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

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ABSTRACT

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

1. Introduction

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

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

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

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

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

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

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

Thomas et al. [56, 57] tackled the challenge of integrated planning and scheduling within a coal supply chain comprising of several independent mines that must share a limited transportation capacity. Their objectives included minimizing total earliness, tardiness, and operational costs while adhering to due dates and transportation constraints. They developed a solution approach based on Lagrangian relaxation, which outperformed traditional MILP models in terms of generating upper and lower bounds and reducing CPU time. Mousavi et al. [34] developed a comprehensive mathematical model for short-term block sequencing, incorporating constraints like precedence relationships, machine capacity, grade requirements, and processing demands. The goal is to minimize total costs, including rehandling, holding, misclassification, and drop-cut costs. The authors proposed a hybrid solution combining branch and bound with simulated annealing, which can produce solutions with an optimality gap of less than 1% compared to the CPLEX solution when a large neighborhood search is utilized. A recent optimization model for short-term open pit planning has been proposed by Nelis and Morales [35]. Their approach maximizes profits while meeting operational constraints. Applied to a real copper mine, the model efficiently defines mining cuts and production plans simultaneously. Results demonstrate its effectiveness in generating mining cut configurations quickly, a task that traditionally requires days, completed in less than fifteen minutes.

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

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

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

Torkamani and Askari-Nasab [58] devised a stochastic discrete event simulation model to analyze truck-shovel material handling and haulage systems in open pit mining. Initially, they formulated an MIP model for optimal truck and shovel allocation across mining faces, integrating these solutions into their simulation framework. Upadhyay and Askari-Nasab [59, 60] applied goal-programming to develop a simulation optimization model for short-term planning in mining. Their approach highlights the integration of proactive decision-making in a dynamic environment, synchronizing operational plans with long-term strategies to minimize opportunity costs while optimizing production and equipment utilization. A similar framework has been proposed by Manriquez [26] to generate an initial schedule and then replicate it to find key performance indexes like equipment utilization using a discrete event simulation software. Incorporating simulation addresses equipment uncertainty in this otherwise deterministic model, making it applicable across various mining contexts, including open pit mines. However, a limitation of the model is its sole focus on maximizing extraction value without considering operational costs in the optimization process.

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

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

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

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

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

2. Problem Definition

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

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

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

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

2.1. Scope and Assumptions of the Proposed Model

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

2.1.1. MILP Assumptions

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

2.1.2. Monte Carlo Simulation Assumptions

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

3. Methodology

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

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

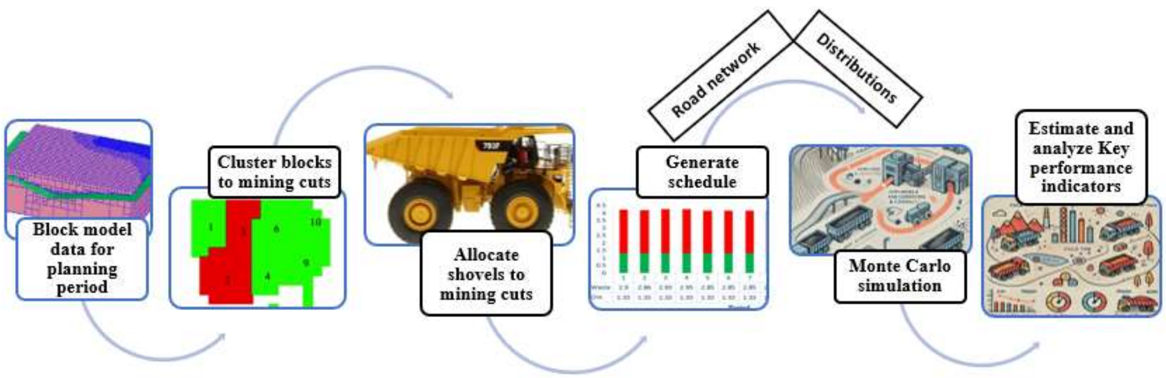

Figure 1. Outline of the proposed simulation-optimization framework.

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

3.1. Mathematical Model Formulation

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

Minimize, f = Mining costs + Ore haulage costs + Waste haulage costs + Ore conveying costs
+ Shovel movement costs – Revenue from selling ore. (1)

Eq. (1)

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

The variables, parameters and indexes are detailed below.

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

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

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

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

The model is subject to the following constants.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

3.2. Monte Carlo Haulage Simulation

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

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

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

3.2.1. Simulation Logic Flow

Ore Haulage

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

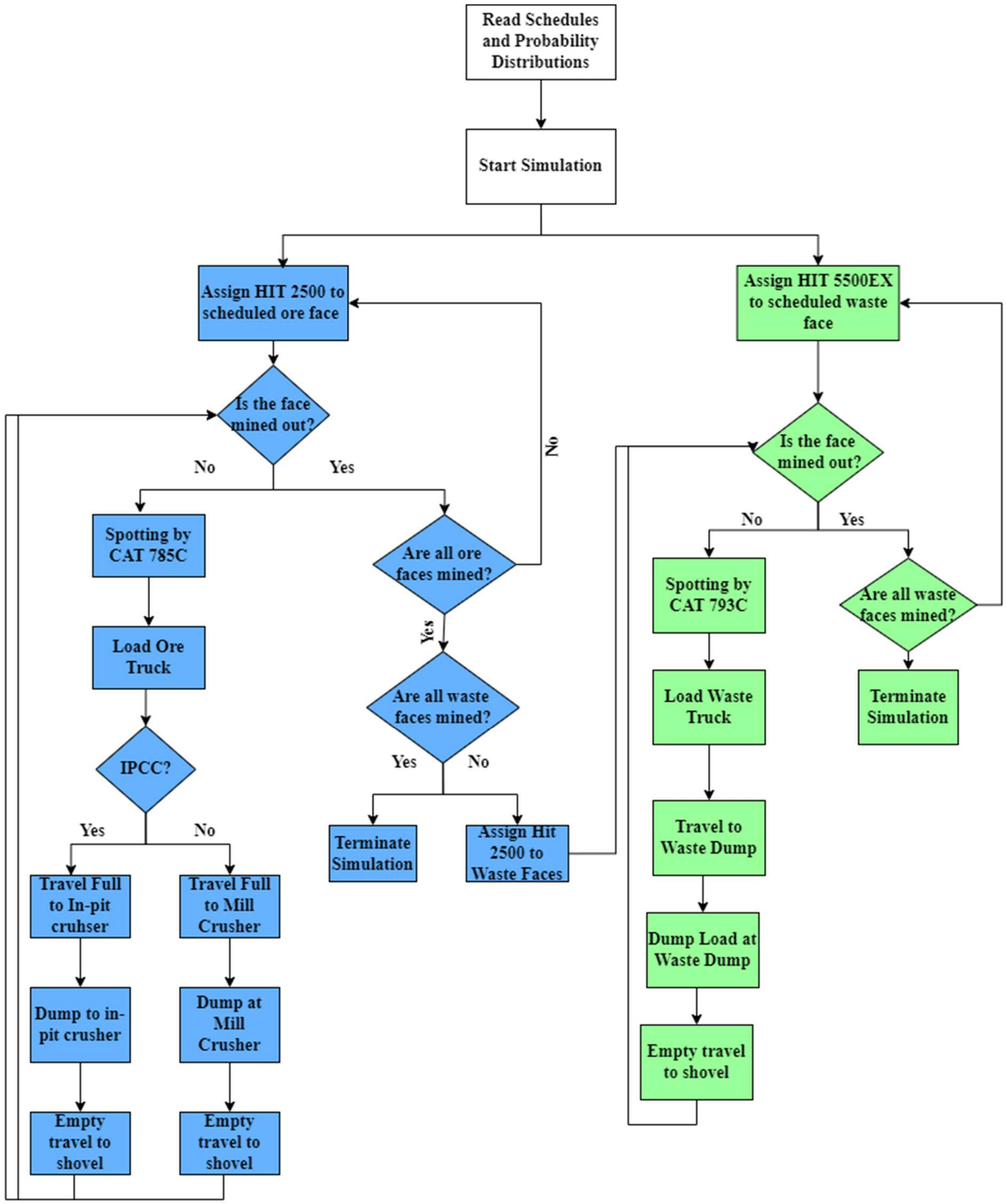

Figure 2. Haulage Simulation flowchart.

