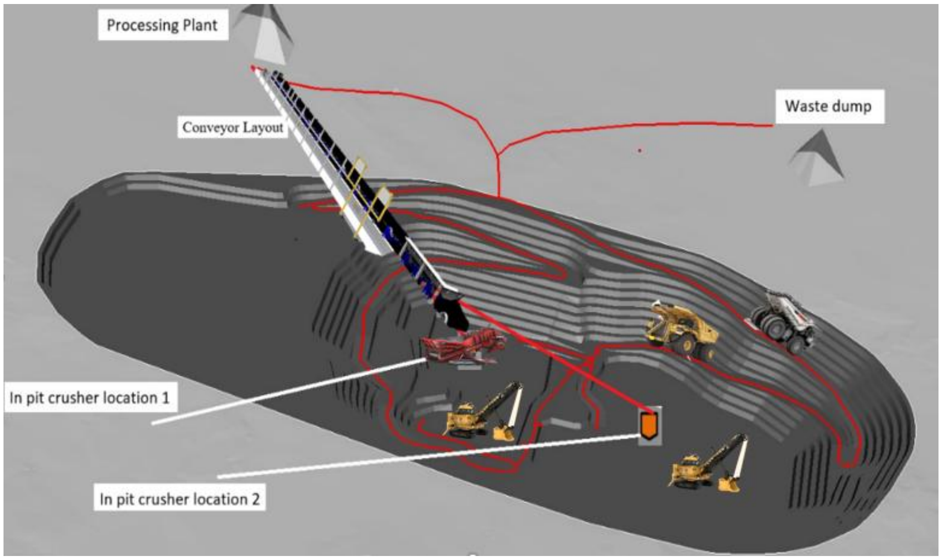


Figure 3. Mine layout for year 11.

Figure 3 shows the mine layout for the 11th year, with distances from mining faces to the waste dump, crusher, and plant calculated based on the road network. The mine ramps have an 8% grade, and the IPCC scenario requires a 2550-meter conveyor belt. The crusher is located on face 3 for the first six months and face 18 for the rest of the year, both at bench 1595. Although several high quality clustering algorithms have been proposed by researchers [2; 57; 65], we utilized the hierarchical clustering algorithm developed by Tabesh and Askari-Nasab [56] to aggregate 4,200 blocks into 170 mining faces across four benches due to the method's ease of use and versatility. Figure 4 and Figure 5 illustrate the clustered ore and waste faces, with face IDs numbered, respectively on benches 1595 and 1610. The red and green shaded faces represent ore and waste respectively. All the faces of the benches on elevation 1730m and 1745m are designated as waste.

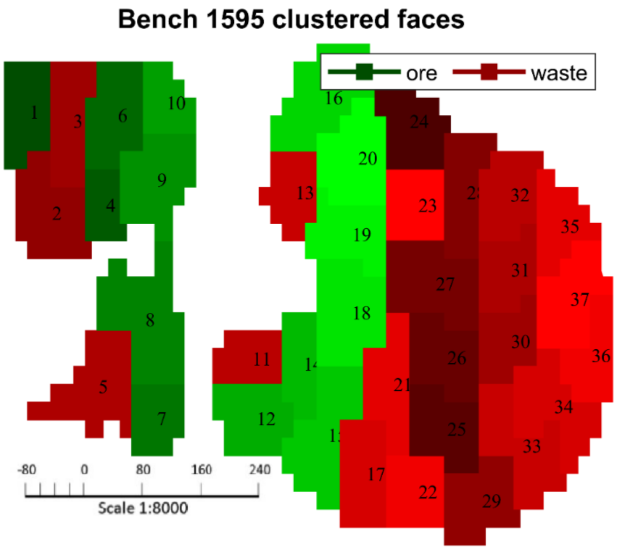


Figure 4. Clustered faces for the ore benches.

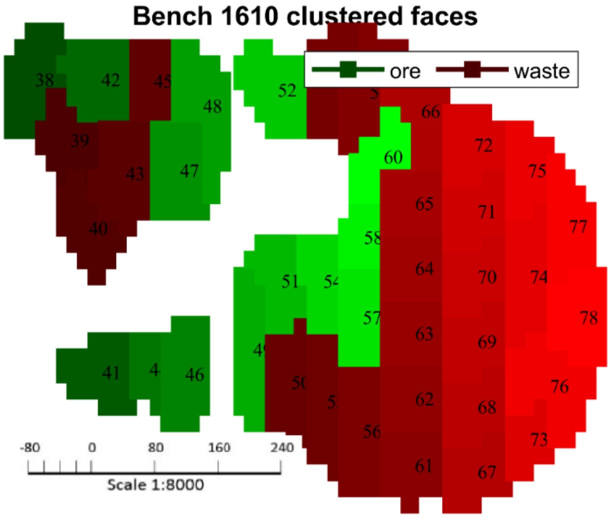


Figure 5. Ore and waste faces on bench 1610.

The mine uses five shovels: two Hit 2500 for ore and three Hitachi 5500Ex for waste. The Hit 2500 shovels have a 12-ton bucket capacity with a 22-second cycle time, while the Hitachi 5500Ex shovels have a 22-ton bucket capacity with a 23-second cycle time. Cat 785C trucks (140-ton capacity) are paired with Hit 2500 shovels, and Cat 793C trucks (240-ton capacity) are paired with Hitachi 5500Ex shovels. The truck-shovel and IPCC scenarios require 10 and 4 ore trucks respectively to the haul the total tonnage of ore mined. The number of waste trucks remain 13 in both the scenarios.

The equipment failures are modelled in the haulage simulation. Only probabilistic distribution functions are required for the MCS model to estimate failures. The mean time between failure (MTBF) and the mean time to repair (MTTR) distribution functions considered in this case study are given in Table. While the truck and shovel failure distributions are generated from historical mining data, the conveyor failure distribution is adopted from Londoño et al. [30] because of the lack of historical IPCC data. As mentioned in Chapter 3, only the failure of the conveyor system is considered in the simulation, while failures of the crusher or other IPCC components are not included. The MTTR and MTBF distributions are assumed to remain the same for truck and shovels across scenarios with and without IPCC. The different failure distributions are summarized in Table 2.

Table 2. MTBF and MTTR distribution functions.

Equipment	MTBF (hr)	MTTR (hr)
Hit 2500	WEIB (32, 216)	GAMM (1.4, 1.5)
Hit 5500Ex	WEIB (32, 216)	GAMM (1.4, 1.5)
Cat 785C	WEIB (27, 200)	GAMM (1.4, 1.5)
Cat 793C	WEIB (27, 200)	GAMM (1.4, 1.5)
IPCC conveyor	WEIB (0.714, 31.9)	GAMM (1.4, 1.19)

It is to be noted from [30] that the conveyor system experiences three distinct types of failures: conveyor take-up, electrical, and mechanical, with MTBF distributions modeled as Weibull(0.48, 36.99), Weibull(0.7, 31.4), and Weibull(0.64, 50.96), respectively. The corresponding MTTRs for these failures follow Gamma distributions, specifically Gamma(1.5, 0.55), Gamma(1.6, 1.1), and Gamma(1.4, 1.7). To simplify analysis, we combined these three failure modes into a single MTBF and MTTR distribution using Monte Carlo simulation. A key assumption in this process was that the failures occur independently. We generated 1000 random values for each of the MTBF and MTTR based on their respective distributions, resulting in 3000 random data points. These were then used to fit the best distribution using ARENA Input Analyzer.

