A Hybrid MIP-DES Framework for Open-Pit Mine Planning Using OPPS: Optimization and Simulation-Based Decision Support

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Optimizing mine planning maximizes economic value and efficiency by designing pit limits, scheduling extraction, allocating equipment, and managing costs. Traditional methods often fail to handle randomness and dynamic field conditions. To overcome these limitations, this research introduces a simulation-optimization framework integrating Mixed-Integer Programming (MIP) for pit limit design with discrete-event simulation (DES) to capture short-term operational variability. MIP indicates greater flexibility in incorporating complex constraints, resulting in a more realistic pit design. The geometry of open-pit layout growth is modeled using an Open Pit Production Simulator (OPPS), implemented in MATLAB and based on a modified elliptical frustum. The OPPS serves as a central tool, seamlessly linking the MIP-derived scheduling outputs with DES-based operational scenarios for realistic system evaluation. The simulator models equipment movements, haulage cycles, and scheduling under uncertain operational conditions. The framework dynamically interacts with a geological-economic block model to compute volumes of ore, waste, and stockpiles, while continuously tracking the Net Present Value (NPV). A case study on a 75,000-block iron ore deposit validates the framework. For 1,000 discrete-event simulation scenarios, the MIP-optimized pit design forms the foundation. At an annual discount rate of 8%, the best-performing scenario (OPPS) achieved an NPV deviation of -1.5%, maintained average ore grades of ~67%, and stripping ratios between 5.2–6.5, with a balanced annual production schedule of ~12 Mt ore and ~7 Mt waste over a 30-year my life. Overall, the proposed MIP-DES framework improves mine planning by combining optimization and simulation, enabling informed, long-term, and realistic operational decisions under uncertainty.

Povzetek: Hibridni okvir združuje mešano celoštevilsko programiranje in diskretno-dogodkovno simulacijo za planiranje površinskih kopov. Pristop omogoča realističnejše odločanje pod negotovostjo ter izboljša NPV, razmerje jalovina–ruda, stabilnost kakovosti in izrabo opreme.

1 Introduction

The extraction of mineral resources is a key pillar of industrial development, and open-pit mining is the most common method to extract ore bodies located near the surface. Open-pit mining is economical due to the ability to sustain large, continuous production, making it advantageous for bulk commodities such as iron ore, copper, and gold [1]. During the last ten years, the mine planning landscape has seen significant changes as a result of increasing geological complexity, varying commodity prices, new environmental legislation, and the complexities of managing extremely large open-pit systems [2]. The decisions of long-term planners, such as the order of block extraction or fleet allocations, tend to have more deliberate outcomes with potentially distinct impacts that often affect the mine's Net Present Value (NPV) across decades. This allows sophisticated tools capable of representing variability, assessing risk, and modifying plans as it unfolds [3]. In open-pit situations, this difficulty is multiplied as the interactions among variables relate to the system over time, while uncertainty is extremely low [4]. Computer-based simulation provides a new way to deal with this complexity and uncertainty. Simulation models replicate the time-dependent behavior of mine systems so that planners can test alternative strategies for the sequence of extraction and allocation of equipment and uncertainties, all at no risk of going on the mine [5]. Combining simulation and mathematical optimization provides an additional pathway to develop their value. While optimization can provide schedules or designs to optimize economic performance, simulation can also verify that the step is still valid successfully as operational uncertainty [6]. As the industry moves forward in hyper-automation, efficiencies, and resiliencies, as a standard for open-pit operations, it is not a choice but a necessity to deliver competitive and sustainable mineral resource use [7].

Research aim: This research intends to construct an intelligent simulation-optimization model (OPPS) for open-pit mine planning that integrates MIP and DES. It aims to evaluate whether this hybrid approach can improve key performance metrics, such as reducing stripping ratio or waste-to-ore ratio, ore grade stability, maximizing equipment utilization, and minimizing NPV deviation under uncertain cycle times, compared to conventional planning methods, and to determine its robustness under operational uncertainties.

The organization of the research is listed as follows: Section 1 discusses the significant background of research; Section 2 offers the prior studies in mining planning of mines using computer simulation technology. Section 3 provides the proposed methodology, Section 4 illustrates the experimental findings, and Section 5 deals with the conclusion and future direction of the research.

2 Related works

Table 1 contains a comparative overview of related works undertaken between 2022 and 2025 relating to Machine Learning (ML) methods, DES, and optimization methods in open-pit mining.