Waste Haulage

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

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

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

4. Case Study

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

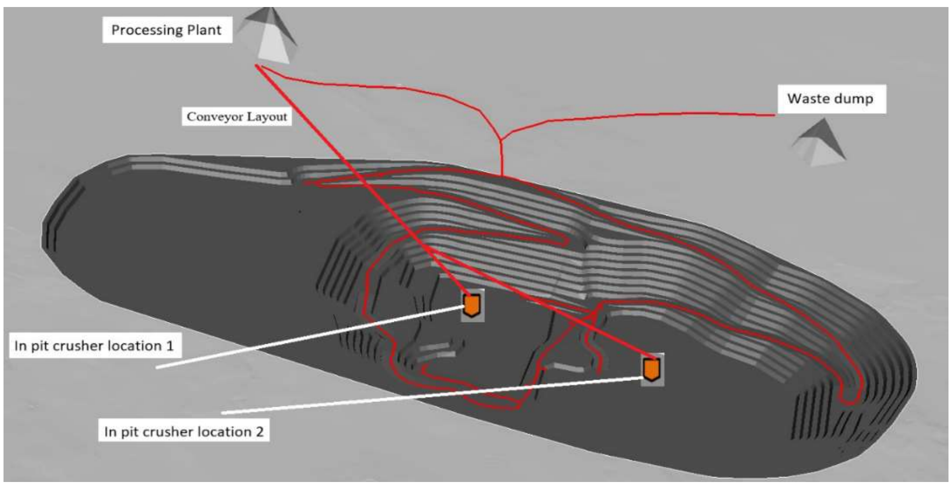

Figure 3. Mine layout for year 11.

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

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

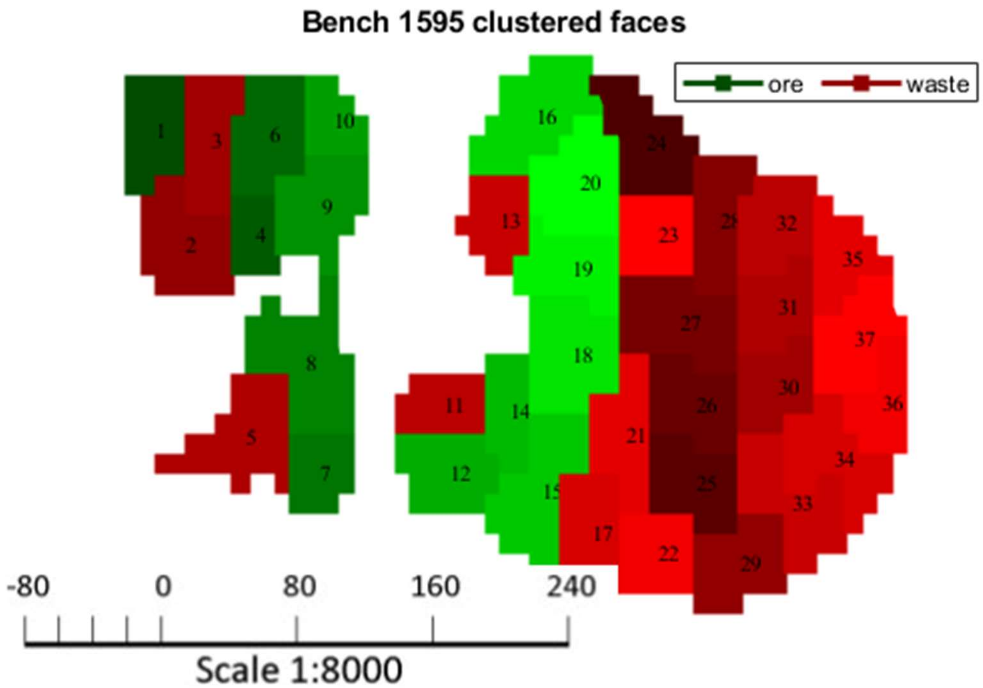

Figure 4. Clustered faces for the ore benches.

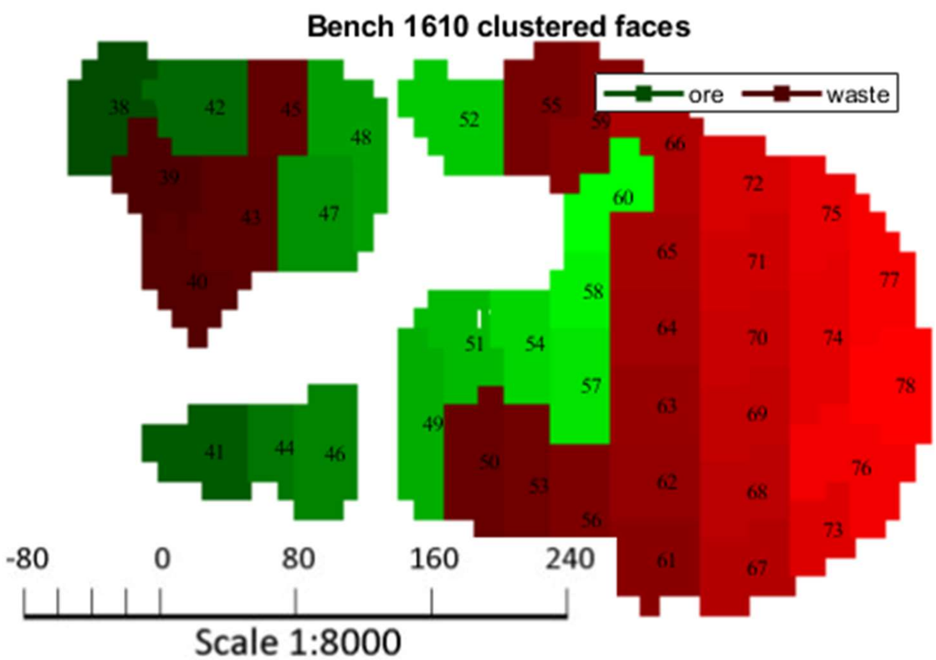

Figure 5. Ore and waste faces on bench 1610.