5. Results

The simulation-optimization framework was developed in MATLAB, solving a MIP model for two scenarios, namely semi-mobile IPCC and pure truck-shovel, over a 12-month horizon using a rolling approach. A global solution required 20 hours with >8% optimality gaps. Reducing the horizon to 6, 4, and 3 months decreased gaps to 3%, 1%, and 0.5%, with computation times of 12, 6, and 4 minutes, respectively. Optimization outputs, along with road network and statistical distributions, are fed into the haulage simulation via a GUI. The simulation, flagged by scenario type, was run 100 times per case on a Dell XPS (16 GB RAM), with each replication taking around 5 minutes. Results are summarized in the following section.

5.1. MILP Model Results

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

5.1.1. Optimal Shovel Allocation

This section summarizes and compares the optimal shovel allocations made by the MILP for the IPCC and truck-shovel scenarios. Figure 6, Figure 7, Figure 8, and Figure 9 illustrate the shovel allocations for benches 1595, 1610, 1730, and 1745, respectively. As shown in these figures, the model ensures that ore shovels (indexes s1 and s2) are assigned exclusively to ore faces, while waste shovels (indexes s3, s4, and s5) are assigned to waste faces. Notably, Face 18 remains unmined in the IPCC scenario, indicating that the model considers the crusher location when allocating shovels. All the other faces have been assigned to a shovel making sure that the model fulfills the production requirements. Shovel 5 is confined to the waste benches at the 1730m and 1745m elevations, primarily because the model aims to minimize shovel movement costs. The model also does not let the shovels to move across faces that are more than one bench apart. Figures 6 to 9 are included to provide visual context for shovel allocation across the four benches. Detailed discussion of these allocations is available in our prior work [20]. Differences in color schemes between figures reflect variations in figure generation and do not indicate differences in model logic or results.

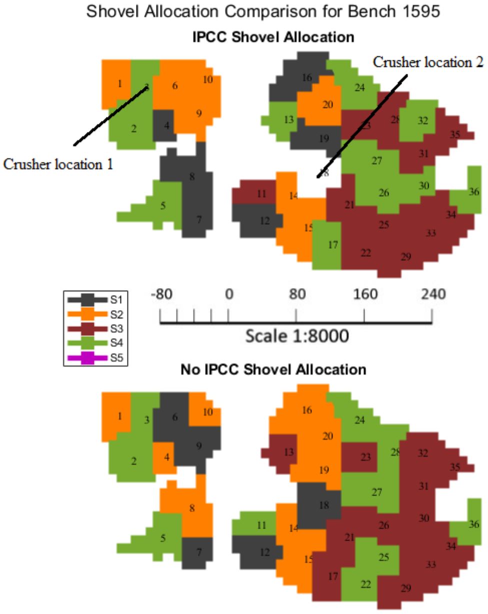


Figure 6. Shovel Allocation to bench 1595 .

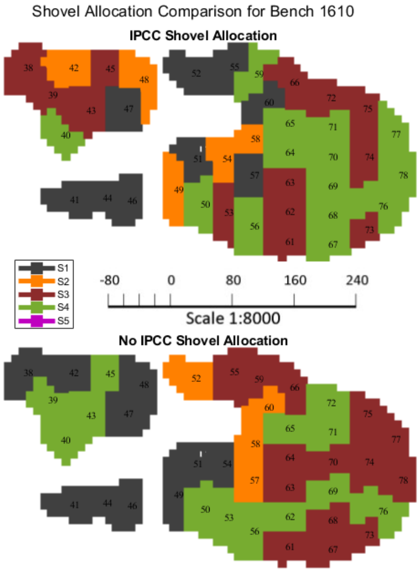


Figure 7. Shovel Allocation to bench 1610.

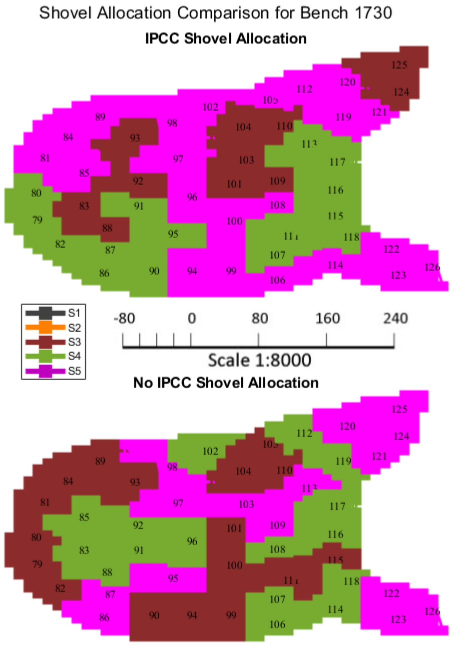


Figure 8. Shovel Allocation to bench 1730.

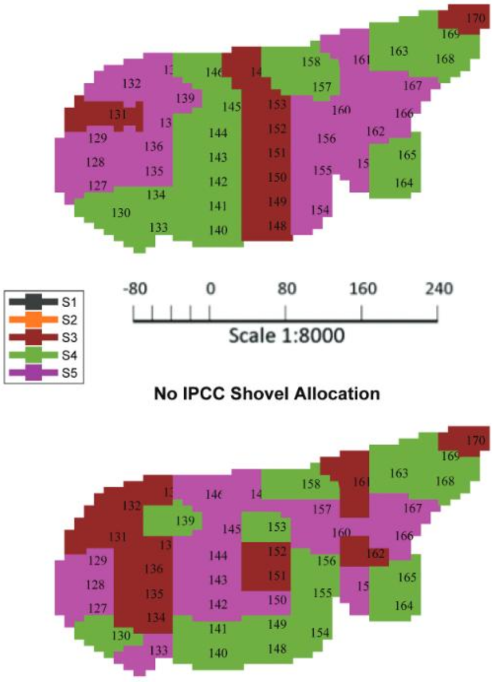


Figure 9. Shovel Allocation to bench 1745.

5.1.2. Mining Period

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

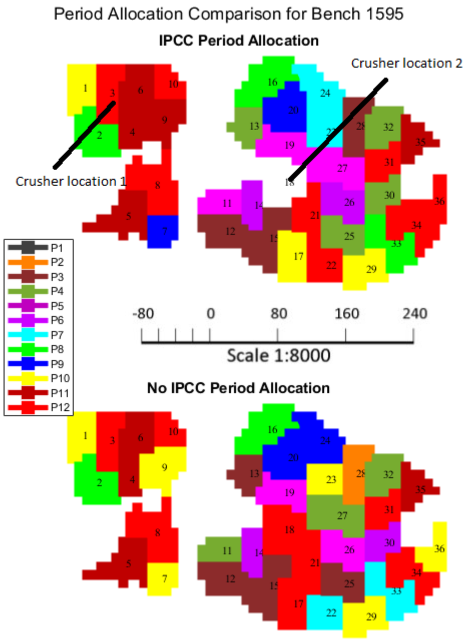


Figure 10. Mining period for faces on bench 1595.

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

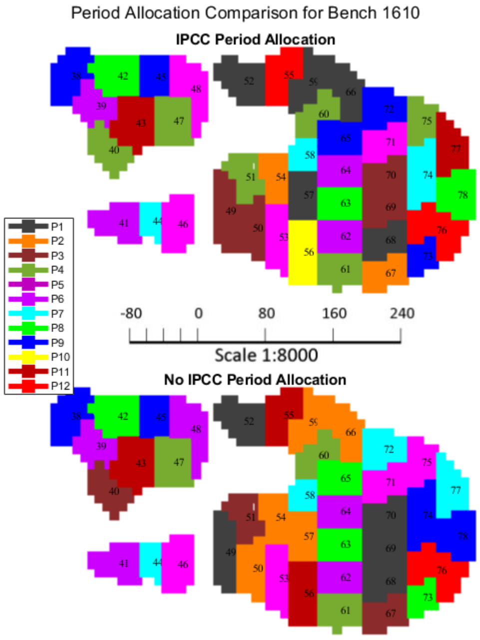


Figure 11. Mining Period for faces on bench 1610.