Table 1: Summary of related works

Ref	Objective	Data Used	Key Result	Limitations
Park et al. [8]	Predict ore production using ML with DES in haulage systems	Limestone underground mine truck data	Particle Swarm Optimization – Support Vector Machine (PSO-SVM) accurately predicted cycle time & ore production.	Focused only on underground limestone mines; not tested on open-pit mines
Qiao et al. [9]	Extract open-pit mining areas from multispectral images using deep learning.	Multispectral satellite imagery	SegMine (Transformer model) outperformed 6 variants in mIoU, precision, and recall.	Geared toward image extraction, not direct mine planning
Quelopana et al. [10]	Technoeconomic assessment of intelligent ore sorting for open-pit mines using an integrated MIP-DES framework	Gold deposit data, operational mine & plant constraints	Proposed integrated methodology optimizes pit design and operational scheduling, handling geological uncertainty and feed variability, improving NPV	Limited to a simulated case study; requires real-time implementation validation
Fan et al. [11]	Forecast ore production using a Deep Neural Network combined with Principal Component Analysis (DNN + PCA) in open-pit mines	Truck haulage and weather data	Deep Neural Network (DNN) achieved high forecasting accuracy for ore tonnage.	Limited focus on prediction; doesn't support operational simulation
Gong et al. [12]	Develop and evaluate the Near-Face Stockpile (NFS) method, integrating IPCC with the pre-crusher stockpile for large open pits.	Oil sands mine case study + MILP optimization + DES simulation	NFS improved production by 5.06%, reduced truck haulage distance by 17.87%, and increased shovel and crusher utilization by ~5%	Requires a wider pit bottom layout; applicability to narrow pits is limited
Quelopana et al. [13]	Assess tech upgrades in open-pit mines using optimization + DES	Mine plan data + processing constraints	Integrated system maximizes throughput despite feed uncertainty	Doesn't address block-level scheduling or grade optimization
Eustace and Hynard [14]	Support rapid weekly/daily mine plan refinement using simulation and optimization to align execution with actual my operations.	Operations data feed from active mines (actual vs. planned state)	Optimization + simulation enabled automated generation of short-term plans that maintained or improved performance objectives of quarterly plans; tested robustness and operational issue mitigation	Example applications discussed; generalizability to all mine types not fully validated; requires integration with live operations data
Xu et al. [15]	Optimize production + haulage planning via bilevel optimization	Open-pit mine block + route data	Joint model reduces costs and adjusts demand temporally	Computational complexity increases with mine size
Icarte-Ahumada and Herzog [16]	Improve truck dispatching with reinforcement learning in open-pit mines	Truck routing + dispatch logs	Learning-based Multi-Agent System for Truck Dispatching (MAS-TD) outperformed the original dispatch system.	Focuses only on dispatch logic, not on full mine scheduling

Li et al. [17]	Forecast mining capital cost (MCC) for open-pit projects	80 open-pit mining projects	SalpSO-CFNN model achieved high accuracy ($R^2 = 0.98$)	Limited dataset, may need more diverse mines
Zheng et al. [18]	Predict coal roadway roof displacement for safety	Dataset of six influencing factors	Random Forest model predicted roof displacement accurately ($R^2 = 0.92$)	Limited to specific coal roadway data

The mining industry faces ongoing challenges in accurately predicting production, optimizing haulage, and coordinating planning under uncertain operational conditions. Traditional machine learning and heuristic approaches often address individual tasks but fail to provide a unified framework for scheduling and simulation. The research [13] examined technology enhancement in open-pit environments and achieved robust throughput under uncertainty by combining mine plan optimization with discrete-event simulation. While the reinforcement learning-based truck dispatching system [16] enhanced dispatch logic, it was unable to optimize total production planning since it just addressed truck routing and did not incorporate comprehensive mine scheduling. The lack of integration of block-level scheduling, uncertainty modeling (ore grade, equipment delays, and market fluctuations), and optimization complexity management in these SOTA approaches further restricts their practicality. To address these limitations, this research implements the Open Pit Production Simulator (OPPS) integrated with Mixed-Integer Programming (MIP) and Discrete-Event Simulation (DES). The OPPS uniquely overcomes the shortcomings of prior methods by incorporating block-level scheduling, uncertainty modeling, and system-wide optimization, thereby ensuring higher planning accuracy and improved economic stability. This hybrid MIP-DES approach enables comprehensive mine planning, capturing both long-term pit design and short-term operational variability, thereby improving production stability, equipment utilization, and economic outcomes.

3 Proposed methodology

Rooted in data-driven mine planning, this methodology integrates the MIP and DES in an effective linear program framework. Figure 1 depicts the flow of the methodology section.

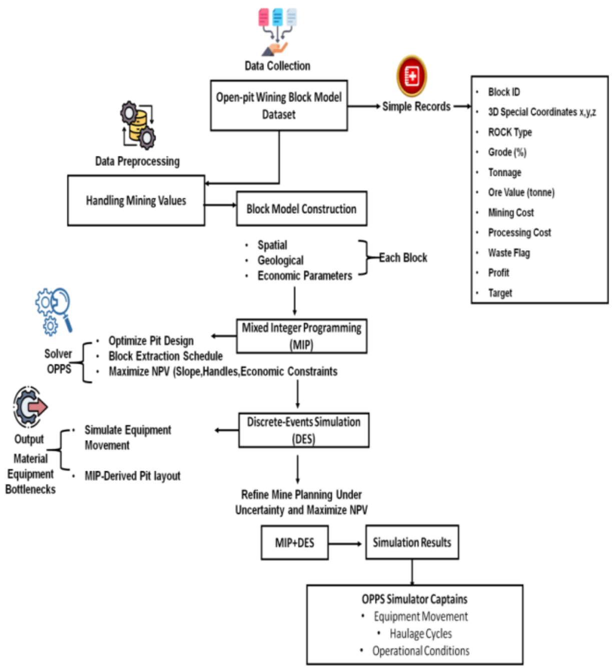

Figure 1: Methodology flow

3.1 Data collection

The open-source dataset (https://www.kaggle.com/datasets/ziya07/open-pit-mining-block-model-dataset/data) used in this research consists of a generated open-pit mining block model of 75,000 blocks. Each block contains a finite quantity of earth material that can be mined. The block model portrays realistic geological, economic, and spatial characteristics indicative of large-scale mineral production operations. Individual blocks are characterized by 3D spatial coordinates (X, Y, Z), rock type (i.e., Hematite, Magnetite, Waste), ore grade (% Fe), tonnage, ore value, operating and processing costs, and profit information. All blocks have a binary target label identifying whether or not it is economically extractable.