5. Results

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

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

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

5.1. MILP Model Results

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

5.1.1. Optimal Shovel Allocation

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

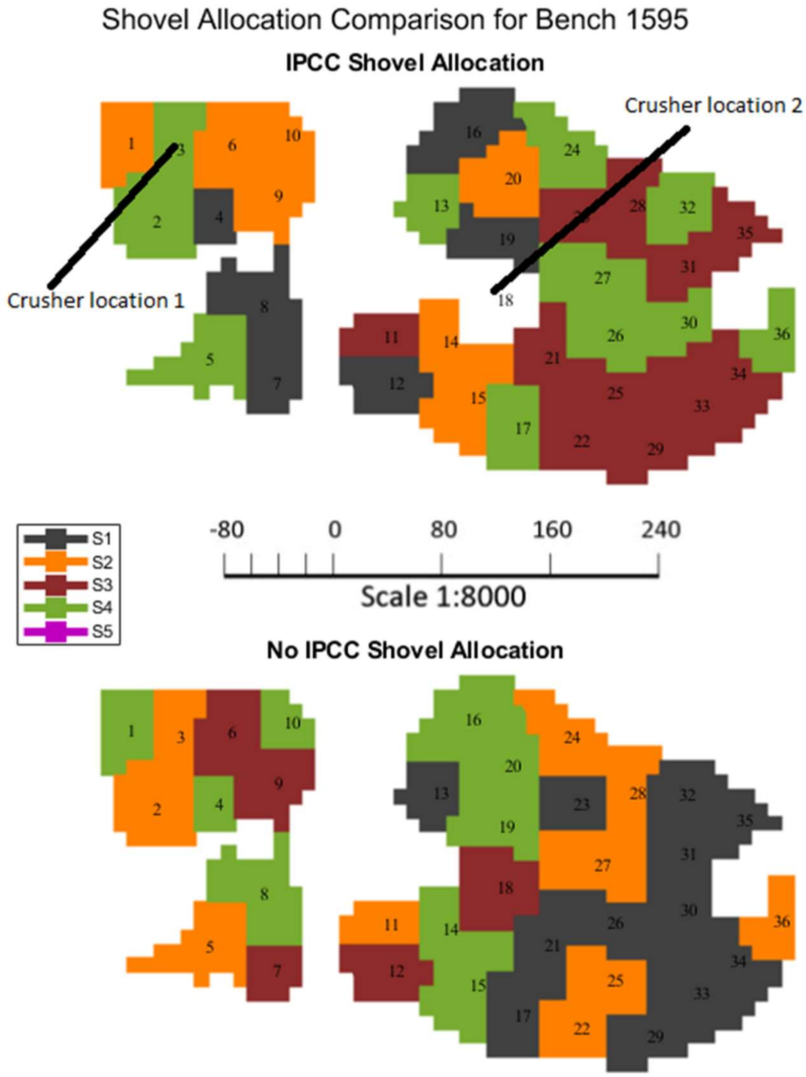

Figure 6. Shovel Allocation to bench 1595.

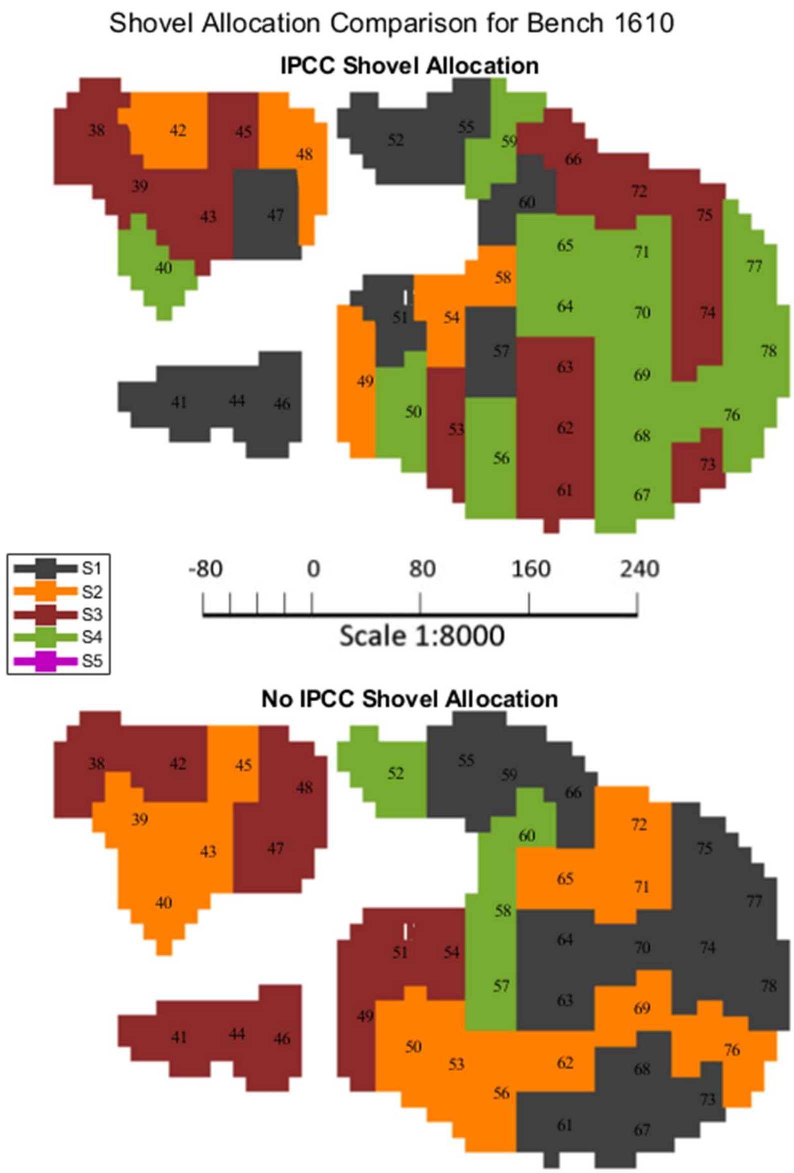

Figure 7. Shovel Allocation to bench 1610.

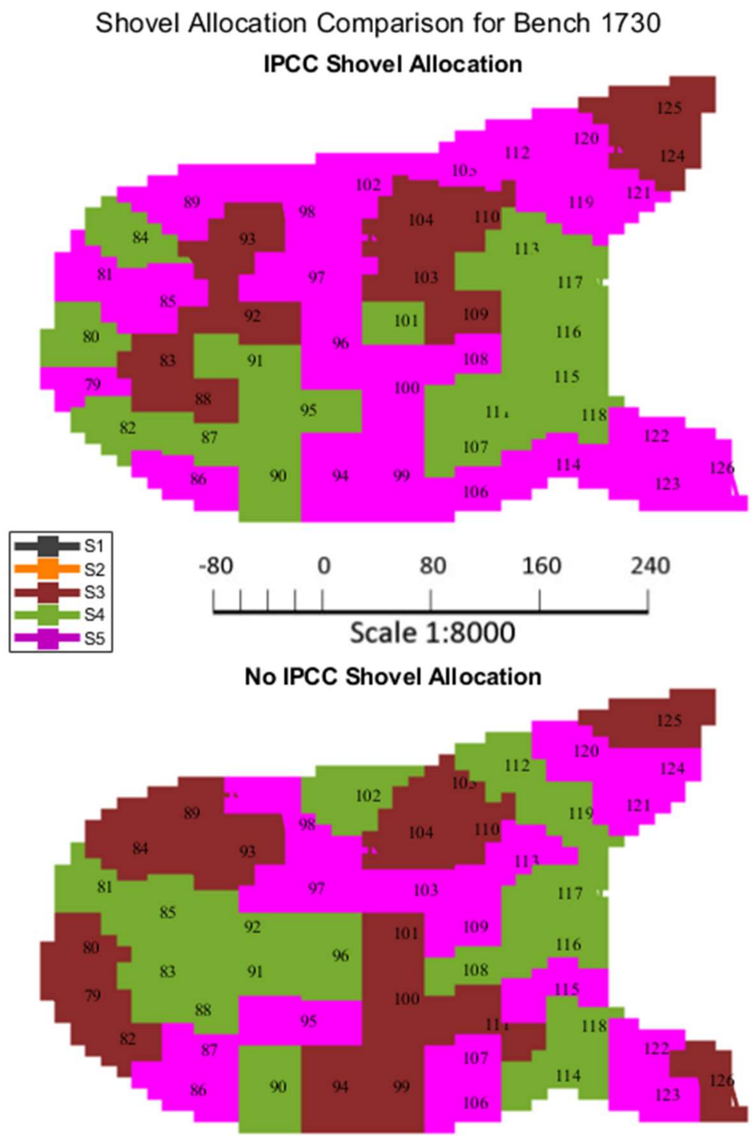

Figure 8. Shovel Allocation to bench 1730.