A closer examination of Figure 10 and Figure 11 show that mining begins in period 1 on bench 1610 but is delayed until period 3 on bench 1595 in both scenarios. This sequencing reflects the precedence constraints, with bench 1610 faces prioritized and mostly mined within the first 11 periods. In contrast, bench 1595 faces are scheduled toward the end, reinforcing that the model respects the defined vertical dependencies between these ore benches.

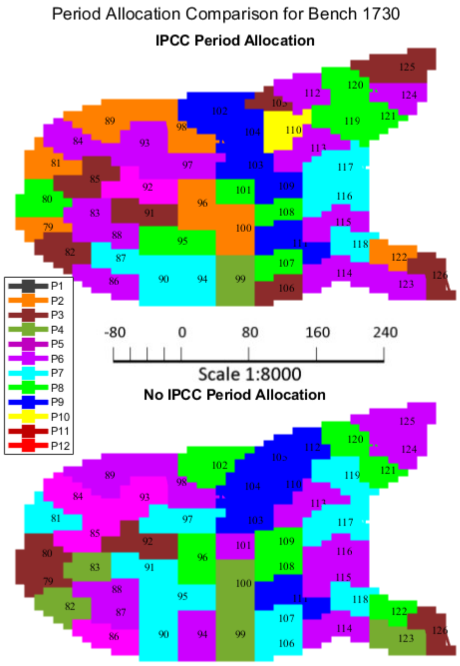


Figure 12. Mining Period for faces on bench 1730.

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

Mining on bench 1745 occurs between periods 1 and 5 for both the IPCC and non-IPCC scenarios. Figure 13 highlights that periods 3 and 4 are the most active for the IPCC scenario, while periods 2 and 4 are the busiest for the non-IPCC scenario. The early mining of faces on bench 1745 is driven by its precedence over bench 1730. More detailed discussion on Figures 10 to 13 can be found in [20].

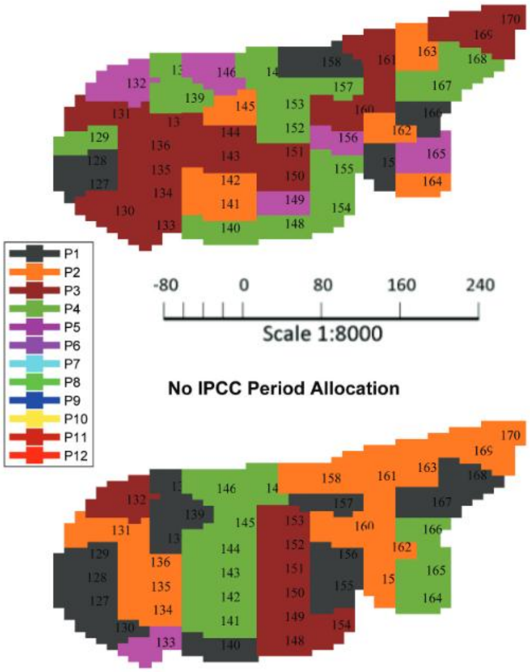


Figure 13. Mining Period for faces on bench 1745.

5.1.3. Monthly Production Schedule

Figure 14 shows that the TS scenario maintains steady ore production at 1.33 MT per period and consistent waste output, with slight fluctuations between 2.85 and 2.96 MT. This reflects balanced ore extraction and efficient waste management.

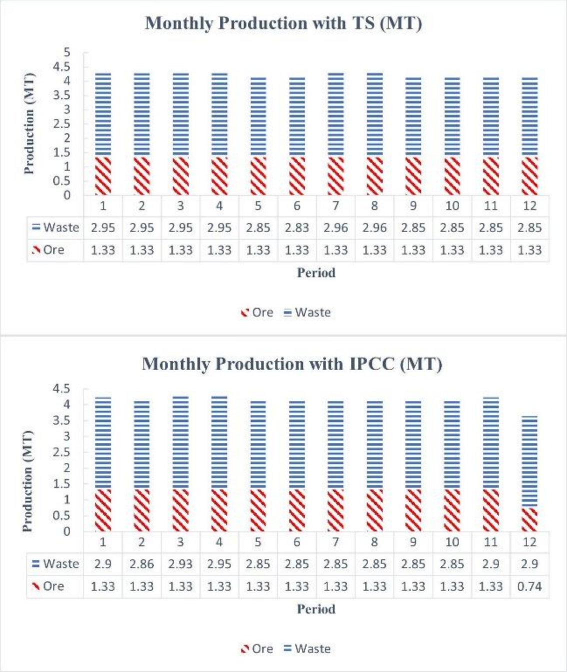


Figure 14. Monthly Production Schedule for IPCC and truck-shovel scenario.

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

Both scenarios maintain steady ore production, with minor variations in waste output. This consistency across periods demonstrates the model’s effectiveness in meeting production targets. The slight dip in ore production in the final period of the IPCC scenario reflects the model’s adherence to crusher location constraints, prompting operational adjustments. These adjustments cause small fluctuations in waste production, particularly in the IPCC case, highlighting the model's flexibility. As shown in Figure 15, overall ore and waste outputs are slightly lower in the IPCC scenario. The reduction in ore is due to in-pit crusher constraints, whereas waste production remains largely unaffected due to its abundance. It is important to note that both the IPCC and truck-shovel scenarios were developed to meet identical long-term production targets for ore and waste. As a result, the stripping ratio remains nearly constant across both cases and is not used as a comparative metric in this analysis. Instead, we focus on monthly and total production outputs to evaluate how each haulage system performs in meeting the targets under operational variability in Figure 14 and Figure 15.

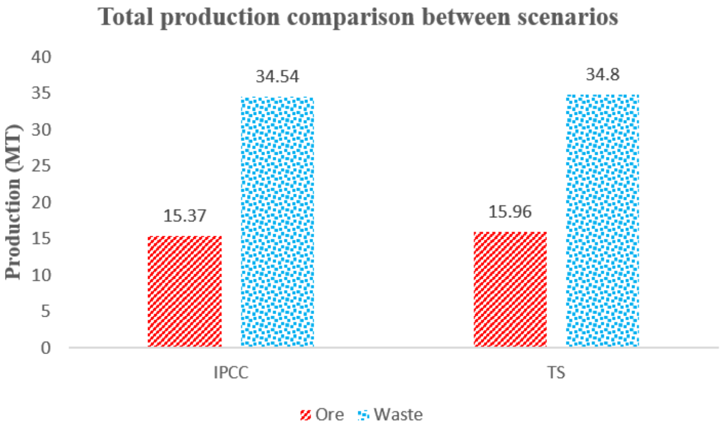


Figure 15. Total production of ore and waste.

5.2. Comparison and Discussion of Simulation Results

The simulation model uses inputs from the optimization model to assess ore and waste production under operational uncertainties for both IPCC and non-IPCC scenarios. Key variables listed in Table 3, are evaluated over 100 replications to ensure statistical reliability. KPI distributions and truck-shovel failure statistics are derived from historical mine data, while IPCC failure distributions are sourced from Londono et al. [30] due to the lack of site-specific data.

Table 3. Key performance indicators (KPIs) to be compared.