3.2 Data preprocessing using missing values handling

Missing values are a common problem in mining datasets due to inconsistencies in geological surveys, data entry errors, or incomplete estimation of ore properties. When it comes to open-pit mine planning, it is essential to account for missing values, as they can affect block classification, economic viability, and ultimately the accuracy of optimization. If missing values are not treated appropriately, this may lead to faulty pit designs, misclassification of ore excess, and inaccurate scheduling conditions. The missing records are considered part of the preprocessing pipeline. For continuous attributes such as ore grade, tonnage, or net present economic value, the missing entries are estimated through imputation techniques, such as mean imputation or spatial averaging of adjacent blocks. For categorical fields (e.g., rock type, waste flag, etc.), mode imputation or rule replacement was used. Blocks with critical values missing in multiple fields or undefined spatial coordinates were also excluded from the modeling process to maintain integrity. By appropriate imputation and respect for the geological structure and economic coherence of the block model, the dataset can be relied upon for simulation and optimization. The OPPS can run without encountering any computation interruptions or bias that may result from incomplete input data.

3.3 Block model construction

A 3D block model is created of the entire ore body and surrounding waste material, with each 3D block having defined spatial coordinates (X, Y, Z) inside the model plus associated geological properties defining rock type and ore grade, and economic properties including mining cost, processing cost, and expected revenue. This structure allows for profitability and feasibility calculations on a block-wise basis, providing a basis for pit design, production scheduling, and economic optimization. Importantly, the cubical block model integrates spatial and economic data to provide ongoing effective planning and decision-making throughout the life of the mine.

3.4 Mixed-integer programming (MIP) for pit design and scheduling

The MIP model calculates the optimal order of extraction for blocks in an open pit over multiple years. The model includes economic values with pit slope constraints and operational parameters to maximize NPV. After the optimized pit shell and schedule are determined, the results are input to the DES model of a real-world mining process, including haulage delays, equipment use, and stockpiling. The MIP model is constructed using a mathematical modeling language such as the open-source solver (OPPS). The decision variables are binary for when to extract a block, and continuous variables for costs and revenues. The solution to the MIP model provides the optimal sequence of block extraction, which can be input into the discrete-event simulation module. This process allows the long-term pit design to conform to technical constraints and financial goals. Using simulation results, operational costs were estimated for each block using MIP. The MIP appeared to be designed in a mathematical programming language and completed through OPPS (optimization software). To optimally plan production, operational costs were removed from revenue to create undiscounted revenue streams for each block's extraction stage. NPVs are determined based on operational results for each haulage option. Open-Pit Mining determined the undiscounted revenues for each block's extraction stage, and this became the basis for optimizing production planning. The goal was to optimize the NPV of every operation through establishing the ideal production plan for every stop (Equation 1).

$$Max\colon \sum_{t,s} m_s \times de_t \times x_{ts} \tag{1}$$

Where$\sum$ the summation is over **all blocks** t and **all time periods** s. m_s is the amount of the discount rate for a time frame, de_t is the undiscounted cash flow for every block, and x_{ts} denotes the binary parameter necessary for reflecting block operational circumstances. The MIP concept also includes different constraints (shown as Equations 2 to 6) that represent the actual boundaries required upon the sublevel stopping mechanism across the long-term planning perspective. These limitations can be classified based on the restrictions they place on supplies, sequencing, and scheduling.

$$\sum_{t\in\beta_s} q_s \times x_{ts} \le td_s \forall s \tag{2}$$

$$\sum_{t\in\beta_s} x_{ts} \ge x_{t's} \forall\, s, |t' \tag{3}$$

$$\in\, mbm_t$$

$$x_{ts} + x_{t's} \tag{4}$$

$$\forall\, t, s \mid t' \in\, mbm_t$$

$$\sum_{t\in\beta_s}^{\le 1} x_{ts} \le 1 \,\forall t \,|k_t > S \tag{5}$$

$$\sum_{t\in\beta_s} x_{ts} = 1 \,\forall t \,|k_t \le S \tag{6}$$

In the above equations, $t \in \beta_s$ represents the truck/shaft/conveyor fleets' moving capability for every single interval s, β_s is the set of blocks considered in the period. q_s is the extraction reserves (s) for every block, td_s is the available hauling. t' is another block that must follow the precedence rules. mbm_t is the set of blocks that are mutually exclusive or have a mining dependency with block and k_t is the block's most recent starting time. $\forall s$ for all time periods and $\forall t$ for all blocks. Constraint (2) prevents the supply of all advancement and block extracting ore from surpassing the truck/shaft/conveyor equipment capacity in any long-term duration. All subsequent operation sequencing among stops is also governed by restrictions (3) and (4). Constraint (5) assures that block output is started only once within an extended planning horizon if the scheduled opening date falls outside of the planning horizon. Block development must commence at a certain point in the long-term planning horizon if the late start time is within that time frame due to Constraint (6). Each of these modeled equations was utilized in the construction of the optimal production scheduling and mining plan corresponding to each haulage type, which considered commodity price volatility, mining rates, fixed costs, operating costs, and differences in ore quality. By restricting block extraction to practical operational, slope, and sequencing circumstances, these limitations together define the viable solution space. While Constraints (3) and (4) impose precedence and dependence restrictions that limit the flexibility of the solution, Constraint (2) ensures that haulage capacity is never exceeded, hence narrowing feasibility. Block start timings are controlled by constraints (5) and (6), which further refine workable schedules. These restrictions decrease unrealistic solutions by restricting the viable region, but they may also raise the computational load, which might have an impact on solver convergence. This trade-off between computational efficiency and solution feasibility results in the observed optimality gap of 1-2 %.

