An Ore-to-Barrel Digital Twin: Simulating Fleet and Plant Development in Oil Sands Mining Operations

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ABSTRACT

Strategic development decisions in large-scale mining carry significant capital risk, necessitating robust, data-driven tools for systematic evaluation. This research addresses this challenge by developing a comprehensive, high-fidelity digital twin of an entire open-pit oil sands operation. Our primary contribution is a novel ore-to-barrel Discrete Event Simulation (DES) model that serves as a quantitative tool to minimize the risk of selecting among complex capital expenditure scenarios such as the implementation of Autonomous Haulage Systems (AHS), transitions to continuous haulage, or new plant layouts. The model holistically simulates all in-pit and plant operations, integrating dynamic variables including equipment downtime, haulage network logistics, real-time dispatching logic, and material grade tracking. By generating key performance indicators (KPIs) and identifying bottlenecks, the digital twin was deployed to rigorously evaluate distinct future development scenarios. The analysis provided critical insights into system trade-offs; for example, different scenarios suggested a potential 15-25% reduction in the required truck fleet compared to the current setup, which in turn led to a 20-70% drop-in average crusher queue times. This work validates the use of a full-scale digital twin as an essential decision-support system for optimizing capital-intensive development plans and quantifying trade-offs in the mining sector.

1. Introduction

The global demand for mineral and energy resources ensures that large-scale surface mining operations remain a cornerstone of the industrial economy. However, these operations are characterized by immense capital investment, significant operational complexity, and exposure to volatile commodity markets. In sectors such as oil sands mining, where profit margins are under constant pressure, operational efficiency is not merely an objective but a critical determinant of long-term viability. These enterprises must continuously move massive volumes of material using complex, co-dependent fleets of ultra-class equipment and dedicated processing facilities.

Strategic planning in this environment is fraught with risk. Decisions regarding the adoption of new technologies, such as Autonomous Haulage Systems (AHS), or the development of major infrastructure, like new In-Pit Crushing and Conveying (IPCC) systems, represent multi-billion-dollar capital expenditures. Traditionally, these decisions have been supported by deterministic models, often based on spreadsheets or simplified analytical methods. These tools, however, frequently fail to capture the dynamic and stochastic nature of a fully integrated mining operation.

ISBN: 978-1-55195-548-3

As a result, operational risks may go unidentified, systemic bottlenecks may persist, and the expected return on investment (ROI) may not be realized. This underscores the urgent need for more systematic and robust decision-support tools [18]. To address these shortcomings, the field of mining systems engineering has increasingly turned to simulation. Discrete Event Simulation (DES) has been widely recognized as a powerful tool for modeling the stochastic behavior of truck-and-shovel haulage cycles [2]. Numerous studies have successfully used DES to optimize truck fleet sizing, evaluate dispatching algorithms, and analyze in-pit bottlenecks [2, 10, 19]. Similarly, separate simulation models have been developed to optimize the performance of mineral processing plants, focusing on throughput, reliability, and asset utilization [6, 14].

A significant gap persists in the literature and in industrial practice: the integration of these two domains. The performance of the processing plant is directly dependent on the feed (tonnage and grade) delivered by the mine's haulage fleet, while the fleet's efficiency is, in turn, dictated by dump-point availability and queue times at the plant and crushers. Siloed models that optimize the pit or the plant in isolation miss these critical, non-linear interdependencies. This can lead to misleading conclusions, as an optimized pit strategy may inadvertently create a bottleneck at the plant, or vice-versa. Therefore, there is a clear need for holistic, high-fidelity models that capture the entire value chain from the mining face to the final product—an ore-to-barrel approach.

This research directly addresses this gap by developing and validating a comprehensive, high-fidelity digital twin of an entire open-pit oil sands operation. We present a novel, integrated DES framework that models the complete ore-to-barrel process. This digital twin serves as a robust, quantitative testbed for de-risking complex capital expenditure scenarios. Unlike fragmented models, our approach provides a holistic system view, enabling the analysis of cascading effects and trade-offs between the mine and the processing plant, particularly in the context of long-term strategic development plans. The developed methodology is rooted in a data-intensive approach. We have leveraged 21 months of extensive operational datasets—including truck dispatch logs, equipment maintenance records, and plant performance data—to build stochastic probability distributions for all key operational parameters. The resulting DES model is modular and scalable, encompassing the truck-and-shovel haulage network, dynamic dispatching logic, equipment failure and repair cycles (MTBF/MTTR), and a detailed sub-model of the extraction plant. This allows for the realistic simulation of material flow, from excavation polygons to primary hoppers, through surge bins and separation cells, ultimately tracking key performance indicators for both fleet production and plant hot bitumen output.

The primary contribution of this work is the application of this validated digital twin to a major industrial case study at a large-scale, open-pit oil sands mine. We rigorously evaluate several mutually exclusive, long-term strategic development scenarios spanning a decade of operations (2031–2040). These include a baseline case, which relies exclusively on long-distance truck haulage to a central processing plant, against various configurations of new, decentralized IPCC systems. The analysis quantifies system trade-offs, particularly the relationship between haulage fleet requirements and plant throughput. Our results demonstrate, for example, how specific infrastructure layouts can reduce the required haulage fleet by 15-25% while simultaneously decreasing dump point queue times by 20-70%, thereby unlocking significant operational efficiencies and avoiding future bottlenecks.

This paper is structured as follows. Section 2 presents a concise review of the relevant literature and theoretical background. Section 3 describes the simulation methodology, including the data analytics pipeline, model architecture, and the validation procedure using historical data. Section 4 introduces the case study, outlining the development scenarios evaluated and the resulting key performance indicators. Section 5 reports the outcomes of the model implementation within the case study. Section 6 provides an in-depth discussion of these findings and their strategic implications for capital planning. Finally, Section 7 concludes the paper by summarizing the main contributions and identifying directions for future research.

2. Literature Review

Large-scale surface mining operations, particularly in sectors like oil sands, are among the most capital-intensive industries in the world. These operations face immense pressure to optimize efficiency, manage high operational costs, and mitigate significant environmental impacts [4]. The material haulage system, dominated by truck-and-shovel fleets, is the single largest contributor to this complexity, often accounting for 50–60% of total operating costs and representing the primary source of energy consumption and GHG emissions [10]. Consequently, strategic decisions regarding fleet management and long-term haulage infrastructure carry billions of dollars of capital risk, necessitating robust, data-driven decision-support tools.