Variable	Distribution	Variable Type
Spotting time (min)	Empirical	Independent
Loading time (min)	Empirical	
Dumping time(min)	Empirical	
Truck Speed (Km/hr)	Triangular	
Truck traveling time (min)		Dependent
Truck cycle time (min)		
Waiting time (min) (Gamma)		
Ore Truck TPGOH (tonne/hr)		
Total Production (tonne)		

It is to be noted that the distribution of waiting time has been derived using M/M/C (exponential arrival and service time) queuing model by considering truck speed, distance traveled, number of trucks and shovels. Since, there are two ore and three waste shovels in this case study, the waiting time distribution does not follow an exponential distribution but is better approximated by a Gamma distribution due to the combined effect of multiple servers working in parallel [10]. The waiting time distributions for ore truck, CAT 785C, are GAMMA (2, 1.18) and GAMMA (2, 1.8) for the scenario without and with IPCC respectively. The distribution of waiting time for the waste truck, CAT 793C, is GAMMA (3,1.62) for both scenarios.

5.2.1. Comparison of Independent variables

The independent variables listed in Table 3 comprise truck cycle time. A summary of the comparative statistics for the indepependent variables is illustrated in Table 4.

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

The confidence intervals (CIs) for the variables in Table 4 are remarkably narrow, indicating a high level of precision in the simulation results. Given that 100 replications were run for each variable, this precision suggests that the simulation model is robust and reliable. For example, the CI for Ore Spotting time (min) under the IPCC scenario is 0.585 ± 0.00015, demonstrating minimal variability around the mean. Similarly, the Ore Loading time (min) has a CI of 3.537 ± 0.0006 for the IPCC scenario, further reinforcing the consistency of the simulation results. This high precision across different variables, whether it is ore Dumping time, or waste loading time, underscores that the simulation outputs are dependable. The narrow CIs imply that the variability in the data is minimal, and the results are not significantly influenced by outliers or anomalies.

Table 4. Comparison of independent variables between scenarios.

Variable	Scenario	Mean	Median	St Dev	95% confidence interval
Ore Spotting time (min)	IPCC	0.58	0.56	0.25	0.58 ± 0.0002
	No IPCC	0.58	0.55	0.25	0.58 ± 0.0001
Ore Loading time (min)	IPCC	3.54	3.46	1.03	3.54 ± 0.0006
	No IPCC	3.54	3.46	1.03	3.54 ± 0.0006
Ore Dumping time (min)	IPCC	1.35	1.46	0.2	1.35 ± 0.0001
	No IPCC	1.35	1.46	0.2	1.35 ± 0.0001
Ore truck speed (km/hr)	IPCC	36.67	36.34	3.12	36.67 ± 0.002
	No IPCC	36.66	36.34	3.12	36.66 ± 0.002
Waste spotting time (min)	IPCC	0.58	0.54	0.25	0.58 ± 0.0001
	No IPCC	0.58	0.54	0.25	0.58 ± 0.0001
Waste loading time (min)	IPCC	4.51	4.51	1.03	4.51 ± 0.0006
	No IPCC	4.51	4.51	1.03	4.51 ± 0.0006
Waste Dumping time (min)	IPCC	1.32	1.46	0.22	1.32 ± 0.0001
	No IPCC	1.32	1.46	0.22	1.32 ± 0.0001
Waste truck speed (km/hr)	IPCC	36.84	36.98	3.49	36.84 ± 0.068
	No IPCC	36.65	36.17	3.02	36.65 ± 0.06

5.2.2. Comparison of Dependent KPIs

Truck travel time, waiting time, cycle time, TPGOH (Tonnes per Gross Operating Hour), and total production are key KPIs influenced by loading, spotting, dumping, travel, and queuing. Shorter cycle times lead to higher production rates and fewer required trucks. IPCC reduces haul distance, lowering both cycle time and truck count. Table 5 provides a comprehensive summary of the statistics for these dependent KPIs, offering a clear view of the system's performance with and without the incorporation of IPCC. The difference between the KPIs are calculated with reference to the no IPCC scenario.

Table 5. Comparison of dependent KPIs.

Variable	Scenario	Mean	Median	St Dev	95% confidence interval
Ore Truck traveling time (min)	IPCC	2.30	2.06	1.31	2.30 ± 0.0007
	No IPCC	13.8	13.82	1.61	13.80 ± 0.0009
Difference (%)		83.35	85	18.63	N/A
Waste Truck traveling time (min)	IPCC	12.19	12.95	3.84	12.19 ± 0.002
	No IPCC	12.18	12.86	2.85	12.18 ± 0.0014
Difference (%)		-0.05	-0.73	-34.77	N/A
Ore truck Waiting Time (min)	IPCC	3.60	2.96	2.68	3.6 ± 0.0014
	No IPCC	2.36	1.74	2.17	2.36 ± 0.0013
Difference (%)		-40.34	-70.11	-23.50	N/A
Waste truck waiting time (min)	IPCC	4.86	3.90	3.82	4.86 ± 0.0019
	No IPCC	4.86	3.90	3.82	4.86 ± 0.0019
Difference (%)		0	0	0	N/A
Ore Truck cycle time (min)	IPCC	9.52	9.28	1.73	9.52 ± 0.001
	No IPCC	21.63	21.33	2.91	21.63 ± 0.001
Difference (%)		56	55.17	40	N/A
Waste truck cycle time (min)	IPCC	23.43	23.32	5.54	23.43 ± 0.003
	No IPCC	23.44	23.32	5.55	23.44 ± 0.003
Difference (%)		0.05	0	0	N/A
Ore Truck TPGOH (tonne/hr)	IPCC	967	956.5	197.35	967 ± 0.12
	No IPCC	376.89	373.34	38.31	376.89 ± 0.022
Difference (%)		-156.57	-156.21	- 415	N/A

Total production (MT)	IPCC	14.16	14.16	0.14	14.16 ± 0.027
	No IPCC	14.32	14.32	0.09	14.32 ± 0.017
Difference (%)		1.12	1.12	-60	N/A

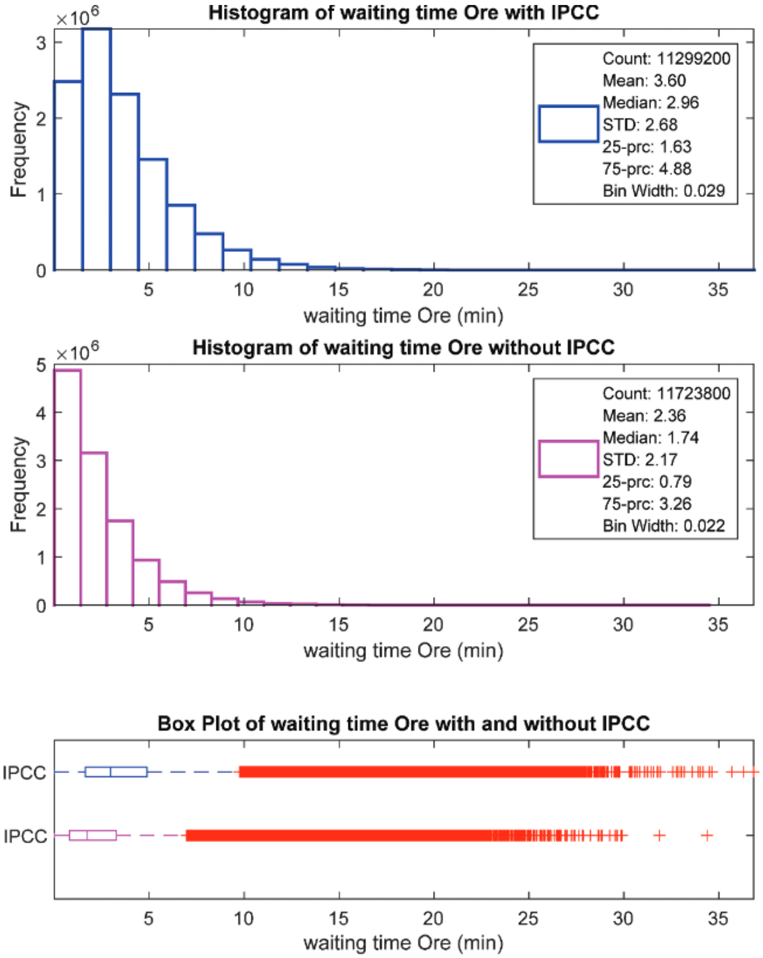


Figure 16. Comparison of ore truck waiting time.