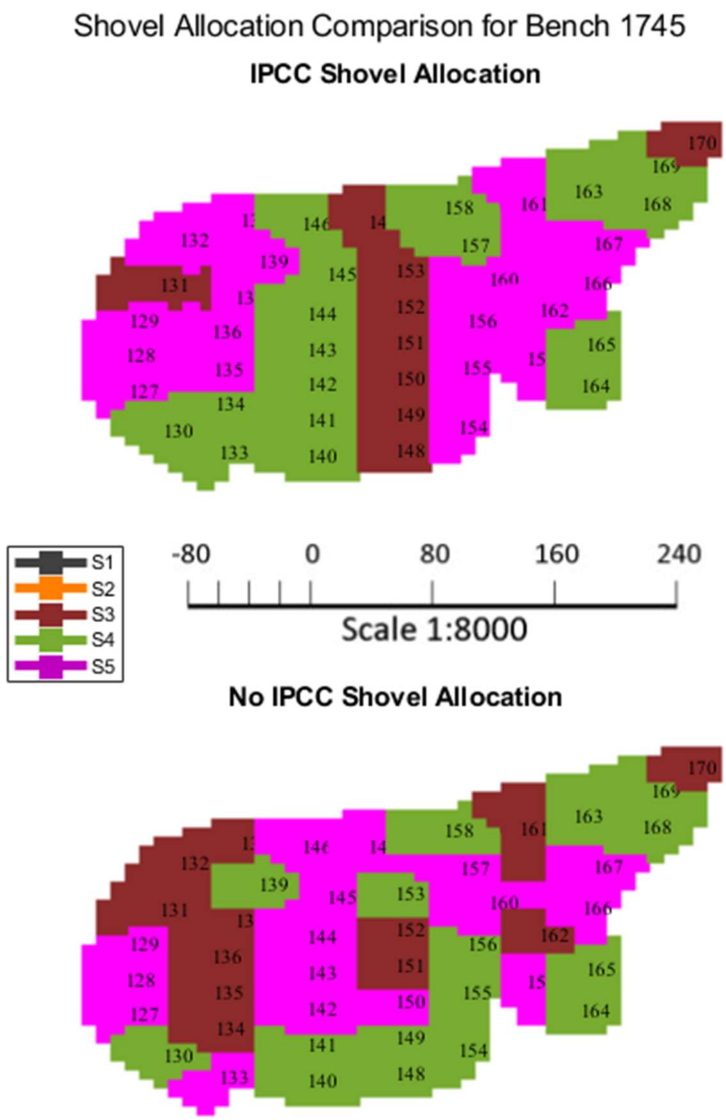

Figure 9. Shovel Allocation to bench 1745.

5.1.2. Mining Period

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

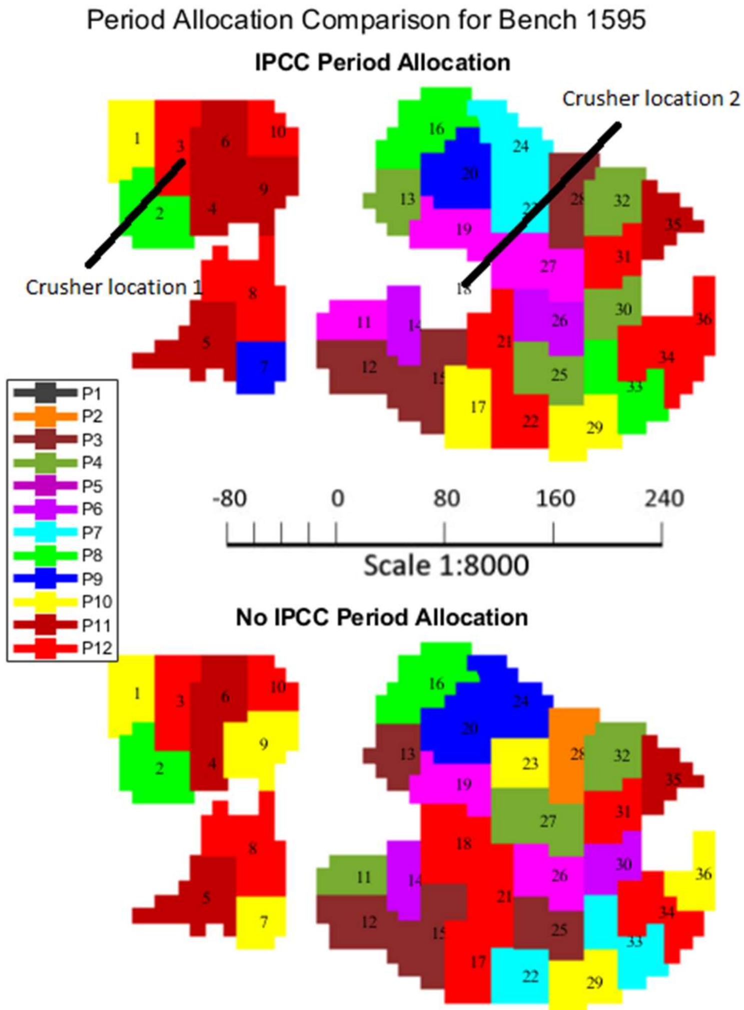

Figure 10. Mining Period for faces on bench 1595.

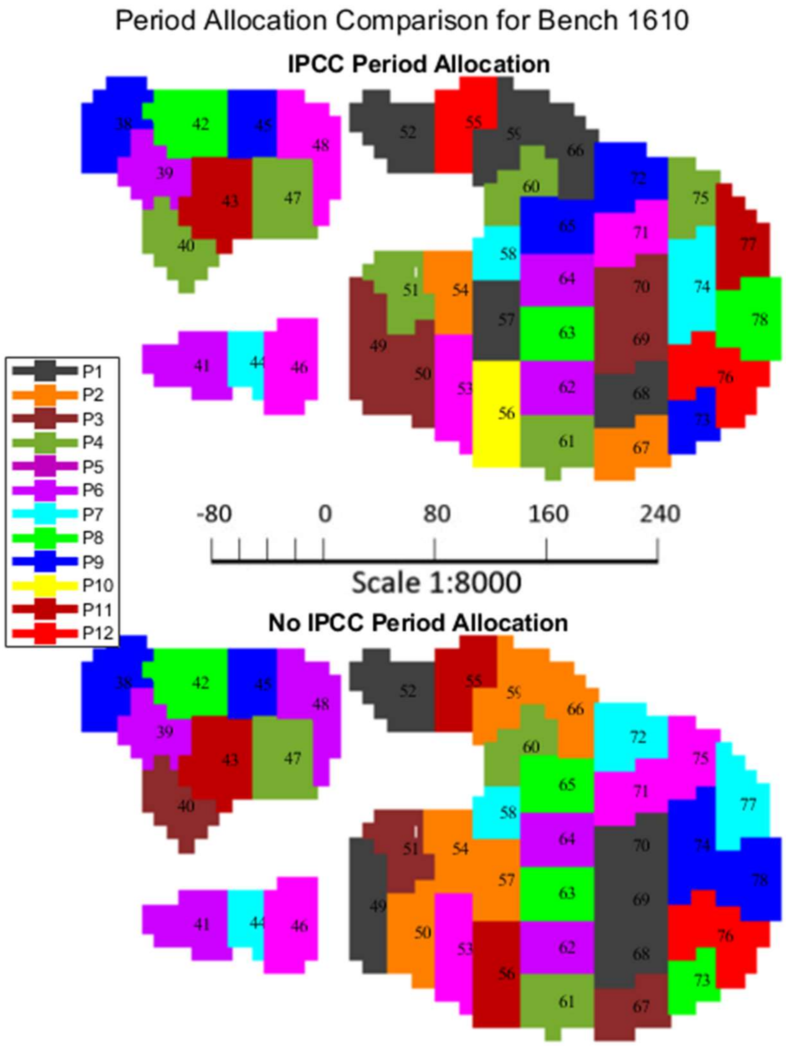

Figure 11. Mining Period for faces on bench 1610.