Deterministic models, such as spreadsheets and the traditional Match Factor approach, have long been used for mine planning and equipment sizing. However, these static methods are fundamentally incapable of capturing the complex, dynamic, and stochastic nature of these operations [1]. As noted by Upadhyay et al. [16], relying on deterministic algorithms often necessitates secondary translation of operational measures, leading to deviations from real-world data. They argue that robust Equipment Selection and Sizing (ESS) requires simulation-based algorithms that can directly incorporate inherent parameter uncertainties—such as cycle times and payload variations—which deterministic models exclude. To address this, DES has been widely adopted and validated as the standard methodology for "what-if" scenario analysis in mining. DES excels at modeling the variability and interdependencies of complex systems, allowing planners to test the impact of decisions before committing capital [15]. The literature on mining simulation, however, has largely evolved into distinct, specialized streams that often operate in isolation.

The most extensive body of research focuses on the optimization of the in-pit truck-and-shovel system. A primary goal in this stream is the development of efficient truck dispatching algorithms to maximize fleet productivity and minimize equipment idle and wait times [2, 12, 18]. Many modern approaches, such as those detailed in [12, 8], propose integrated simulation and optimization frameworks, often using Mixed Integer Linear Programming (MILP) or Goal Programming (GP) to find optimal dispatch solutions that honor short-term production targets. Building on this integration, Yeganejou et al. [17] emphasized that accurately predicting fleet productivity—specifically Tonne Per Gross Operating Hour (TPGOH)—requires rigorous modeling of the empty truck return logic. By embedding a linear programming dispatch model within a Monte Carlo framework, they demonstrated that aligning simulation logic with the actual distance-minimization heuristics used in fleet management systems significantly reduces the error in empty travel distance estimation, a critical variable often oversimplified in purely stochastic models.

This pit-focused optimization stream is continuously evolving. Recognizing the computational burden and myopic nature of traditional mathematical programming in real-time environments, recent studies have begun applying Artificial Intelligence (AI). Noriega et al. [13] for example, propose a Deep Reinforcement Learning (DRL) based dispatching system. In this approach, an AI agent is trained within a DES environment to learn a complex dispatching policy that outperforms traditional heuristics by accounting for the full, stochastic state of the mine.

Furthermore, the objective functions for dispatching have expanded beyond pure productivity. Driven by growing climate concerns, a significant sub-stream of research now focuses on green dispatching. Ashtiani et al. [3] introduced an energy-efficient framework that explicitly includes truck fuel consumption as a key objective, seeking to simultaneously mitigate GHG emissions while enhancing operational efficiency.

A second, distinct research silo is concerned with the downstream processing plant and the use of stockpiles. Open-pit mines are a union of a discrete mining system and a continuous processing system, a mismatch that creates significant operational challenges in maintaining a consistent quantity and quality of feed. The challenge of linking these systems spans temporal horizons. Ben-Awuah et al. [5] established foundational hierarchical frameworks using discrete-event simulation to bridge the gap between deterministic long-term strategic plans (such as those generated by Whittle) and short-term operational schedules. Their work demonstrated that without stochastically modeling the constraints of crushing availability and stockpiling strategy, mines face significant feed shortfalls and deviations from optimal Net Present Value (NPV).

Consequently, stockpiles are the primary tool used to decouple these systems, acting as a buffer for material quantity and a tool for blending to manage material quality. Modeling stockpile operations is inherently non-linear and complex. Tabesh et al. [15] directly addressed this by proposing a two-stage clustering-MILP algorithm for long-term production planning that integrates multi-range stockpiles. More recently, the granular strategy of stacking has come under scrutiny regarding plant performance. Martins et al. [11] utilized an integrated simulation-optimization tool to investigate the specific impact of stockpile size on plant feed rates. Their findings introduce a critical trade-off: while larger stockpiles reduce inter-pile grade variability, they introduce production losses due to the extended waiting times required to form them. This suggests that dynamic strategies prioritizing smaller pile sizes may actually maximize mass throughput despite higher grade variance, a nuance lost in static planning models. This focus on optimizing blending and grade control via stockpiles is a common theme, as seen in other studies that seek to manage grade variability and maximize resource value.

A third, parallel stream of literature addresses the specific capital investment at the center of our case study: the transition from traditional truck haulage to IPCC systems. As mines deepen, haulage distances and fuel consumption make all-truck fleets economically and environmentally unsustainable. IPCC systems, which move the crusher into the pit and use conveyors for material transport, are a proven solution to reduce truck reliance, operational costs, and emissions.

This specific engineering challenge has generated its own specialized modeling literature. A key problem is determining the optimal location and relocation strategy for semi-mobile crushers. Kamrani et al. [9] proposed a two-step mathematical model to first identify optimal "crusher panels" (practical locations for the crusher) and then develop a long-term schedule that honors these new spatial constraints. This work emphasizes the critical need to integrate the actual road and conveyor networks into the optimization model to accurately capture haulage costs.

Furthering this concept, Gong et al. [7] introduced a novel mining method called the Near-Face Stockpile (NFS), which combines an IPCC system with a pre-crusher stockpile located at the pit bottom. This design acts as both a buffer and a blending tool, decoupling the mining and crushing subsystems to improve system stability and grade control. The authors then used an integrated simulation-optimization framework to quantify the system-wide benefits, demonstrating a significant reduction in truck transport distance and an increase in equipment utilization.

This review highlights three robust, yet largely separate, streams of research: (1) in-pit fleet and dispatch optimization, (2) plant-side stockpile and blending optimization, and (3) IPCC location and scheduling. The critical research gap, which this paper addresses, lies at the intersection of all three. Models that optimize dispatch often use simplified plant destinations; models that optimize stockpiles use simplified mining inputs; and models that optimize IPCC placement focus on location and scheduling but not always on the stochastic, real-time interactions with the fleet and plant. This siloed approach misses the crucial, non-linear feedback loops that define the entire operation. For example, a full surge bin (a plant/stockpile problem) creates a queue that propagates backward, idling the truck fleet (a dispatch problem) and, ultimately, the shovels. No isolated model can capture this systemic effect. The contribution of this research is the development of a holistic, ore-to-barrel digital twin that integrates the stochastic truck-shovel fleet, dynamic dispatch logic, and a detailed, capacity-constrained extraction plant sub-model into a single simulation framework. This integrated tool is essential for realistically evaluating and de-risking complex capital decisions, such as selecting between competing IPCC technologies and layouts, an application not adequately addressed by existing fragmented models.

3. Methodology

The methodological framework for this research was designed to develop a comprehensive, high-fidelity digital twin capable of simulating an entire ore-to-barrel mining value chain. The primary objective was to create a robust, data-driven, and flexible decision-support tool. As shown in Figure 1, our approach integrates extensive data analytics, stochastic DES, and a modular software architecture to ensure the model is both reusable and scalable. The methodology was executed in five distinct stages: (1) Data Analytics and Input Modeling, (2) Model Configuration and Development Framework, (3) Integrated Simulation Logic and Sub-Model Development, (4) Model Verification and Validation, and (5) Predictive Scenario Design.