Waste truck travel, waiting, and cycle times remain similar across both scenarios due to the absence of a waste IPCC system. However, ore truck waiting time is notably higher in the IPCC scenario (3.6 min vs. 2.36 min), as shown in Figure 16. This is due to shorter haul distances, trucks return to loading points more quickly, increasing queue frequency.

The dramatic reduction in ore truck cycle time in the IPCC scenario stems from reduced haul distances: 0.65 km vs. 3.1 km in the no IPCC case. This results in shorter travel time (2.29 vs. 13.8 min) and lower average cycle time (9.52 vs. 20.26 min). As shown in Table 5, Figure 17 and Figure 18, IPCC also reduces variability, reflecting more consistent performance. Minor bumps in the IPCC histogram suggest occasional delays, possibly from brief maintenance stoppages.

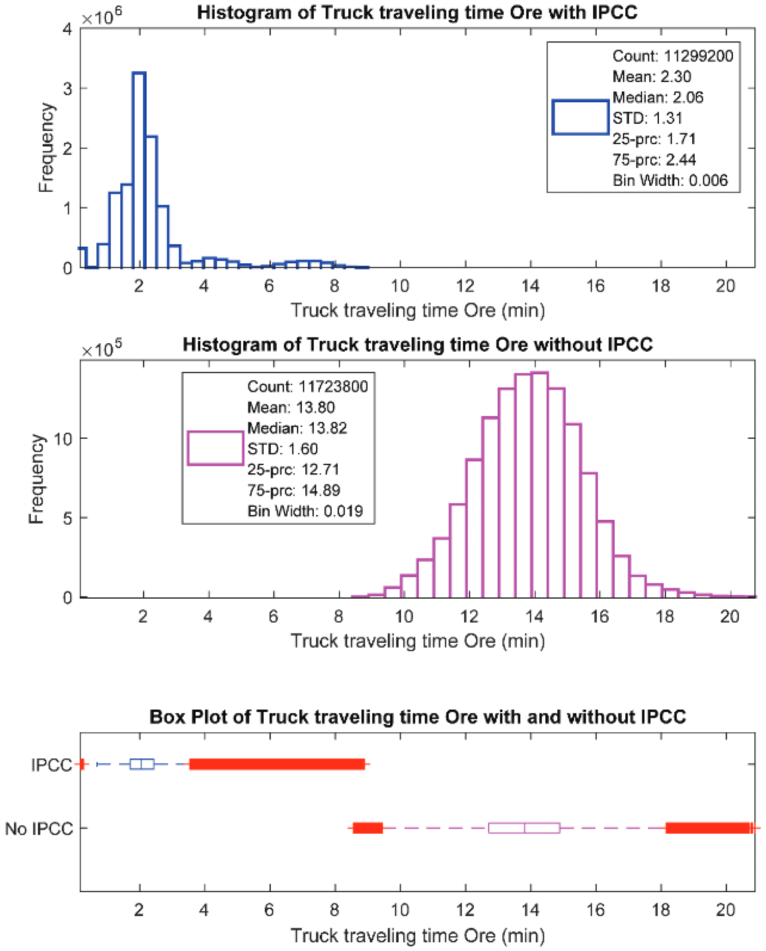


Figure 17. Comparison of ore truck traveling time.

Figure 19 and Figure 20 illustrate the relationship between Tonnage per Hour (TPGOH) and distance to the crusher under IPCC and no IPCC scenarios. In the IPCC scenario, trucks consistently achieve higher TPGOH values, particularly at shorter distances, with values ranging from 1500 to over 3000 tonnes per hour. As distance increases, there is a gradual decline in TPGOH, but the system maintains relatively high productivity due to the continuous operation of the conveyor system, which minimizes truck cycle time and maximizes throughput. However, the IPCC scenario also shows greater variability in TPGOH, suggesting that while productivity is enhanced, the system introduces additional operational complexities, likely due to IPCC-related failure probabilities. Despite this, four trucks are sufficient to meet the required annual ore tonnage.

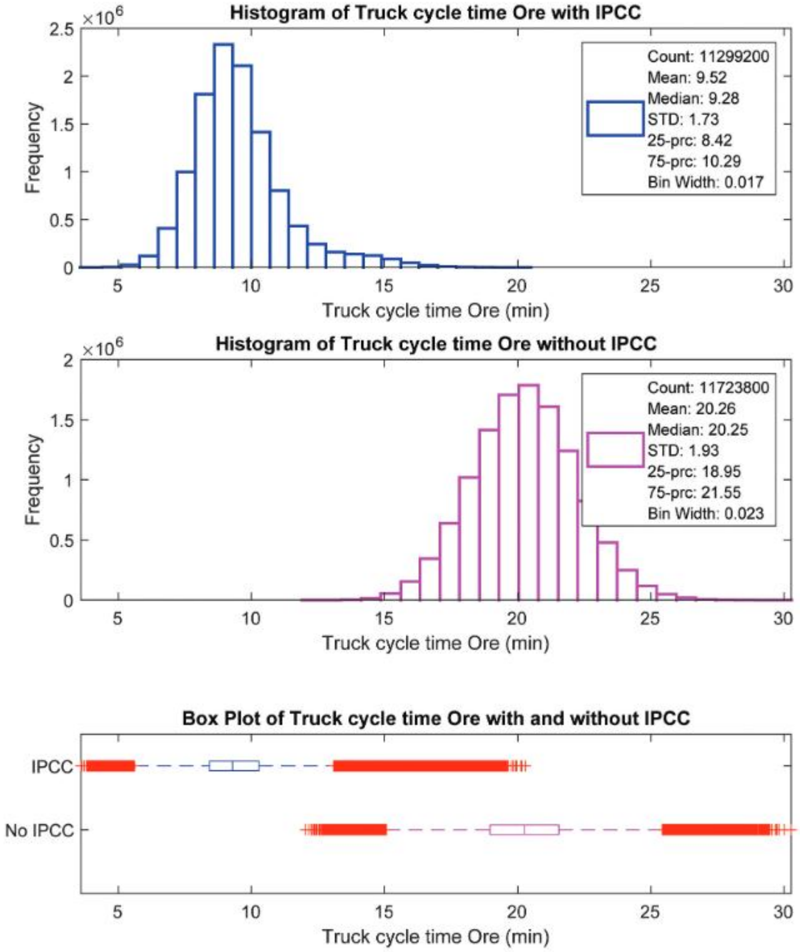


Figure 18. Ore truck cycle time comparison.