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

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

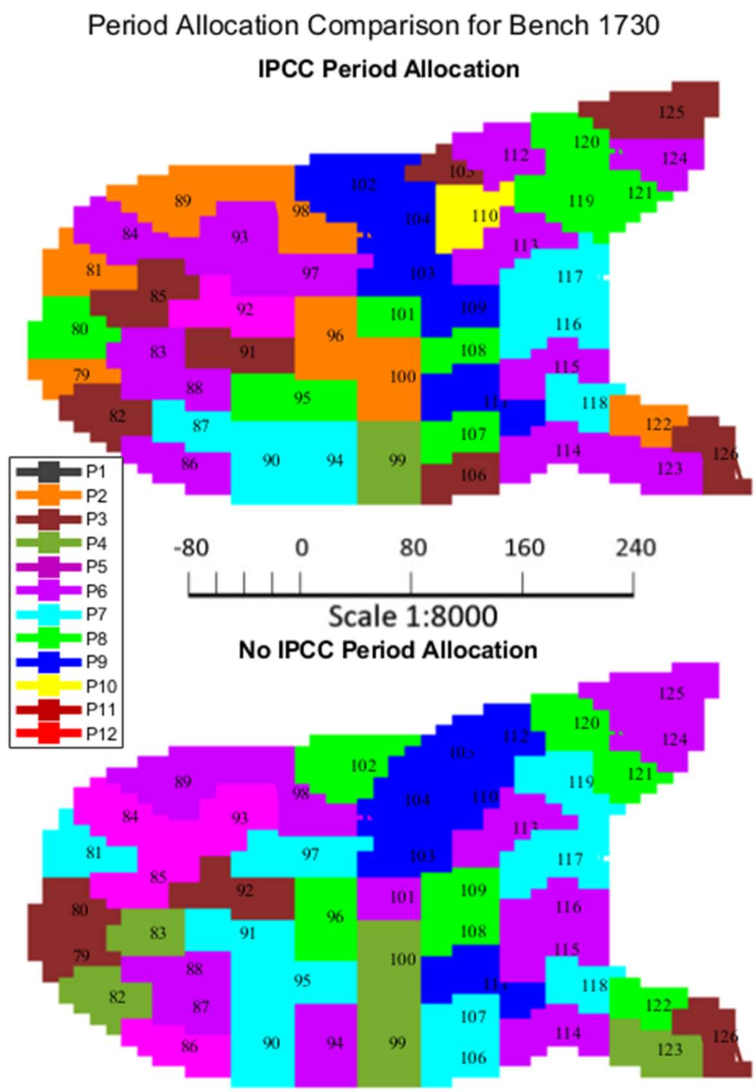

Figure 12. Mining Period for faces on bench 1730.

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

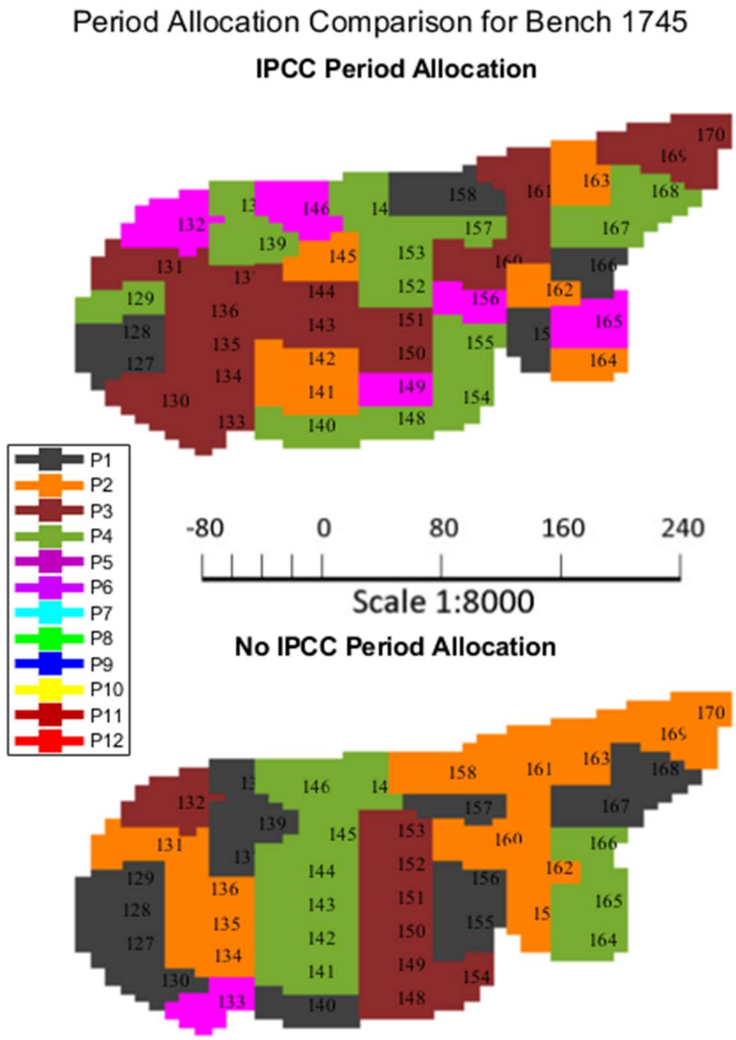

Figure 13. Mining Period for faces on bench 1745.

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

5.1.3. Monthly Production Schedule

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

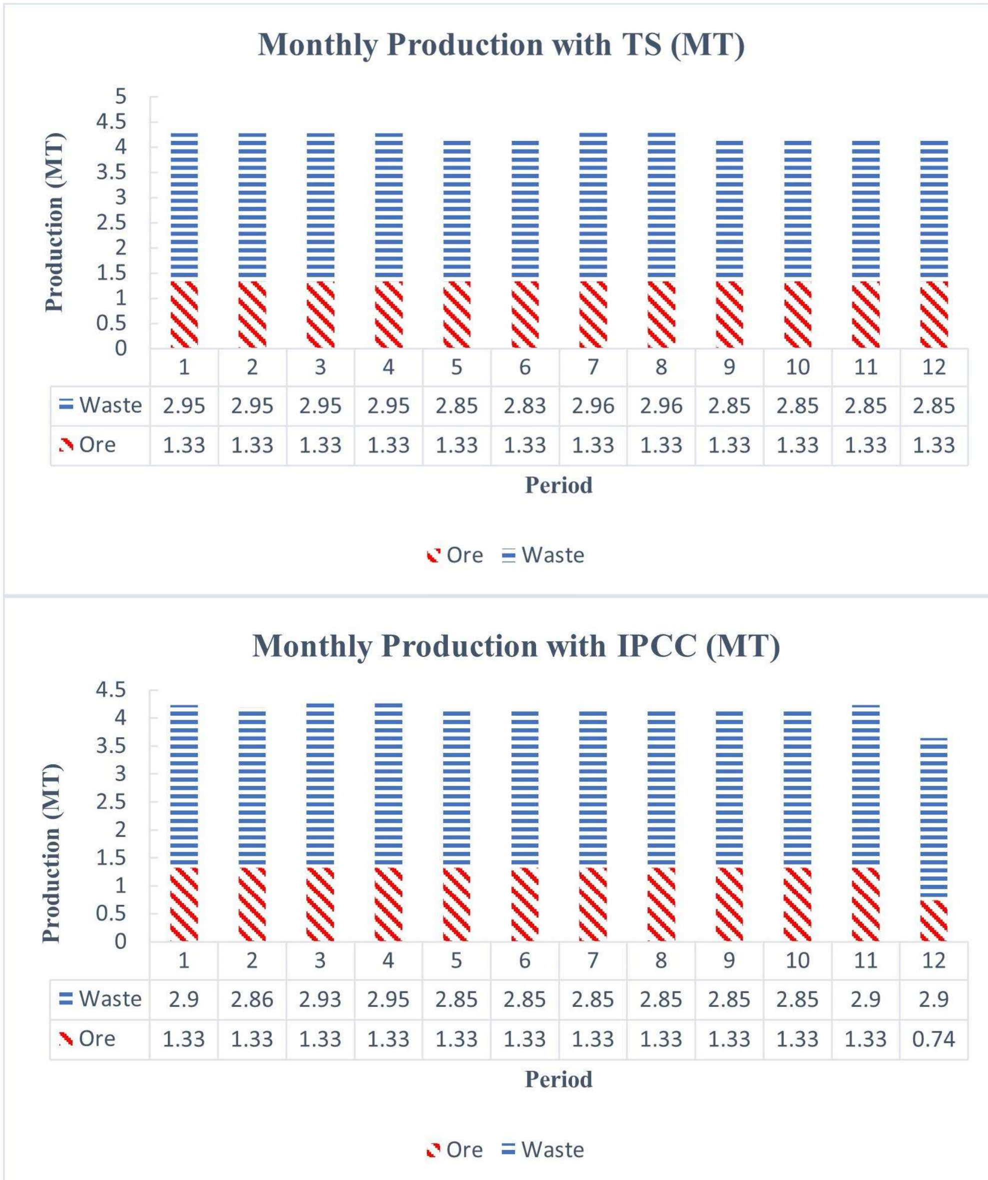

Figure 14. Monthly Production Schedule for IPCC and truck-shovel scenario.