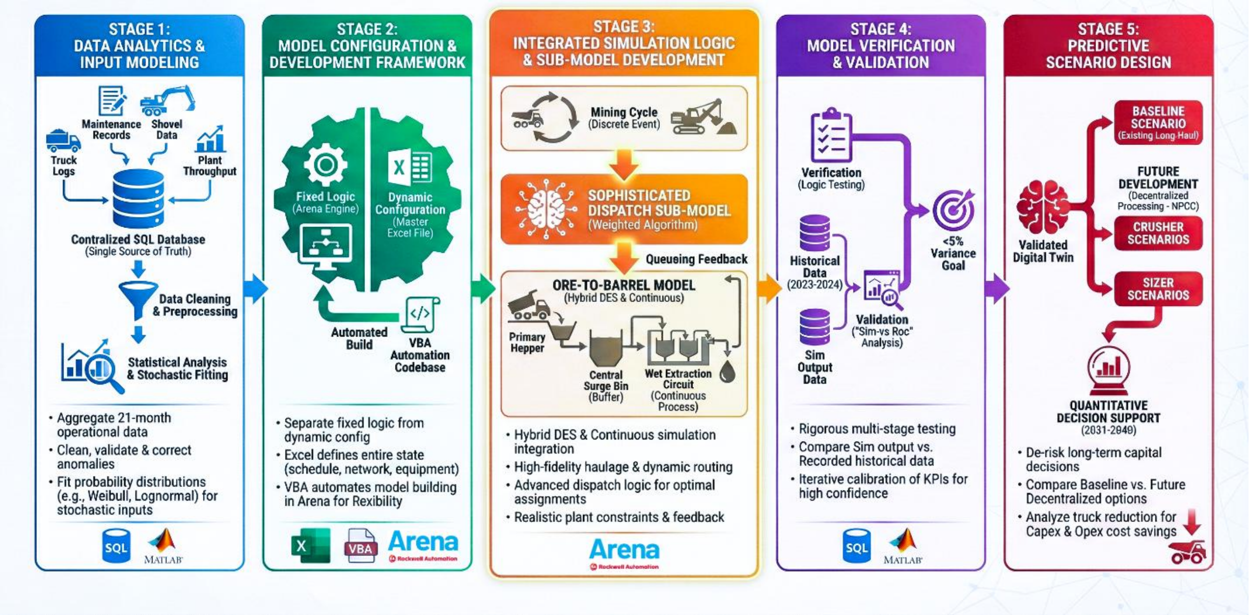


Figure 1. Schematic overview of ore-to-barrel digital twin architecture.

3.1. Stage 1: Data Analytics and Input Modeling

The foundation of the digital twin is built upon extensive operational data collected over a 21-month period from the subject mine. This dataset included raw truck dispatch logs, equipment maintenance and failure records, shovel operation data, and detailed plant processing throughput. The first step involved a rigorous data engineering process: all disparate data sources were aggregated into a centralized Structured Query Language (SQL) database. This single source of truth enabled comprehensive data cleaning, preprocessing, and validation to identify and correct anomalies, handle missing data, and remove recording errors.

Following data aggregation, a detailed statistical analysis was performed using MATLAB and SQL queries. This analysis was critical for capturing the stochastic nature of the operation. Key operational parameters, including but not limited to, truck loading times, bucket tonnage variations, equipment Mean Time Between Failures (MTBF), and Mean Time to Repair (MTTR), were extracted. These raw data were fitted to appropriate probability distributions (e.g., Weibull, Lognormal, Exponential) to serve as stochastic inputs for the simulation model, ensuring the digital twin accurately represents the inherent variability and uncertainty of real-world operations.

3.2. 3.2. Stage 2: Model Configuration and Development Framework

To ensure maximum flexibility and reusability, the simulation model was architected with a clear separation between fixed logic and dynamic configuration. The fixed-logic component, which contains the core simulation engine and process flows, was developed in the Arena simulation software. The dynamic component, which contains all specific inputs, parameters, and scenario definitions, is managed externally.

A master Microsoft Excel-based configuration file serves as the central interface for all model inputs. This file defines the entire state of the mining system, including the production schedule (mining polygons, tonnage, material type), the complete haul road network (segments, distances, gradients), equipment lists (shovels, trucks), and all stochastic probability distributions derived during Stage 1. A custom-developed Visual Basic for Applications (VBA) codebase automates the model-building and updating process. Upon execution, this code reads the Excel configuration file and dynamically builds the corresponding model in Arena, creating all necessary resources, transporter networks, variables, and logic. This approach allows the model to be rapidly reconfigured for new time periods or scenarios without requiring any changes to the core simulation logic.

3.3. Stage 3: Integrated Simulation Logic and Sub-Model Development

The core simulation logic governs the dynamic representation of the entire ore-to-barrel process. The model is driven by a detailed production schedule, which defines the sequence of mining polygons to be extracted. Truck entities are generated and cycle through the primary mining activities: traveling to a shovel, spotting, being loaded, receiving a dispatch assignment, hauling to a destination, dumping, and returning for a new assignment specified by dispatch module. This main loop is influenced by stochastic events, including unscheduled equipment downtimes (based on the MTBF/MTTR distributions), scheduled maintenance, shift changes, and seasonal efficiency variations.

A critical component of the model is the high-fidelity haulage and dispatch sub-model. The entire mine road network is replicated as a network of nodes and guided-path segments. This allows the model to simulate truck-following logic, safe-distance constraints, and the formation of platoons or queues at intersections, accurately capturing traffic congestion. Truck velocities also are not static; they are dynamically calculated for each segment based on truck-specific rimpull characteristics, road gradient, and rolling resistance. Furthermore, a custom dispatching sub-model was developed to emulate the logic of the site's fleet management system, assigning empty trucks to shovels based on a weighted algorithm of factors including shovel production requirements, material priority, and truck travel time.

The model's primary innovation is the holistic integration of the downstream extraction plant, creating a single, unbroken ore-to-barrel system. When a truck is dispatched with ore, it travels to the Oil Processing Plant (OPP). The OPP sub-model is a hybrid continuous-discrete system. Truck dumping events are discrete arrivals, feeding material into primary hoppers (e.g., 1,000-tonne capacity). These hoppers, in turn, feed a central surge bin (e.g., 10,000-tonne capacity).

The surge bin acts as the critical buffer between the discrete mining operation and the continuous plant process. Material is drawn from the surge bin at a defined rate (e.g., 16,000 tonnes per hour) and fed into the wet extraction. This circuit is modeled with its key components, including slurry separation cells and final froth tanks. The model applies material-specific recovery rates (e.g., 92.3%) to track the conversion of ore tonnage into the final processed product. This tight integration ensures that system constraints are propagated realistically; for example, a full surge bin (a plant bottleneck) dynamically blocks the hopper dump locations, forcing the dispatch logic to re-route ore trucks and creating realistic queueing feedback for the mine fleet.