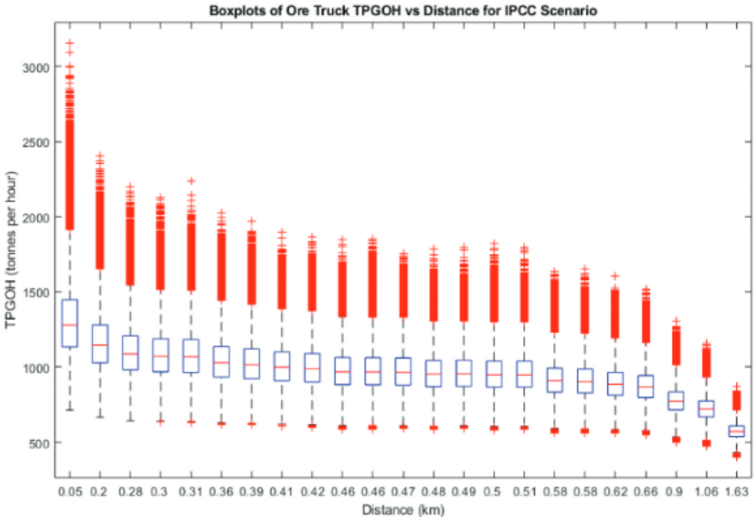


Figure 19. Box plot of ore truck TPGOH vs distance in the IPCC scenario.

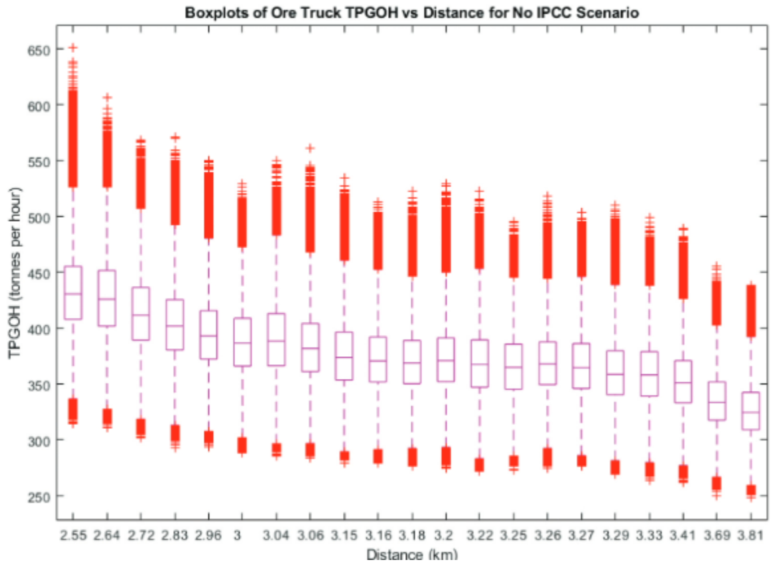


Figure 20. Box plot of ore truck TPGOH vs distance in the no IPCC scenario.

Conversely, In the no-IPCC scenario, TPGOH values range between 300 and 600 tonnes per hour and decline more sharply with distance, indicating consistent but lower truck productivity. This reduced efficiency requires ten trucks to meet production targets. In contrast, the IPCC system achieves higher productivity with fewer trucks, highlighting its operational and cost advantages.

Figure 21 reinforces this comparison: TPGOH steadily declines with distance in both scenarios, but the IPCC system maintains significantly higher values. The scatter plots show broader variability and higher throughput for IPCC, with its minimum TPGOH exceeding the maximum observed without IPCC. These results emphasize the positive impact of reduced haulage distances in IPCC configurations.

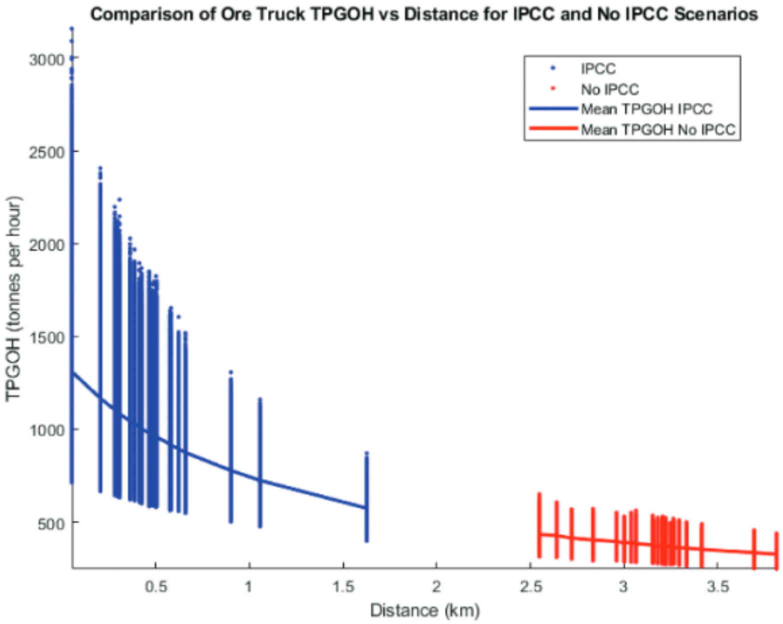


Figure 21. TPGOH vs distance.

5.2.3. System Performance and Reliability

To evaluate the effectiveness of haulage systems, it is essential to consider both operational efficiency and system reliability. This section presents a comparative analysis of failure statistics for key components—trucks, shovels, and the IPCC system. Time between failures and repair durations are modeled using Weibull and Gamma distributions, respectively. Downtimes (MTTR) are computed for each component and aggregated to estimate total system downtime. The model assumes independent failures across components, each governed by its specific MTBF and MTTR. By comparing scenarios with and without IPCC, we assess how IPCC integration affects reliability and operational uncertainty. Table 6 summarizes the downtime statistics, with percent differences calculated relative to the no-IPCC scenario.

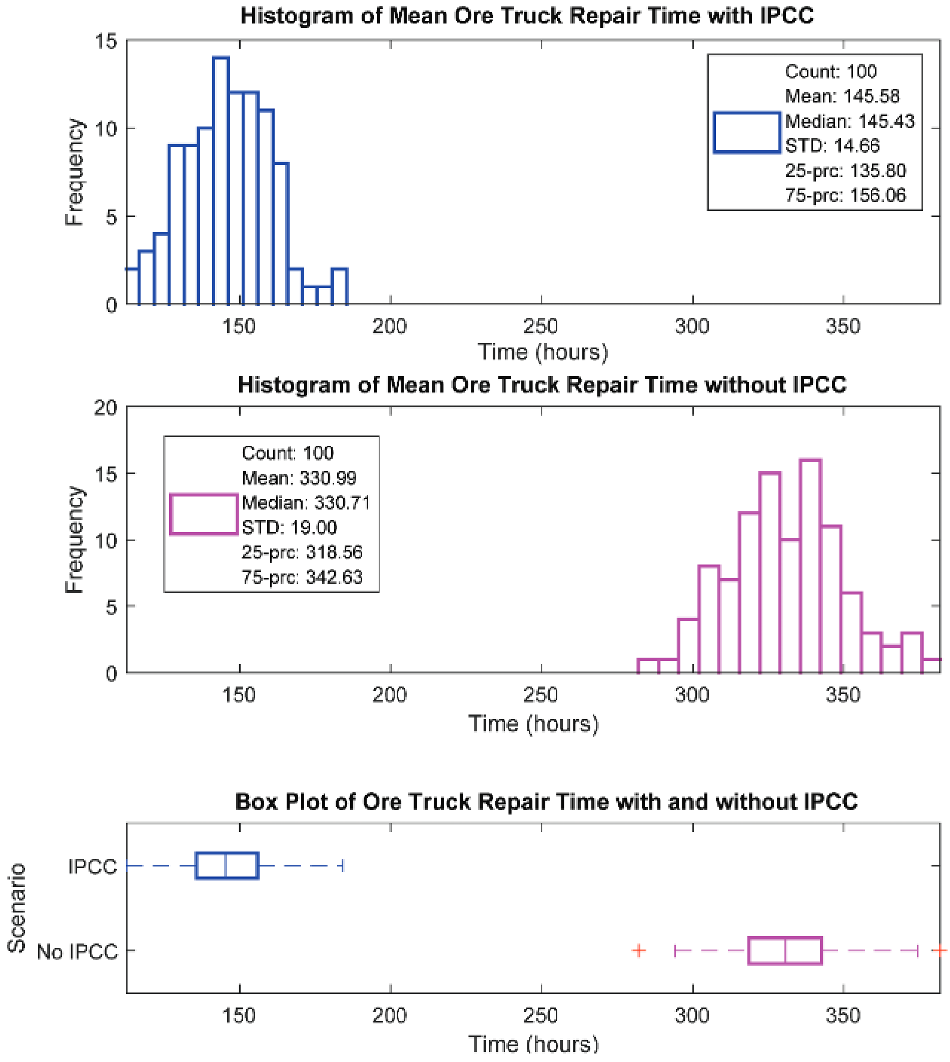
Table 6: Comparison of downtime or repair time statistics