Figure 2 represents the planimetric layout of an open-pit mine, divided into four directional quadrants: Northwest (NW), Northeast (NE), Southwest (SW), and Southeast (SE). The layout illustrates the key dimensional parameters:

a_w: Horizontal distance from the center to the western edge of the pit.

a_e: Horizontal distance to the eastern edge

b_N: vertical distance from the center to the northern edge

b_s: Vertical distance to the southern edge

The arrow indicates measurement directions, and the N arrow provides orientation with true north.

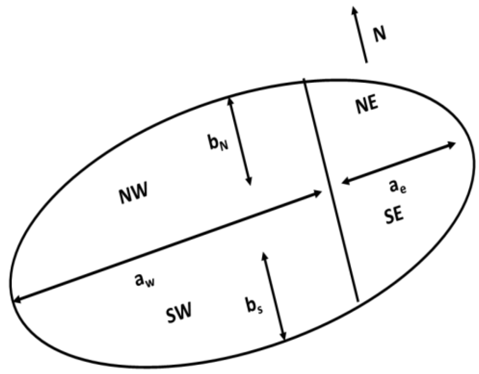

Figure 2: Planimetric layout of an open-pit mine

The MIP solver configuration for the open-pit mine planning model is summed up in Table 2. Convergence behavior, runtime, and iteration limitations, decision variables, solver type, and imposed restrictions are all included. By taking into consideration actual operational constraints, these parameters guarantee that the optimization produces workable, nearly ideal solutions.

Table 2: MIP solver settings for open-pit mine planning

Parameter	**Value / Description**
Solver Type	MILP solver in OPPS
Mathematical Model	Mixed-Integer Programming
Decision Variables	Binary (block extraction) and continuous
Runtime Limit	8 hours per scenario
Convergence Behavior	>90% scenarios converged to near-optimal; remaining within 1–2% of best-known objective
Iteration Limit	Default OPPS settings
Optimality Gap	1–2%
Constraints	Pit slope, haulage/equipment capacity, extraction sequencing, scheduling regulations
Hardware Used	MATLAB 2021b, 8 GB RAM, 2.4 GHz processor

3.5 Discrete event simulation (DES) for operational dynamics

A Discrete-Event Simulation (DES) model is employed to capture the short-term variability and intricate real-world dynamics of mining operations. Discrete-event simulation permits the time-based events in the system, including truck loading, hauling delays, queuing, equipment downtimes, and production rate realities. Events in the simulation occur at discrete time events, permitting a detailed, realistic evaluation of mine system performance. Geological uncertainty is also accounted for with the use of probabilistic distributions for ore grade, cycle times, and equipment availability. This dynamic simulation enables "what-if" analysis and supports decision-making on the strength of the MIP-optimized schedule and the variability of operations. In addition to those what-if answers, the output of the DES also includes metrics on performance, including material movement, equipment usage, delays in scheduling, and an NPV effective display. DES approaches simulate the relationships of important process parameters and their settings in response to a series of discrete events across the year. The system's adoption of different modes of operation and management mechanisms, including stockpiling, enables it to accommodate variation in inputs and departures from anticipated ore ratios. The trade-offs of operational strategies were assessed, and the thresholds for the implementation of those strategies were determined. The modeling of extended operational periods enables the detection of possible faults or bottlenecks in integrating unit operations within the intended network.

The structure created for the research obtained ore blocks derived from the long-term planning optimization MIP, as well as the previously established variables, including functioning styles, metallurgical wellness, metal cost, maximum processing capability, and related cost. Additional control settings include manufacturing campaigns and maintenance durations, stockpile stages, and essential ore concentrations. The DES concept tries to optimize ore processing productivity, which impacts the project's overall net present value. The result is an improved risk assessment with total NPV. For efficient open-pit mine planning, this research integrates MIP for long-term block scheduling with DES to capture operational realities over short time scales. The MIP model maximizes NPV, subject to economic constraints, slope stability, haulage capacity, and precedence rules, to conclude the optimal sequence of extraction of blocks. Binary decision variables indicate the extraction state of each block at each time step, while revenues and costs are continuous variables. Through scenario-based NPV analysis, stochastic modeling of equipment cycles, and probabilistic distributions, the system also manages ore grade, equipment delays, and price changes, allowing for sound decision-making in the face of real-world uncertainty.

The DES was implemented in MATLAB 2021b (8 GB RAM, 2.4 GHz) using a custom event-driven simulation engine, with parameters summarized in Table 3. Equipment attributes, operating conditions, haulage and processing variations, ore grade distributions, stockpile restrictions, and economic considerations are all included. Together with the MIP-optimized schedule, these factors guarantee that the simulation accurately depicts short-term unpredictability, operational restrictions, and financial performance, facilitating trustworthy decision-making. According to the model, equipment failures are random occurrences with a uniform probability that corresponds to 2% to 5% of operating hours. In order to capture stochastic operational disruptions, the event-driven simulation incorporates the downtime that each failure causes for the impacted equipment.