3.4. Stage 4: Model Verification and Validation

Prior to its use for predictive analysis, the digital twin underwent a rigorous, multi-stage verification and validation process. Verification involved systematically testing each sub-model and the overall logic to ensure the model was functioning as intended (e.g., trucks followed correct paths, dispatch logic selected the nearest suitable shovel). Validation was performed by configuring the model with historical inputs from the past two years of operation (2023–2024).

The simulation was run for this historical period, and its outputs were compared directly against the actual, recorded operational data. This "Sim-vs-Rec" analysis used a purpose-built post-processing workflow. Simulation output data was automatically written to a SQL database, and a suite of MATLAB scripts performed a detailed statistical comparison. Key Performance Indicators (KPIs)—such as total ore and waste production, truck-hour utilization, average cycle times, and plant throughput—were compared. The model was iteratively calibrated until its outputs matched the historical data with a high degree of statistical confidence, achieving less than a 5% variance on all major KPIs.

3.5. Stage 5: Predictive Scenario Design

Once validated, the digital twin was re-purposed as a predictive tool to de-risk long-term strategic capital decisions. This study focused on evaluating the development of a New Pit Crushing and Conveying (NPCC) system. The simulation model was adapted to represent several mutually exclusive future development scenarios for a ten-year period (2031–2040). These scenarios included: (1) a "Baseline" case, which continued reliance on the existing long-haul to OPP; (2) "Crusher" scenarios, which involved installing new in-pit crusher hoppers at various locations (South-only or South-North combinations); and (3) "Sizer" scenarios, which modeled an alternative in-pit processing technology.

For the NPCC scenarios, the model logic was extended to include the new dump hoppers, their respective throughput capacities (e.g., 14,000 t/h vs. 16,000 t/h), and the new conveyor systems, which all fed into the existing central surge bin. This allowed for a direct, quantitative comparison of system-wide performance under each capital investment option. By running multiple replications of each scenario, the analysis produced statistically robust forecasts of fleet requirements, production throughput, and potential bottlenecks, thereby providing a quantitative basis for capital decision-making.

4. Case Study: Strategic Development Analysis

The validated ore-to-barrel digital twin was deployed to evaluate long-term strategic development plans at a large-scale, open-pit oil sands mining operation. The mine moves approximately 320 million tonnes of material annually, utilizing a conventional ultra-class truck-and-shovel fleet. The operation was facing a critical, multi-decade capital investment decision regarding the implementation of new haulage and processing infrastructure required to support accelerated entry into a new, more distant pit. The primary objective of the study was to quantify the systemic impact of moving from OPP to a new, decentralized IPCC system. The digital twin was used to conduct a comparative analysis of multiple, mutually exclusive future scenarios, providing a quantitative basis to mitigate the risk of major strategic decision.

4.1. Baseline Scenario: Centralized OPP-Only

The Baseline Scenario represented the do-nothing option. In this configuration, the simulation assumed that all ore from all mining areas, including the new, distant pits, would be hauled exclusively to the existing centralized OPP with two input hoppers. This scenario was characterized by progressively increasing haulage distances as the mine plan advanced. This baseline served as the benchmark against which all alternative IPCC scenarios were measured for truck fleet requirements, production throughput, and operational efficiencies.

4.2. Future Development Scenarios: IPCC Configurations

Six alternative scenarios were modeled to evaluate the new IPCC system. These scenarios were designed to test trade-offs between two competing IPCC technologies (Crusher vs. Sizer) and two different layout strategies (South-only vs. South-North). The South-only layout placed new units near the existing pit, while the South-North layout placed them to more effectively balance haulage from both the existing pit and the new pit expansion. The specific scenarios evaluated were:

- 1Cr-S: One Crusher unit in the South location.
- 1Sz-S: One Sizer unit in the South location.
- 2Cr-S: Two Crusher units in the South location.
- 2Sz-S: Two Sizer units in the South location.
- 2Cr-SN: One Crusher unit in the South and one in the North.
- 2Sz-SN: One Sizer unit in the South and one in the North.

In all IPCC scenarios, the new in-pit stations were modeled to feed the existing central surge bin via a new 5–7 km conveyor system, effectively acting as an alternative feed source to the main plant.

4.3. Simulation Parameters and Time Horizon

A critical differentiator between the competing technologies was their nominal throughput capacity. This was modeled based on vendor specifications:

- Crushers: 16,000 tonnes per hour (summer) / 14,000 tonnes per hour (winter).
- Sizers: 14,000 tonnes per hour (summer) / 12,000 tonnes per hour (winter).

To isolate the impact of this throughput difference, all other parameters, such as equipment downtime and conveyor availability, were held identical between the crusher and sizer scenarios. The analysis did not simulate the entire 10-year period continuously. Instead, a time-slice approach was used to model six representative quarters across the mine life: 2031Q1, 2031Q2, 2035Q1, 2035Q2, 2040Q1, and 2040Q2. This approach was selected to capture operational performance at different stages of the mine plan, particularly as haulage distances and tonnage targets increased in the 2035–2040 period. The scale of the simulation was significant, with a single quarter's run processing over 270,000 individual truckloads.

4.4. Key Performance Indicators (KPIs) for Comparison

The performance of each of the seven scenarios (Baseline + 6 IPCC alternatives) was evaluated using a comprehensive set of KPIs drawn from both the mining fleet and the processing plant perspectives. The primary metrics used to compare the scenarios included:

- Truck Fleet Requirements: The total number of haul trucks required to meet production targets.
- Queueing at Dump: The average and total time trucks spent waiting to dump at the plant hoppers.
- Dump Time: The average time taken for the dumping process, reflecting plant throughput capacity.
- Haulage Distances: The total loaded haulage distance (tonne-kilometers) for the ore fleet.
- Truck Hours (Ore): The distribution of truck time between productive work and non-productive time (e.g., idle, waiting).
- Truck Working Efficiency (%): The percentage of total truck time spent in a productive state.

5. Results and Findings

The developed digital twin was run for the seven defined scenarios (Baseline OPP and six IPCC alternatives) across the six representative quarters (2031Q1, 2031Q2, 2035Q1, 2035Q2, 2040Q1, and 2040Q2). The simulation generated a comprehensive set of KPIs for each scenario, allowing for a robust comparative analysis.

The results are presented as the percentage difference between each IPCC scenario and the Baseline (OPP) scenario for the corresponding quarter. A negative value (e.g., -25%) indicates a reduction in the metric, while a positive value (e.g., +10%) indicates an increase. The detailed comparative results for each quarter are presented in Tables 1 through 6, followed by a summary of the key findings.