Variable	Scenario	Mean	Median	St Dev	95% confidence interval
Ore truck downtime (hr)	IPCC	145.58	145.43	14.66	145.58 ± 2.87
	NO IPCC	330.99	330.71	19	330.99 ± 3.72
Difference (%)		56	56	22.84	N/A
Waste truck downtime (hr)	IPCC	445.09	443.23	27.12	445.093 ± 5.317
	NO IPCC	437.63	439.84	26.82	437.63 ± 5.26
Difference (%)		-1.7	-0.77	-1.12	N/A
Ore shovel downtime (hr)	IPCC	288.65	285.08	26.71	288.65 ± 5.23
	NO IPCC	334.91	332.02	22.31	334.91 ± 4.37
Difference (%)		13.81	14.14	-19.72	N/A
Waste shovel Downtime (hr)	IPCC	447.12	446.88	22.54	447.12 ± 4.42
	NO IPCC	443.55	442.16	22.51	443.55 ± 4.41
Difference (%)		-0.8	-1.1	-0.13	N/A
IPCC downtime (hr)	IPCC	293.79	289.78	26.73	293.79 ± 5.24

Ore truck downtime is significantly lower in the IPCC scenario, with a mean of 145.6 hours compared to 331.0 hours in the no-IPCC case, a 56% reduction driven by shorter haul distances. Variability also decreases, with standard deviation dropping from 19.0 to 14.7 hours. Figure 22 illustrates these improvements. However, the IPCC system itself adds a mean repair time of 293.8 hours, representing a trade-off. Waste truck and shovel downtimes remain largely unchanged between scenarios, as IPCC only affects ore haulage in this study.

The slight variation in waste truck and shovel repair times between the scenarios is not driven by any systemic model difference, as the waste haulage process remains identical in both cases. The observed difference is attributed to the inherent variability in the Monte Carlo simulation.

Mean ore shovel repair time improves by 13.8% in the IPCC scenario (288.7 vs. 334.9 hours), indicating moderate gains compared to the sharper reduction seen in truck downtime. Figure 23 compares aggregate equipment repair times across 100 simulations. IPCC scenarios range from ~1300 to 1550 hours, while No IPCC ranges from ~3700 to 4100 hours, highlighting the clear advantage of IPCC in reducing total downtime. Although IPCC adds conveyor repair time, the smaller truck fleet (4 vs. 10 trucks) and shorter haul distances significantly reduce overall repair needs. The box plot confirms lower variability in the IPCC case, demonstrating greater system stability despite less redundancy.


Histogram of Mean Ore Truck Repair Time with IPCC

Histogram of Mean Ore Truck Repair Time without IPCC

Box Plot of Ore Truck Repair Time with and without IPCC

Figure 22: Comparison of mean ore truck downtime

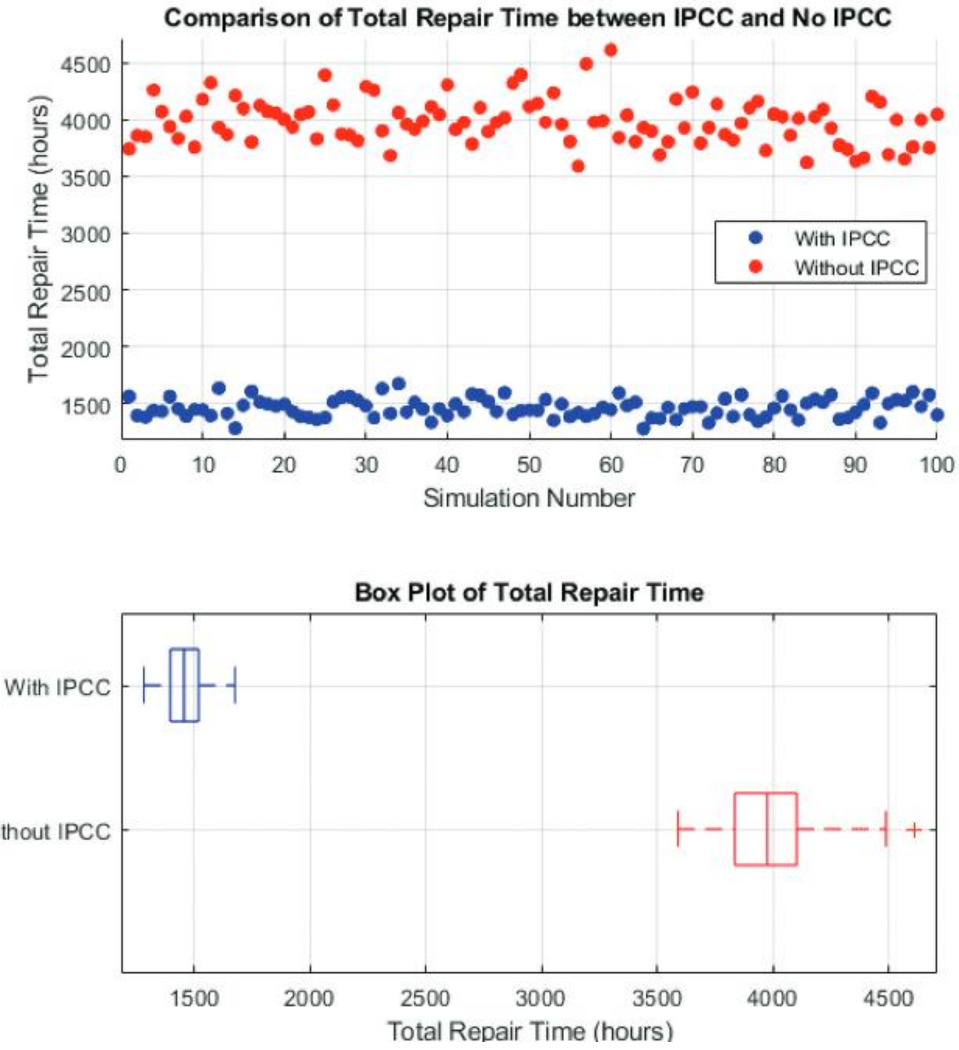


Figure 23: Mean total equipment repair time comparison between the scenarios

5.3. Comparison between Simulated and Optimal Production

This section compares simulated production against the MILP-defined optimal targets for both IPCC and truck-shovel (TS) scenarios. While the optimal plan assumes ideal conditions, the simulation introduces uncertainties such as equipment failures and parameter variability, revealing deviations from target production.