Table 3: Key discrete-event simulation (DES) parameters for open-pit mine planning

Parameter	Description / Value
Number of trucks	10–20
Loader capacity	5–10 tonnes per cycle
Haulage cycle time	18–25 min (with variability)
Equipment downtime	2–5% of operational hours
Stockpile limit	15,000–20,000 tonnes
Ore grade distribution	60–70% Fe
Extraction sequence	From the MIP model
Simulation horizon	30 years, daily events
Economic factors	Costs, revenues, and NPV with 8% discount rate

The hybrid modeling approach allows scenarios to be created to expose bottlenecks in the system or delays in processing status, assess the toughness of the system, and improve planning in periods of operating uncertainty. In conclusion, integrating the MIP and DES processes enables better prediction of profitability and adds realism and reliability to planning an open-pit mine. Algorithm 1 illustrates the MIP-DES method, which uses MIP to schedule block extraction, DES to simulate short-term operations, MIP to handle equipment restrictions, and NPV and ore production to facilitate decision-making.

Algorithm 1: MIP-DES framework

```
# Step 1: Initialize mine data and parameters
blocks = load_mine_blocks()        # Load all mining blocks
time_periods = range(1, N + 1)       # Planning horizon
resources = initialize_equipment()  # Trucks, loaders, etc.
MIP_schedule
= {}             # Dictionary to store MIP block schedule
DES_results = {}               # Dictionary to store DES results
# Step 2: Solve MIP for long − term optimal pit schedule
for block in blocks:
  For t in time_periods:
    # Check feasibility constraints for block extraction
    if slope_ok(block) and capacity_ok(block, resources):
      MIP_schedule[block] = t  # Schedule block extraction
      break              # Stop after assigning earliest feasible period
    else:
      MIP_schedule[block] = None
# Step 3: Run DES for short − term operational simulation
for t in time_periods:
  for block, scheduled_time in MIP_schedule.items():
    if scheduled_time == t:
      # Check if equipment is available
      if equipment_available(resources):
        extracted, ore_grade = extract_block(block, resources)
        DES_results[block] = {
          'time': t,
          'extracted': extracted,
          'grade': ore_grade
        }
      else:
        # Equipment unavailable, delay extraction
        DES_results[block] = {
          'time': t,
          'extracted': 0,
```

```
        'grade': None
    }
# Step 4: Compute performance metrics
total_NPV = 0
total_ore = 0
for block, result in DES_results.items():
  if result['extracted'] > 0:
    total_NPV +
= compute_NPV(result['extracted'], result['grade'])
    total_ore += result['extracted']
# Step 5: Output results
print("Total NPV:", total_NPV)
print("Total Ore Extracted:", total_ore)
print("Block − wise DES Results:", DES_results)
```

4 Result

The computational run time on a MATLAB 2021b system with 8 GB RAM and 2.40 GHz processor was ~6 hours for 1,000 scenarios. Compared with heuristic tools like Whittle, OPPS achieved more stable stripping ratios, ore grades, and NPV values, highlighting a trade-off between computation times and planning accuracy.

Computational metrics of the MIP-DES mine planning

The MIP-DES mine planning framework's primary performance metrics are compiled in the Table 4. Practical viability is demonstrated by the computational runtime (~6 hours per 1,000 cases). Sustainability is reflected in energy use (12–15 kWh/ton) and environmental effect (5–7 kg CO_2/ton). The convergence/optimality gap (1–2%) shows that solutions are close to optimal, whereas equipment utilization (80–90%) shows effective resource use. When combined, these measures evaluate the suggested mine planning model's dependability, operational effectiveness, and environmental responsibility.

Table 4: Performance, Sustainability, and Computational Metrics of the MIP-DES Mine Planning Framework

Parameter	Description / Value
Computational runtime	~6 hours per 1,000 scenarios
Energy consumption	12 – 15 kWh/ton (approx.)
Environmental impact	5 – 7 kg CO_2/ton
Equipment utilization	80 – 90%
Convergence/optimality gap	1–2%

The statistical validation of the MIP-DES simulation results based on 1,000 scenarios is shown in Table 4. Average performance parameters, such as equipment utilization, NPV deviation, ore grade, and stripping ratio, are indicated by the mean values. Assuring the robustness and dependability of the suggested mining planning framework, standard deviations (σ) illustrate the variability among scenarios, while 95% confidence intervals indicate the range within which the real mean is anticipated to reside.

Table 4: Statistical Validation of MIP-DES simulation results

Metric	Mean Value	Standard Deviation (σ)	95% Confidence Interval
Stripping Ratio	5.85	0.35	5.78 – 5.92
Ore Grade (%)	67	2.1	66.6 – 67.4
NPV Deviation (%)	-1.5	0.6	-1.62 – -1.38
Equipment Utilization (%)	85	4	84 – 86

The OPPS framework efficiently handled the 75,000-block dataset used in this study. Sensitivity tests indicate that it maintains stable NPV, stripping ratios, and equipment utilization under variations in ore grade and operational parameters, demonstrating robustness.