5.1. Comparative Analysis by Time Period

For each of the six selected quarters, the model outputs were examined to assess the relative performance of the evaluated scenarios over time. Each quarterly evaluation consists of a complete execution of all scenarios, after which the resulting indicators are examined to identify temporal patterns and performance deviations. The assessment focuses on the quantitative outputs produced by the model and the additional operational measures defined in Section 4.4, which together enable a structured comparison across quarters.

The aggregated results of these time-based evaluations are summarized in Tables 1 through 6, each table corresponding to one of the representative quarters. To maintain clarity and avoid redundancy, only a single illustrative visualization—derived from the normalized results of the OPP scenario for 2031Q1—is included. The normalization of the presented figures is applied to comply with confidentiality requirements while still conveying the relative trends and comparative insights.

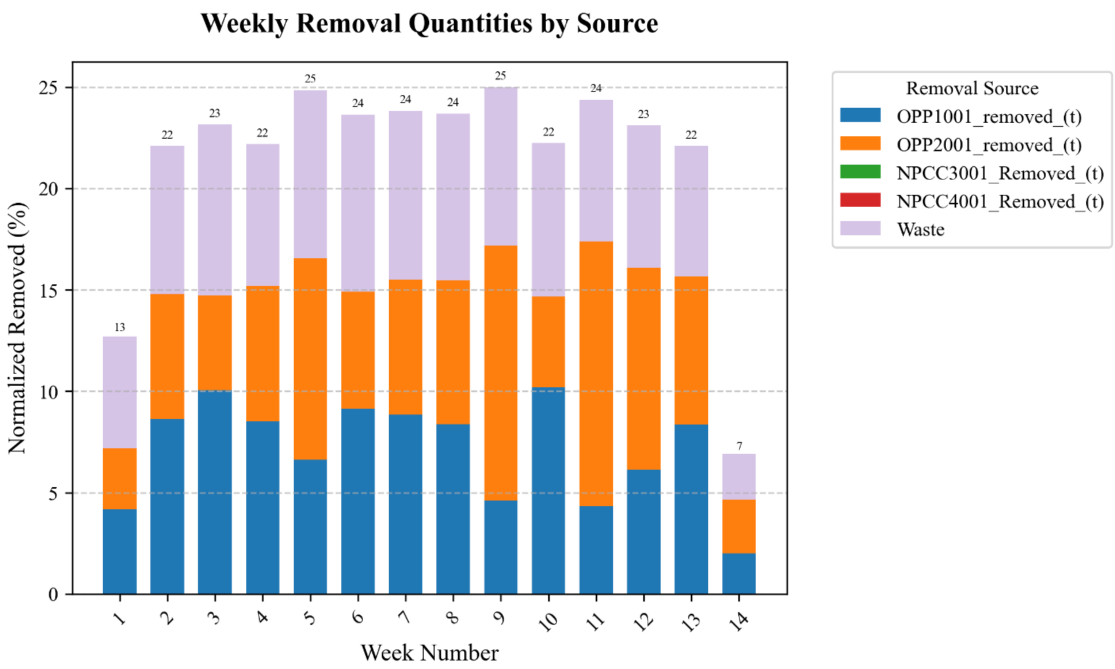


Figure 2. Normalized weekly production for OPP scenario in 2031 Q1.

Figure 2 illustrates the total processed load (ore and waste combined) across the processing facilities. As noted, OPP1001 and OPP2001 correspond to the two hoppers of the existing processing plant. The NPCC units will only become operational following the deployment of the IPCC modules in future stages of mine development. Figure 3 presents a similar visualization for the two crushers located in the northern and southern areas of the site, reflecting a balanced configuration within the IPCC system.

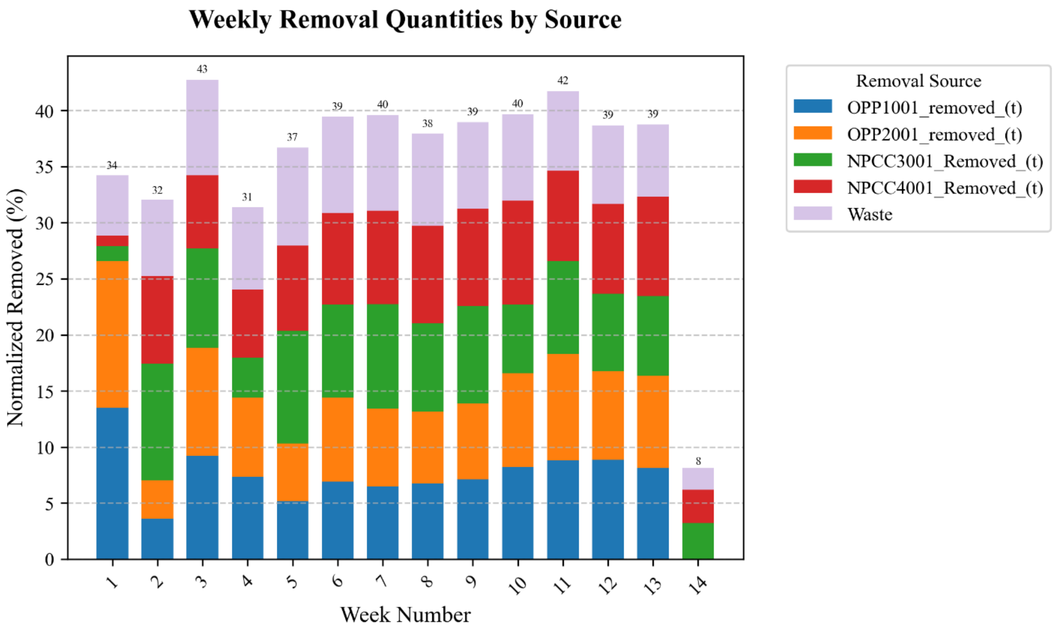
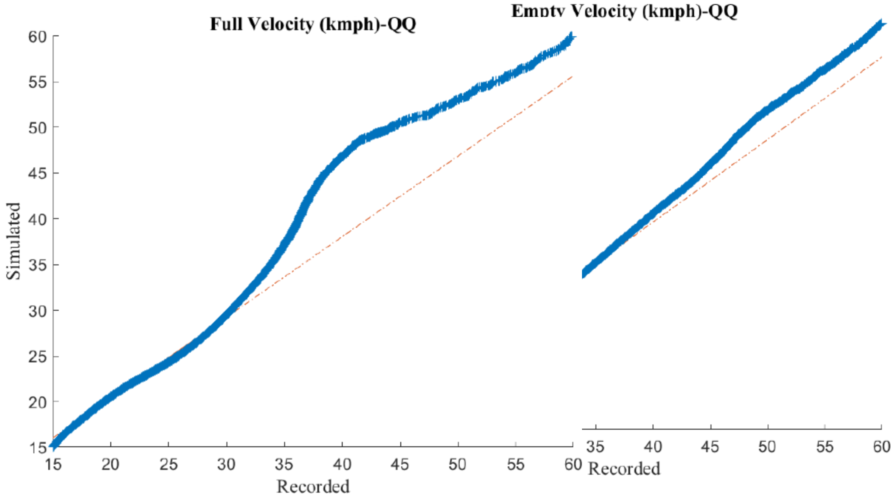


Figure 3. Normalized weekly production for 2 crushers located at south and north scenario in 2031 Q1.