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

Overall, both scenarios exhibit steady ore production, with minor variations in waste production. The consistent production of ore across all periods for both scenarios substantiates the model's capability to maintain production requirements throughout the planning horizon. While there is a dip in ore production in the final period for the IPCC scenario, it demonstrates that the model respects the IPCC location constraint, ensuring that operational adjustments are made to accommodate the presence of the IPCC system. These adjustments are reflected in the slight fluctuations in waste production, particularly in the IPCC scenario, highlighting the model's flexibility in optimizing production while adhering to specific constraints. Figure 15 below presents a comparison of total ore and waste production for the two scenarios generated by the optimization model. Overall, both ore and waste production are slightly lower in the IPCC scenario compared to the truck-shovel scenario. The reduced ore production in the IPCC scenario can be attributed to the location of the crusher inside the pit, which imposes additional constraints on the mining operations. However, the difference in waste production between the scenarios is minimal, given the large amount of waste available to be mined. This suggests that while the IPCC system affects ore production due to its specific location requirements, it does not significantly impact the overall waste production.

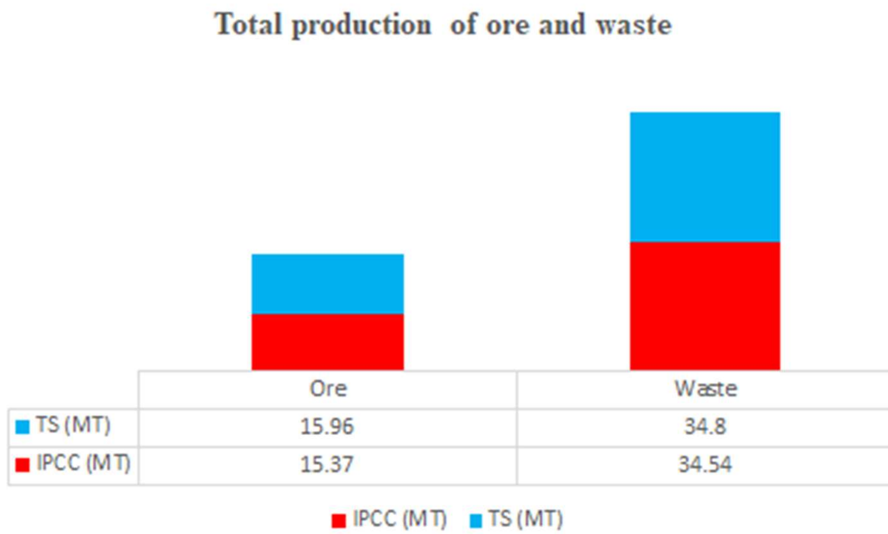

Figure 15. Total Production of ore and waste.

5.2. Comparison and Discussion of Simulation Results

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

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

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

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

5.2.1. Comparison of Independent KPIs

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

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

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

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

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

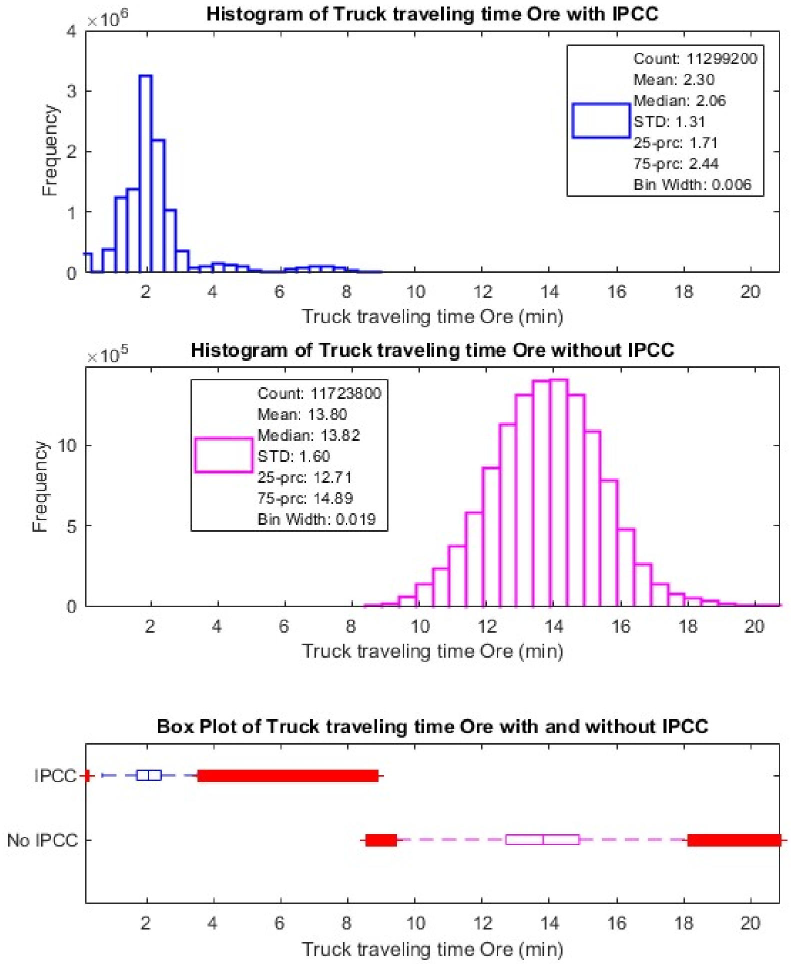

Figure 16. Comparison of ore truck traveling time.

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

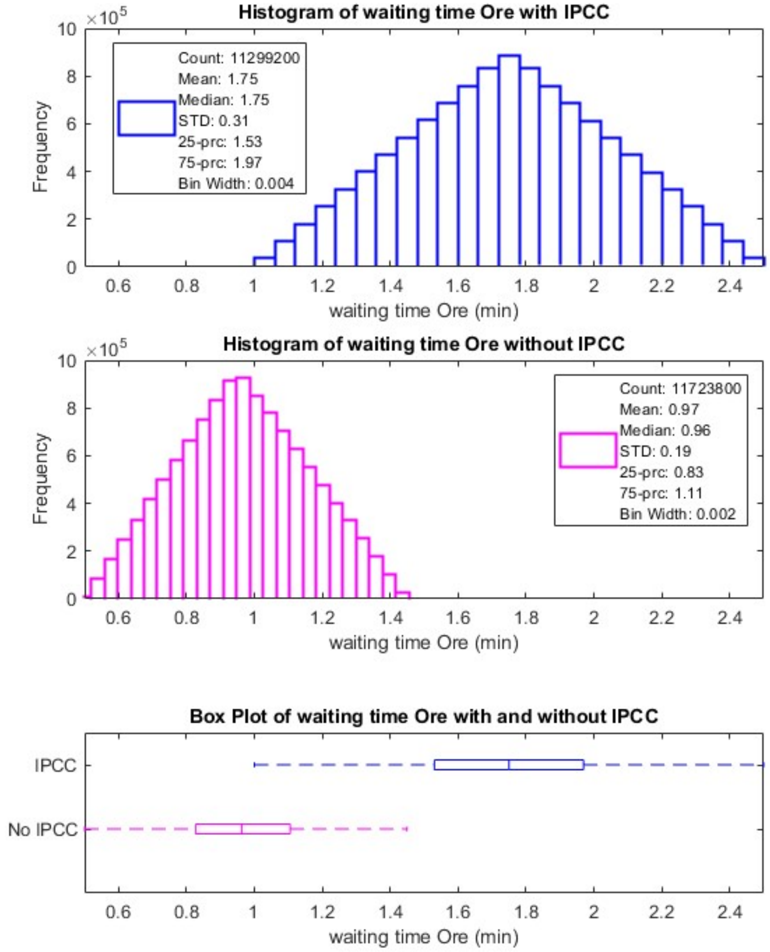

Figure 17. Comparison of truck queuing between scenarios.