4.1 Dimensions of the open pit

Figure 3 illustrates the temporal evolution of key geometric parameters of the open-pit mine over a 30-year horizon. The dimensions include: **aW** increases steadily from ~830 m to ~1100 m, while **aE** expands linearly from ~100 m to over 500 m. **bN** and **bS** both rise from ~200 m and ~30 m, respectively, to ~260 m and ~55 m. **h**, The depth of the pit, grows consistently from ~85 m to ~200 m by year 30. This growth indicates a controlled and continuous expansion of the pit geometry, directly aligning with block extraction and scheduling decisions. These trends reflect the model's ability to simulate realistic pit evolution over time, accounting for both spatial constraints and economic viability.

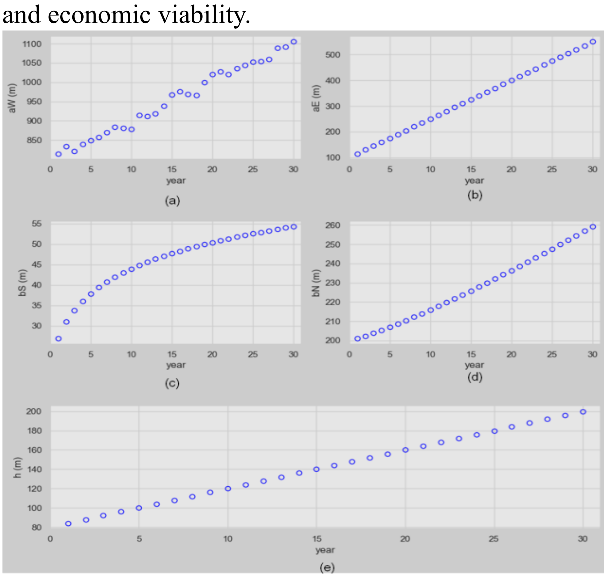

Figure 3: Yearly modification in open-pit the dimensions

4.2 Expansion of the open-pit mine

Figure 4 illustrates the progressive expansion of the open-pit mine layout between years 24 and 26, referred to as "pushbacks." Each colored layer represents a different depth and lateral extent of material removal for that period, with colored points corresponding to individual blocks planned for extraction. Numerically, the vertical axis (Elevation) shows increasing pit depth over time, while the horizontal axes (Easting and Northing) demonstrate spatial growth. The dense clustering and tiered shape imply systematic bench development concerning slope and safety constraints. Additionally, cumulative NPV and extracted tonnage overlays have been added to each pushback layer, showing the economic and production impact alongside spatial expansion. This demonstrates how the MIP-DES framework effectively integrates long-term pit planning with short-term operational outcomes. In this research, the figure highlights how the MIP-generated schedule integrates with the DES-driven operational simulation to accurately model real-world pit expansion. It confirms the effectiveness of the hybrid framework in tracking ore-waste sequencing while maintaining pit stability and spatial consistency across multi-year schedules.

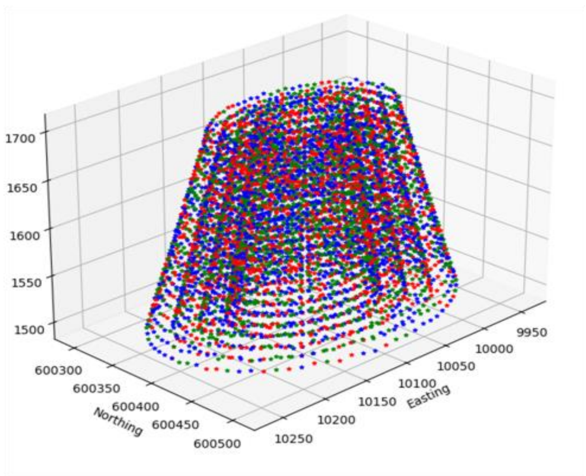

Figure 4: Simulated pushback progression using hybrid MIP-DES framework

4.3 Stripping ratio

Stripping ratio (SR) is the ratio of waste material removal to ore material extracted. SR is a crucial metric for mine planning because SR affects overall cost and economics. As shown in Figure 5, OPPS consistently maintains a low and stable SR between 5.2 and 6.5, highlighting its superior efficiency in managing waste-to-ore extraction. In contrast, Gurobi shows moderate variability with a sharp spike to 10 at year 15, while Whittle exhibits erratic behavior, peaking at 14, 18, and 16 in years 5, 12, and 20, respectively. The consistent performance by OPPS demonstrates its robust and cost-effective approach for long-term open-pit my planning. The lower and stable SR values reflect OPPS's capability to minimize waste removal, making it more suitable for sustainable and economically optimized mining operations.

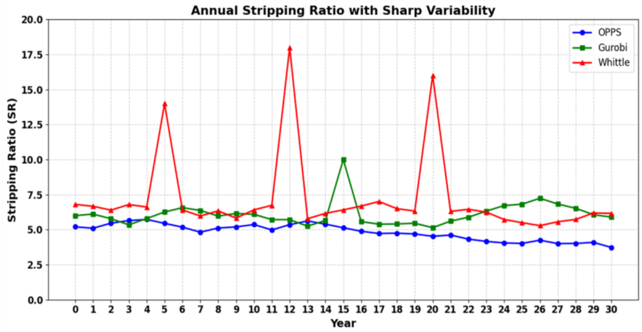

Figure 5: Annual stripping ratio with sharp variability

4.4 Average grade (%) of iron ore content

Average grade (%) indicates the iron content within the ore blocks mined annually, directly influencing the economic value of extracted material. Higher grades lead to better revenue per processed tonne. In Figure 6, OPPS maintains the highest and most stable grade, around 67%, Gurobi fluctuates near 64.5%, and Whittle trails with more volatile values, averaging ~62%. No values fall below 60% across the methods. The consistently higher ore grade in OPPS scheduling suggests better block selection aligned with profit optimization. This supports the strength of OPPS in maximizing ore quality, enhancing processing efficiency, and NPV.