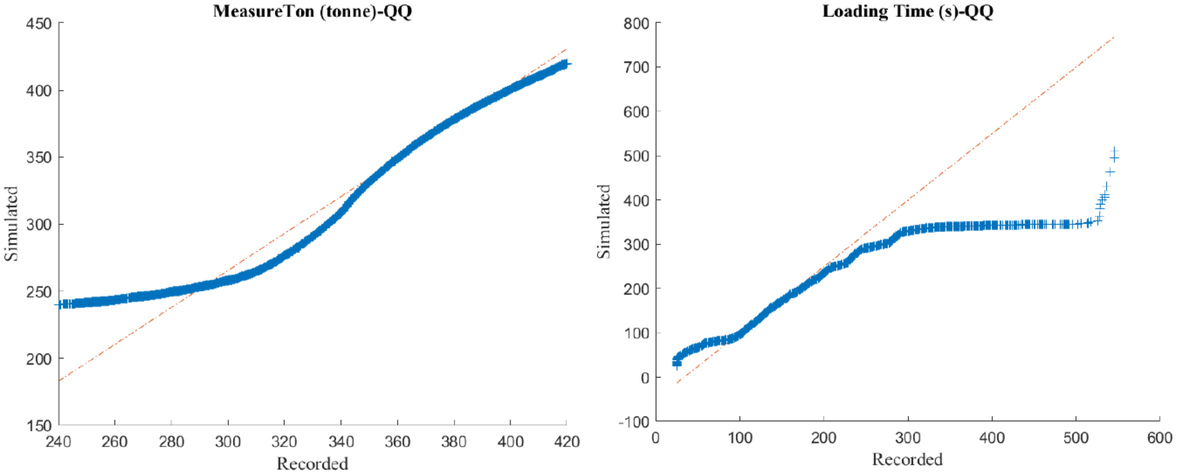
It should be noted that all simulation outputs that could be directly compared with available operational data were validated against historical records to ensure the credibility of the results. These metrics include full-haul and empty-haul velocities, as well as loading times for various truck–shovel combinations. Figure 4 presents these comparisons using Quantile–Quantile (Q–Q) plots for 2031 Q1.


Full Velocity (kmph)-QQ

Empty Velocity (kmph)-QQ

a. Empty velocity Q-Q plot

b. Full velocity Q-Q plot


MeasureTon (tonne)-QQ

Loading Time (s)-QQ

c. Truck payload tonnage Q-Q plot

d. Truck loading time Q-Q Plot

Figure 4. Q-Q plots of simulated parameters vs. recorded.

Table 1. 2031Q1 - Percentage difference between the OPP (Baseline) scenario and IPCC alternatives.

KPI (Percentage Difference %)	1Cr-S	1Sz-S	2Cr-S	2Sz-S	2Cr-SN	2Sz-SN
Truck Fleet Requirements	-24.8%	-26.2%	-27.5%	-28.2%	-26.8%	-28.2%
Queue Time at Dump (AVG)	-45.9%	-49.6%	-69.2%	-71.8%	-71.1%	-73.0%
Queue Time at Dump (SUM)	-45.4%	-48.7%	-68.3%	-70.7%	-70.3%	-71.2%
Dump Time	-7.5%	-6.6%	-10.0%	-8.1%	-9.6%	-8.1%
Full Distance (SUM)	-9.6%	-9.6%	-9.7%	-9.7%	-10.0%	-10.0%
Non-productive (hour)	-41.5%	-44.5%	-63.7%	-66.5%	-65.1%	-67.2%
Truck Working Efficiency (%)	7.9%	8.5%	12.3%	12.8%	12.6%	13.0%
Ore Truck Prod (hour)	-14.1%	-14.9%	-16.4%	-17.0%	-16.0%	-17.0%

Table 2. 2031Q2 - Percentage difference between the OPP (Baseline) scenario and IPCC alternatives.

KPI (Percentage Difference %)	1Cr-S	1Sz-S	2Cr-S	2Sz-S	2Cr-SN	2Sz-SN
Truck Fleet Requirements	-2.7%	-2.7%	-6.7%	-4.7%	-6.7%	-4.7%
Queue Time at Dump (AVG)	-40.6%	-38.6%	-66.2%	-63.8%	-64.7%	-62.3%
Queue Time at Dump (SUM)	-40.6%	-38.6%	-66.1%	-63.8%	-64.7%	-62.3%
Dump Time	-7.2%	-6.5%	-10.4%	-9.2%	-10.3%	-9.1%
Full Distance (SUM)	-9.4%	-9.4%	-9.7%	-9.6%	-10.0%	-10.0%
Non-productive (hour)	-36.4%	-34.8%	-59.5%	-57.4%	-58.4%	-56.2%
Truck Working Efficiency (%)	6.2%	5.9%	10.4%	10.0%	10.1%	9.7%
Ore Truck Prod (hour)	-10.9%	-10.7%	-13.6%	-12.9%	-13.5%	-12.8%

Table 3. 2035Q1 - Percentage difference between the OPP (Baseline) scenario and IPCC alternatives.

KPI (Percentage Difference %)	1Cr-S	1Sz-S	2Cr-S	2Sz-S	2Cr-SN	2Sz-SN
Truck Fleet Requirements	-16.7%	-13.3%	-21.1%	-17.8%	-20.0%	-15.6%
Queue Time at Dump (AVG)	-37.8%	-33.9%	-57.7%	-53.4%	-57.4%	-52.7%
Queue Time at Dump (SUM)	-37.7%	-33.8%	-57.6%	-53.4%	-57.3%	-52.6%
Dump Time	-3.7%	-2.8%	-5.7%	-4.1%	-5.6%	-4.0%
Full Distance (SUM)	-9.6%	-9.3%	-9.9%	-9.5%	-10.9%	-10.7%
Non-productive (hour)	-31.7%	-28.7%	-48.1%	-44.0%	-47.9%	-43.4%
Truck Working Efficiency (%)	5.3%	4.8%	8.2%	7.4%	8.2%	7.3%
Ore Truck Prod (hour)	-11.9%	-10.9%	-14.6%	-13.2%	-14.3%	-12.7%

Table 4. 2035Q2 - Percentage difference between the OPP (Baseline) scenario and IPCC alternatives.