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

5.2.2. Comparison of Dependent KPIs

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

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

Table 3. Comparison of dependent KPIs.

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

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

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

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

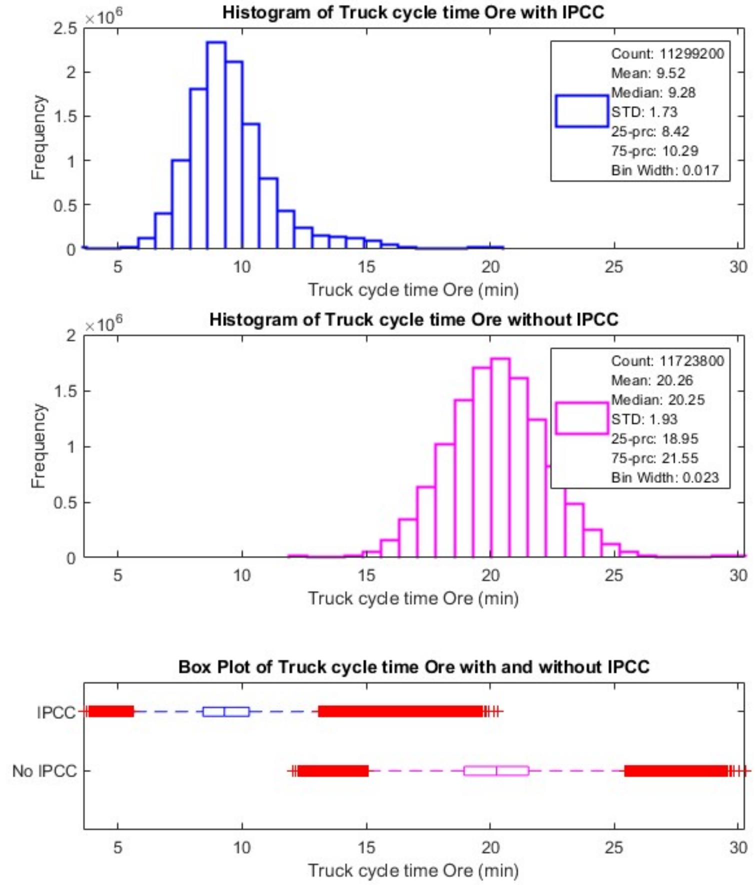

Figure 18. Ore truck cycle time comparison.

5.2.1. System Performance and Reliability

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

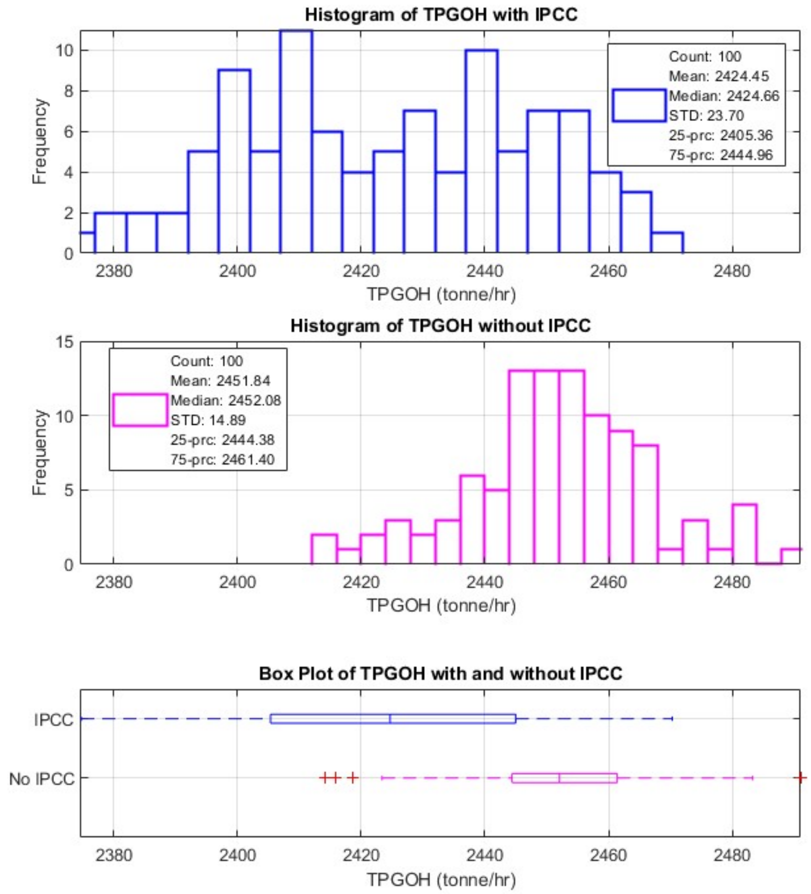

Figure 19. Comparison of simulated TPGOH.

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

Table 4. Comparison of downtime statistics.

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

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

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

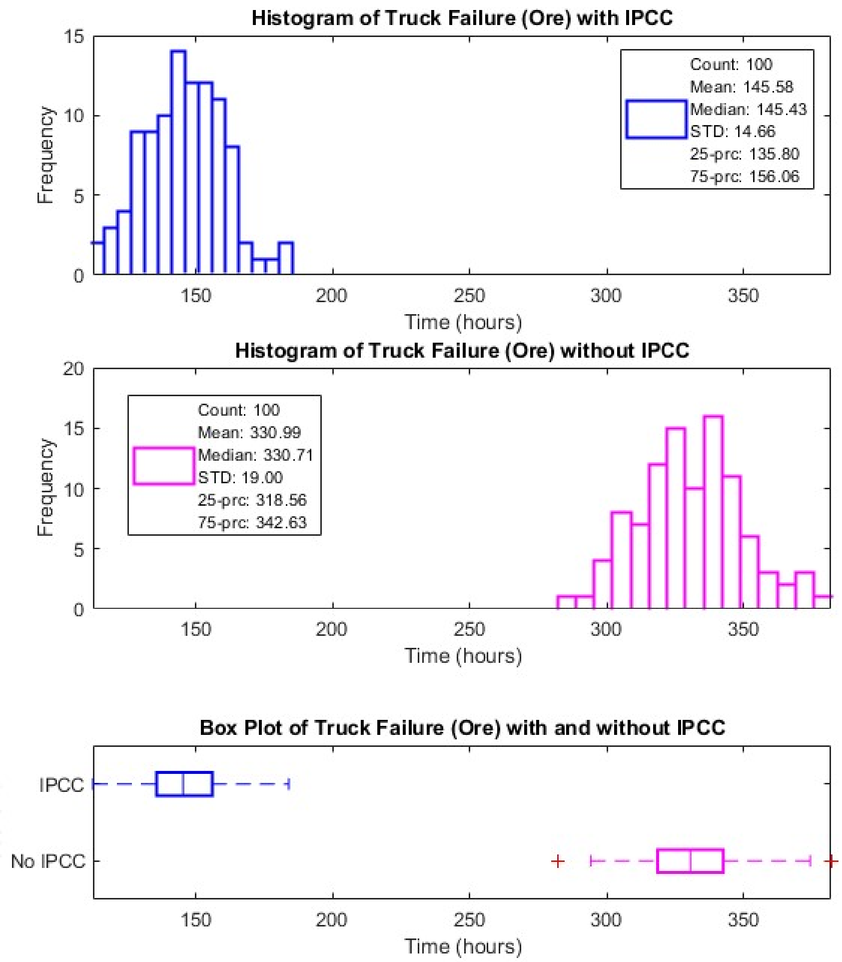

Figure 20. Comparison of ore truck downtime.