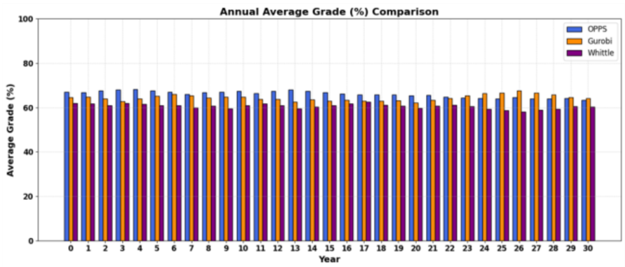

Figure 6: Annual average grade (%) comparison

4.5 Haulage cycle time

Haulage cycle time refers to the average time taken by mining trucks to complete a full load-haul-dump-return cycle. It directly impacts productivity, fuel usage, and scheduling efficiency in my operations. In Figure 7, OPPS shows the lowest cycle time, ranging around 18–19 mins, Gurobi remains moderate between 20–21.5 mins, and Whittle records the highest times, peaking near 24–25 mins across the years. The shorter haulage times under OPPS reflect better scheduling and reduced equipment idle time. This implies that OPPS ensures faster material movement, improving operational throughput and lowering logistical costs.

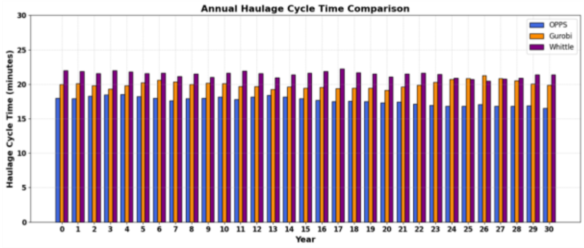

Figure 7: Annual haulage cycle time comparison

4.6 Equipment utilization rate

Equipment utilization rate measures how effectively mining machinery is used over time, expressed as a percentage of operational time versus available time. High utilization indicates efficient deployment and minimal downtime. In Figure 8, OPPS maintains a high utilization rate of around 89-91%, Gurobi ranges around 84-87%, while Whittle lags with more variation, fluctuating between 78-83%. All models stay within acceptable operational thresholds. The consistently higher utilization under OPPS highlights superior operational coordination and scheduling accuracy.

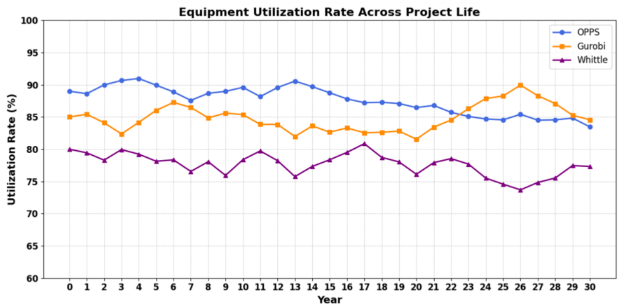

Figure 8: Equipment utilization rate across project life

4.7 Stockpile volume

Stockpile volume refers to the number of ore temporarily stored on-site before processing. It reflects production variability, blending strategies, and buffering to mitigate fluctuations in plant feed rates. In Figure 9, OPPS maintains a steady stockpile of around 15,000 and 17,000 tonnes, Gurobi fluctuates more widely between 17,500–20,500 tonnes, and Whittle accumulates the highest levels, spiking up to 26,000+ tonnes. Lower and stable stockpiles in OPPS suggest better production-processing alignment and reduced overproduction. This efficiency minimizes storage overhead and indicates better synchronization across operational stages.

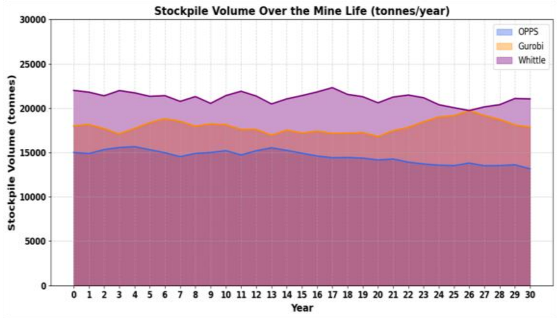

Figure 9: Stockpile volume over the mine life

4.8 Net present value (NPV) deviation

Net Present Value (NPV) deviation indicates how much the actual achieved NPV in each year deviates from a pre-defined financial target. It reflects the financial accuracy and reliability of my planning under real-world conditions. In Figure 10, OPPS consistently shows minimal deviation near -1.5%, Gurobi fluctuates around -3%, and Whittle experiences the largest deviations, nearing -6 to -7%, indicating weaker financial alignment over time. The Minimize NPV deviation under uncertain cycle times in OPPS highlights its robustness in maintaining projected economic goals under operational variability.