KPI (Percentage Difference %)	1Cr-S	1Sz-S	2Cr-S	2Sz-S	2Cr-SN	2Sz-SN
Truck Fleet Requirements	-17.6%	-14.1%	-20.4%	-17.6%	-22.5%	-19.7%
Queue Time at Dump (AVG)	-36.6%	-33.3%	-53.4%	-54.7%	-53.6%	-54.9%
Queue Time at Dump (SUM)	-36.5%	-33.2%	-53.3%	-54.6%	-53.5%	-54.8%
Dump Time	-3.9%	-3.0%	-5.8%	-5.6%	-5.8%	-5.6%
Full Distance (SUM)	-9.6%	-9.2%	-9.7%	-9.5%	-11.0%	-10.8%
Non-productive (hour)	-30.9%	-28.2%	-45.1%	-46.1%	-47.1%	-48.3%
Truck Working Efficiency (%)	5.5%	5.0%	8.2%	8.4%	8.7%	8.9%
Ore Truck Prod (hour)	-13.0%	-11.8%	-15.1%	-15.1%	-16.4%	-16.4%

Table 5. 2040Q1 - Percentage difference between the OPP (Baseline) scenario and IPCC alternatives.

KPI (Percentage Difference %)	1Cr-S	1Sz-S	2Cr-S	2Sz-S	2Cr-SN	2Sz-SN
Truck Fleet Requirements	-1.3%	-0.7%	-2.0%	-3.3%	-3.3%	-2.6%
Queue Time at Dump (AVG)	-13.7%	-14.8%	-24.8%	-28.7%	-28.0%	-27.3%
Queue Time at Dump (SUM)	-13.6%	-14.7%	-24.7%	-28.6%	-27.9%	-27.2%
Dump Time	-0.6%	-0.8%	-1.2%	-1.1%	-1.6%	-0.8%
Full Distance (SUM)	-2.9%	-2.9%	-2.9%	-3.0%	-3.6%	-3.6%
Non-productive (hour)	-12.1%	-13.1%	-21.9%	-25.2%	-24.6%	-24.0%
Truck Working Efficiency (%)	2.1%	2.3%	3.9%	4.5%	4.4%	4.3%
Ore Truck Prod (hour)	-3.1%	-3.2%	-3.8%	-4.8%	-5.0%	-4.5%

Table 6. 2040Q2 - Percentage difference between the OPP (Baseline) scenario and IPCC alternatives.

KPI (Percentage Difference %)	1Cr-S	1Sz-S	2Cr-S	2Sz-S	2Cr-SN	2Sz-SN
Truck Fleet Requirements	-4.1%	-2.3%	-6.4%	-4.7%	-5.2%	-2.9%
Queue Time at Dump (AVG)	-21.9%	-17.5%	-36.4%	-31.2%	-32.6%	-26.3%
Queue Time at Dump (SUM)	-21.8%	-17.4%	-36.3%	-31.1%	-32.5%	-26.2%
Dump Time	-2.0%	-1.3%	-3.5%	-2.6%	-3.0%	-2.1%
Full Distance (SUM)	-3.9%	-3.7%	-4.1%	-4.0%	-4.5%	-4.3%
Non-productive (hour)	-19.4%	-15.5%	-32.2%	-27.6%	-28.8%	-23.3%
Truck Working Efficiency (%)	3.5%	2.8%	5.9%	5.0%	5.3%	4.2%
Ore Truck Prod (hour)	-5.5%	-4.3%	-8.0%	-6.7%	-7.0%	-5.1%

5.2. Summary of Key Findings

Analysis of the simulation output across all scenarios and time periods reveals several key findings critical for strategic planning. The performance of each scenario is summarized by the major KPIs.

5.2.1. Truck Fleet Requirements

The IPCC scenarios consistently reduce the required haulage fleet compared to the Baseline (OPP) scenario. The two-unit configurations (e.g., 2Cr-S, 2Cr-SN) provide the largest reductions, minimizing the required fleet by 15-28% in the 2031-2035 periods (Tables 1-4).

Critically, the high-throughput Crusher (16,000 t/h) scenarios consistently require fewer trucks than the equivalent Sizer (14,000 t/h) scenarios. This advantage is most pronounced in the high-tonnage quarters of 2035 and 2040. For example, in 2035Q2 (Table 4), the 2Cr-SN scenario requires 22.5% fewer trucks than the baseline, whereas the 2Sz-SN scenario's reduction is only 19.7%. This demonstrates the long-term fleet savings of selecting the higher-capacity technology.

5.2.2. Queueing at Dump

Queueing time at the dump hoppers emerged as the strongest differentiator between scenarios and the primary driver of truck fleet inefficiency.

- All IPCC scenarios dramatically reduced queueing. In the 2031-2035 period, the two-unit scenarios (2Cr and 2Sz) reduced average queue times by 50-73% compared to the baseline (Tables 1-4).
- Even in the high-demand 2040 quarters, where haul distances are longest, the IPCC scenarios maintained a 25-36% reduction in average queue time (Tables 5-6).
- This KPI highlights the robustness of the Crusher (Technology A) scenarios. While sizers performed well in early years, the crushers' higher throughput provided more reliable queue mitigation as system demand increased.

5.3. Dump Time and Plant Throughput

Dump time, a direct reflection of the plant's ability to accept material, consistently favored the Crusher scenarios. The 16,000 t/h capacity of the crushers resulted in shorter dump times across all six quarters compared to the 14,000 t/h sizers (e.g., in 2031Q1, 2Cr-S achieved a -10.0% reduction vs. -8.1% for 2Sz-S). This throughput advantage is the root cause of the reduced queueing and higher fleet efficiency seen in other KPIs.

5.4. Haulage Distances and Layout Strategy

All IPCC scenarios successfully reduced the total ore haulage distance. However, the simulation clearly demonstrated the superiority of the South-North (SN) layout strategy. By placing infrastructure to serve both mining areas, the 2Cr-SN and 2Sz-SN scenarios consistently achieved the largest reduction in Full Distance (SUM), beating the South-only (S) layouts in nearly every quarter. This balanced layout minimizes extreme haul paths and improves overall cycle stability.

5.5. Non-Productive Time and Working Efficiency

The reduction in fleet size, queueing, and travel time translates directly into improved fleet efficiency.