Figure 24 shows that in the TS scenario, the optimal target of 15.96 MT is reduced to 14.32 MT in simulation, a shortfall of 1.64 MT, highlighting the impact of longer haul distances and operational inefficiencies on actual production.

In the IPCC scenario, the optimal production target is 15.37 MT, while simulated production reaches 14.16 MT, resulting in a shortfall of 1.21 MT. Although IPCC improves efficiency by reducing haul distances and cycle times, added operational complexities and system downtime slightly limit its ability to achieve optimal production levels

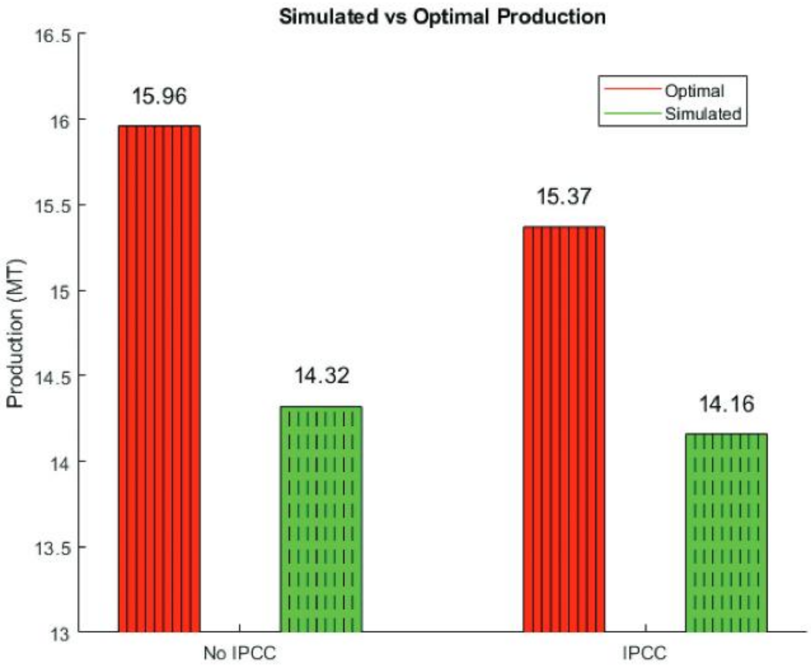


Figure 24: Simulated vs optimal production

Figure 25 presents a scatter plot comparing the proximity to optimal production across 100 simulations for both IPCC and non-IPCC scenarios. Each dot shows the fraction of optimal production achieved in a simulation, with blue representing IPCC and red indicating the no IPCC case. The black dashed line marks the normalized optimal target. The IPCC scenario consistently reaches a higher fraction of the optimal, typically between 0.91 and 0.95, while the no IPCC scenario ranges from 0.88 to 0.92, demonstrating the IPCC system's superior reliability in meeting production goals.

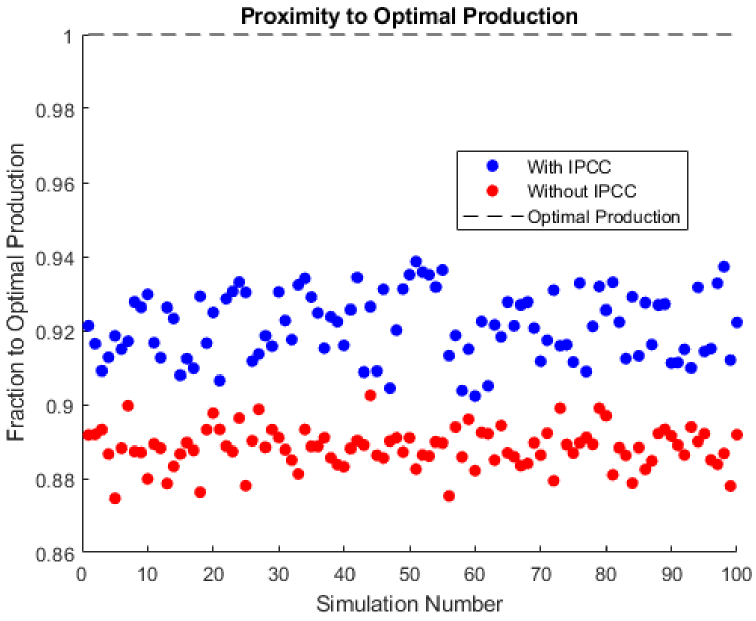


Figure 25: Proximity to optimal production.

The comparison in Figure 24 and Figure 25 reveals that while both scenarios fall short of their respective optimal production targets, the IPCC scenario has a slightly smaller deviation from the optimal production compared to the truck-shovel scenario. This suggests that the IPCC system, despite its operational complexity and potential for increased downtime, outperforms the traditional truck-shovel system in maintaining closer proximity to optimal production targets. However, both systems demonstrate the need for further improvements to bridge the gap between simulated and optimal production.

6. Conclusions

This paper provides a comprehensive analysis of short-term planning and haulage systems in open-pit mining, specifically comparing the performance of IPCC systems to traditional truck-shovel operations. The developed simulation-optimization framework effectively captures operational uncertainties, delivering reliable and realistic assessments of system performance, as evidenced by the narrow confidence intervals in key performance indicators. The findings underscore that the IPCC system significantly reduces ore truck cycle time and haulage distance, thereby enhancing overall operational efficiency. Specifically, the IPCC scenario reduced the average truck cycle time from 21 minutes to 9.5 minutes and lowered the ore truck requirement from 10 to 4 trucks compared to the traditional system. Despite a slight decrease in ore production (15.37 Mt vs. 15.96 Mt) due to crusher placement constraints, the overall system efficiency and cost savings support the benefits of IPCC integration.

Although the cumulated mean repair time of all the equipment is substantially lower in the IPCC scenario at 1400 hours compared to 3900 hours in the truck-shovel scenario, the study also identifies challenges, particularly the added downtime associated with IPCC conveyor components. These findings highlight the need for robust maintenance and operational strategies to fully capitalize on the benefits of IPCC technology. The increased complexity and potential for downtime with IPCC systems underscore the necessity for further research into maintenance and reliability. Additionally, the focus on a single case study means the results may not be universally applicable across all mining operations.

Future research directions should include exploring a broader range of case studies, encompassing different mine types and operational conditions to validate the robustness and generalizability of the simulation-optimization framework. Additionally, developing dynamic optimization models that adapt to real-time changes in mining conditions and equipment performance could significantly enhance short-term planning effectiveness. Advanced reliability analysis of IPCC components could also help in better understanding and mitigating the additional downtimes introduced by the IPCC system. Furthermore, the study will be extended to include a waste IPCC scenario to assess its impact on haulage efficiency and overall system performance. Future work will also incorporate carbon emissions and energy consumption metrics to enable a comprehensive sustainability assessment of truck-shovel and IPCC haulage systems. Finally, future work may also consider integrating the MILP model with the stochastic simulation in a more tightly coupled loop, where the schedule is re-optimized under varying input conditions, to explore sequencing robustness and sensitivity to uncertainty in a more dynamic manner.

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

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used Grammarly and ChatGPT in the writing process to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Data Availability

Due to confidentiality agreements and sensitive nature of the data, the mining data used in this study cannot be publicly shared.

Disclosure Statement

The authors report there are no competing interests to declare.

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