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

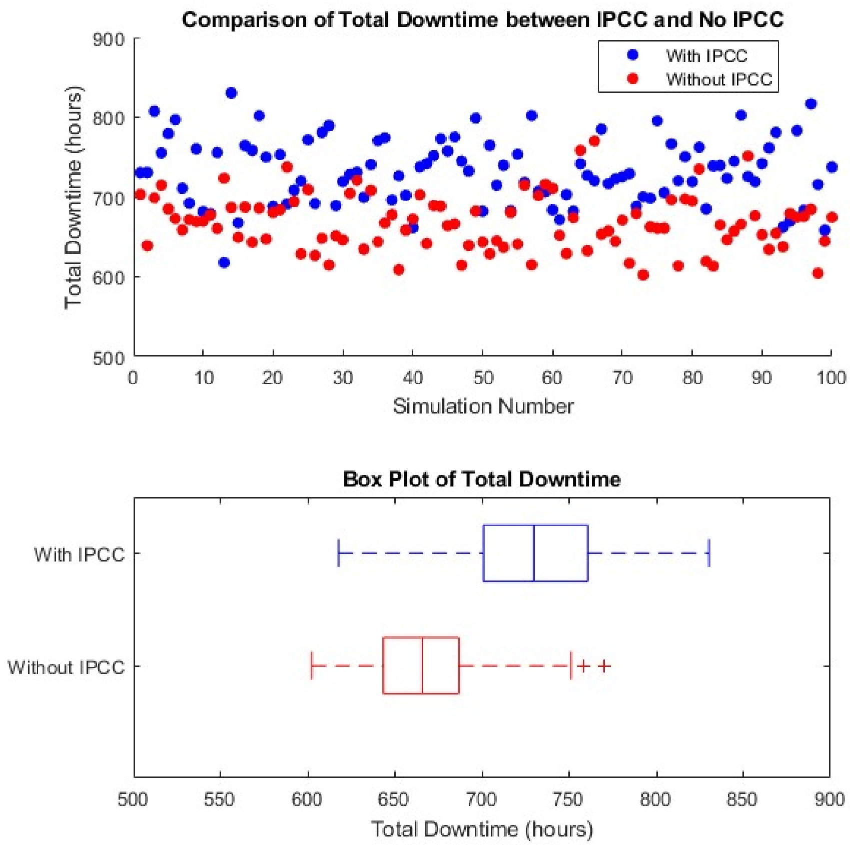

Figure 21. Total downtime comparison between the scenarios.

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

5.3. Comparison between Simulated and Optimal Production

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

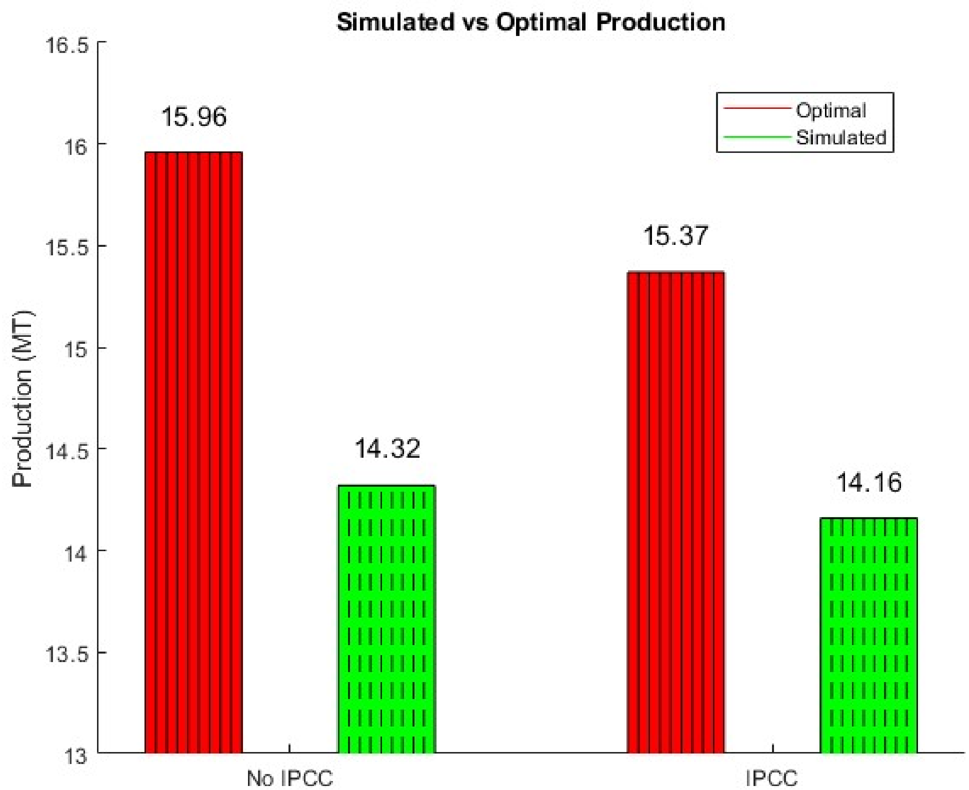

Figure 22. Simulated vs optimal production.

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

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

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

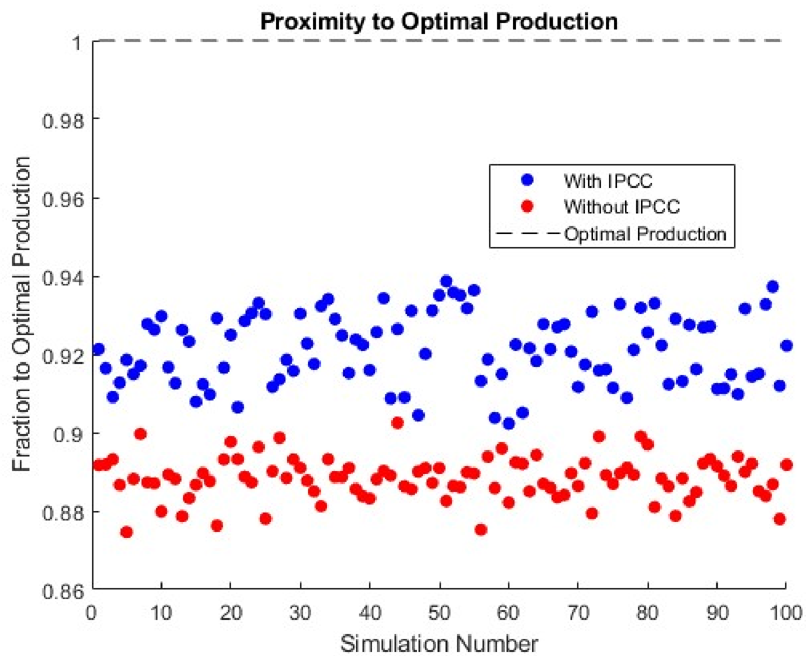

Figure 23. Proximity to optimal production.

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

6. Conclusion

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

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

Future research directions should include exploring a broader range of case studies, encompassing different mine types and operational conditions to validate the robustness and generalizability of the simulation-optimization framework. Additionally, developing dynamic optimization models that adapt to real-time changes in mining conditions and equipment performance could significantly enhance short-term planning effectiveness. Advanced reliability analysis of IPCC components could also help in better understanding and mitigating the additional downtimes introduced by the IPCC system.

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

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