- Non-Productive Time: The Non-productive metric, which captures total idle and waiting time, saw the most significant reductions in the two-unit crusher scenarios. The 2Cr-SN scenario, for example, reduced non-productive time by 65.1% in 2031Q1 and maintained a 46-47% reduction even in the 2035-2040 period (Tables 1, 4, 5).
- Working Efficiency: Consequently, Working Efficiency (%) showed the most substantial gains in the IPCC scenarios. In 2031Q1, the 2Cr-SN and 2Sz-SN scenarios improved truck working efficiency by 12.6-13.0 percentage points over the baseline. As the mine aged, the Crusher scenarios maintained a clear efficiency advantage, delivering a 9-point improvement in 2035Q2 and a 6-point improvement in 2040Q1, compared to 7-8 points and 5 points, respectively, for the Sizer scenarios. This demonstrates the crushers' superior ability to sustain fleet efficiency under high system load.

6. Discussion of Findings and Strategic Implications

The results of this ore-to-barrel simulation provide critical, quantitative insights into the long-term strategic development of the mining operation. The findings move beyond simple deterministic calculations to reveal complex, dynamic system interdependencies that have profound implications for capital planning. The discussion is structured around three key areas of contribution: the validation of capital investment, the strategic quantification of technology risk, and the operational value of infrastructure layout.

A primary finding of the study is the definitive quantification of the baseline scenario's unsustainability. The "do-nothing" option, which relies exclusively on the OPP, is consistently the least efficient configuration. As the mine plan progresses and haul distances increase, the model shows a severe degradation in fleet efficiency, driven primarily by escalating non-productive truck time. This validates the core premise for capital investment in a new IPCC system. The simulation demonstrates that any of the six IPCC scenarios provide a dramatic improvement over the baseline, chiefly by de-coupling the haulage fleet from the central plant, shortening haul cycles, and mitigating systemic congestion.

The most significant strategic insight emerges from the direct comparison between the two alternative processing technologies: the high-throughput option ("Crusher," 16,000 t/h) and the standard-throughput option ("Sizer," 14,000 t/h). In the early-life quarters (representing 2031), the performance difference between the two is marginal. Both systems appear competitive, and a decision-maker focusing on this period might incorrectly conclude the technologies are interchangeable, potentially favoring the one with a lower initial capital expenditure.

However, the simulation of the mid- and late-life quarters (representing 2035–2040) reveals a critical hidden risk. As mining progresses into more distant areas and tonnage demands on the system increase, the performance of sizer technology (the 14,000 t/h option) begins to plateau and degrade. Its lower nominal capacity becomes the new system bottleneck. This results in longer dump times, which propagate backward through the system as escalating truck queues at the in-pit hoppers. Consequently, the truck fleet's non-productive time increases, and its overall working efficiency diminishes.

Conversely, crusher technology (the 16,000 t/h option) demonstrates superior robustness. Its higher throughput capacity allows it to absorb the increased production targets in the later years more effectively. It consistently sustains shorter dump times and, therefore, lower dump queues. This translates directly into higher truck fleet efficiency, reduced non-productive time, and a lower overall truck fleet requirement—by as much as 3-5 percentage points compared to sizer in the high-tonnage years. This finding is paramount for capital planning: selecting the standard-throughput technology would introduce a significant, compounding operational risk over the life of the mine, ultimately requiring a larger, more expensive haul fleet to meet production targets.

The simulation results further underscore that technology selection alone is insufficient; infrastructure layout is a critical, co-dependent factor. The analysis of the Proximal Layout (S-only) versus the Balanced Layout (SN) reveals that the spatial distribution of the IPCC hoppers directly impacts haulage efficiency. The Balanced Layout, which places processing units to serve both the existing pit and the new expansion, provides a measurably better balance of haulage flows. This configuration reduces overall travel distances and, more importantly, prevents localized congestion at a single processing area, further reducing dump-side congestion and improving cycle stability.

The clear superiority of the two-unit, balanced layout scenario using the high-throughput technology (the 2Cr-SN equivalent) exemplifies the power of a holistic simulation approach. This decision could not have been reached with confidence using siloed models. A mine-only simulation would have failed to capture the bottleneck effect of the plant's throughput (crusher vs. sizer) on truck queueing. The OPP only model would have no concept of haulage network optimization (Proximal vs. Balanced Layout). Our integrated ore-to-barrel model, by contrast, captured the critical, non-linear feedback loop between the pit, the haulage network, and the plant, allowing for the quantification of systemic trade-offs.

7. Conclusions

This research has demonstrated the development and application of a comprehensive, high-fidelity ore-to-barrel digital twin for a large-scale open-pit mining operation. We have shown that by holistically integrating the in-pit haulage fleet with the downstream extraction plant, it is possible to create a robust, data-driven simulation framework that moves beyond siloed analyses. The primary contribution of this work is the validation of this integrated DES model as an indispensable quantitative tool for de-risking multi-decade, capital-intensive strategic decisions.

The key findings from the case study confirm the strategic value of this holistic approach. The simulation results quantitatively proved that a transition to IPCC system would yield significant operational benefits over the baseline, with the optimal 2Cr-SN equivalent configuration reducing truck fleet requirements by 15-25% and dump-point queue times by over 50% in early-to-mid-life years. More critically, the model revealed a significant long-term risk: the lower-throughput Sizer, while competitive in early years, would become a systemic bottleneck under higher tonnage demands, leading to degraded fleet efficiency. The high-throughput Crusher technology, combined with a spatially balanced (i.e., South-North) layout, was identified as the most robust long-term solution, minimizing future operational risk and lowering the total OPEX.

While the model achieved a high degree of validation against historical data, certain limitations in its current scope must be acknowledged. The model's primary focus was the mine-plant interface; consequently, the internal logic of the extraction plant sub-model was simplified, and ore stockpiles were not modeled. The model also used an average bitumen grade for all material rather than modeling grade variability by polygon, which could impact plant recovery calculations. Finally, the dispatch logic, while calibrated to emulate site practices, was not a fully dynamic, real-time optimization algorithm.

These limitations provide clear and promising avenues for future research. An immediate enhancement would be the incorporation of stochastic grade and tonnage distributions at the mining-polygon level, linking in-pit geological variability directly to plant throughput and recovery. The dispatch sub-model could also be replaced with a dynamic optimization engine, potentially using reinforcement learning to discover novel dispatch strategies that further minimize congestion.

A more significant research direction involves the integration of predictive, AI-driven modules to replace static, independent stochastic inputs. For instance, instead of relying on traditional

MTBF/MTTR distributions, an AI-based failure module could be developed. Such a model could be trained on historical maintenance, operational, and sensor data to predict not only the timing of an equipment failure but also the probable type and category of the failure event based on complex operational precursors. This would enable a far more dynamic and realistic simulation of operational downtime. This framework could also be extended to evaluate the full-system impact of transitioning to AHS or to track energy consumption and GHG emissions, allowing for the optimization of development scenarios based on both economic and environmental sustainability goals.

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