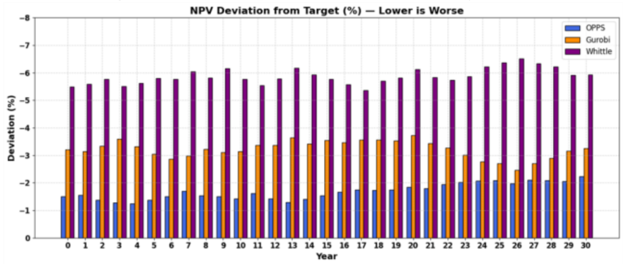

Figure 10: NPV deviation from target (%)

4.9 Annual production schedule of OPPS, gurobi, and whittle

The production schedule graph presents the annual tonnage of ore and associated waste. This material split illustrates the movement of material, boilerplate mining rate, and waste management over the life of the project. The OPPS model provides a better, lower waste extraction due to a better ore-to-waste tonnage balance compared to the Gurobi and Whittle (Figure 11). This results in reduced stripping ratios by reducing waste removal. In order to maintain steadier grades, it also selects ore blocks of greater quality. OPPS reduces haulage times and increases equipment usage by mimicking truck and equipment delays. Finally, it aligns ore transportation with processing, maintaining stable inventories and minimal NPV fluctuations. This further confirms its potential to produce better pit designs relative to market conditions and the workload required of operators of the mine over its planned life.

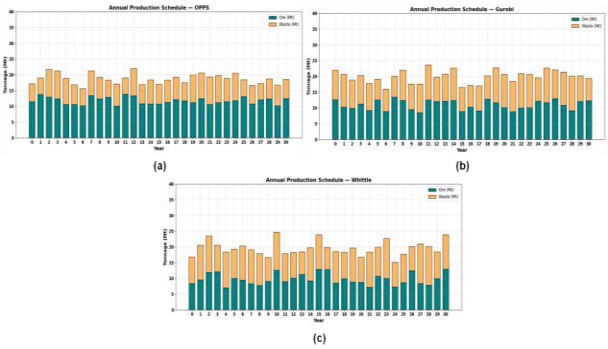

Figure 11: Annual production schedule (a) OPPS, (b) gurobi, and (c) whittle

4.10 Comparative evaluation of MIP-DES framework

The performance comparison of the suggested MIP-DES framework with current predictive and hybrid models utilized in open-pit mine planning is shown in Table 5. The measures assess how well the models predict ore output, scheduling results, and operational efficiency. The MIP-DES framework that was suggested was compared to Gurobi and Whittle. The same mining planning restrictions, such as pit slope limitations, haulage capacity, extraction sequencing, and scheduling guidelines, were applied to all benchmarks. To ensure a fair comparison, solver-specific options were set to the default ideal values suggested by each tool. This alignment ensures that the MIP-DES integration, not different constraints or parameter settings, is the cause of the observed performance variations.

The MIP-DES framework exhibits better predicted accuracy and reduced error rates across several performance metrics, R-squared (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE), when compared to traditional machine learning techniques, Random Forest (RF), XGBoost, Gradient Boosted Decision Trees (GBDT), and a hybrid model, Salp Swarm Optimization -feedforward neural network (SalpSO-CFNN). This demonstrates how well long-term optimization and short-term operational simulation may be combined to capture both strategic planning and actual variability. All things considered, the suggested framework offers mine planning and operational management a more dependable and stronger decision-support tool.

Table 5: Comparative performance metrics of predictive models for open-pit mine planning

Models	R^2	MAE	MSE	MAPE	RMSE
RF [17]	0.91	5.16	42.66	11.52	6.53
XGBoost [17]	0.88	5.41	52.86	14.11	7.27
GBDT [17]	0.89	5.37	50.11	11.46	7.07
SalpSO-CFNN [18]	0.980	179.567	-	-	248.401
MIP-DES [Proposed]	0.992	3.25	21.45	5.12	4.63

5 Discussion

Recent developments in intelligent mine planning have opened up opportunities for a variety of optimization and simulation. The research [8] explored the use of particle swarm and support vector machines in a framework of discrete-event simulation to forecast ore production schedules in underground haulage systems, improving the precision of predicted cycle times and expected loads. The author of [11] explored the use of deep neural networks with principal component analysis to predict ore production in open-pit systems and found that a significant level of confidence was attained with processing non-linear, large data. As pointed out by a researcher [15], a bilevel optimization model was proposed to create a joint schedule for production and haulage route planning, minimizing operational costs. Unlike previous methods that focus on individual tasks such as ore prediction, haulage optimization, or partial scheduling, the proposed MIP-DES framework integrates long-term pit design with short-term operational simulation in a single system. This unified approach optimizes ore/waste schedules, stripping ratio, haulage, equipment utilization, and NPV simultaneously. Testing on 75,000 blocks demonstrates improved stability, higher ore grades (~67%), lower stripping ratios (5.2–6.5), and minimal NPV deviation (-1.5%), clearly showing advantages over existing mine planning methods, Furthermore, the framework's robustness is shown by sensitivity testing on important variables including haulage cycle length, equipment downtime, and ore grade fluctuation.

The model may be further expanded to include predictive models or real-time operational data for dynamic scheduling changes. The processes in each case took 8 hours to run and were stopped, regardless of whether the convergence towards an optimal solution was achieved. During these runs, over 90% of the scenarios converged to near-optimal solutions, while the remaining achieved results within 1–2% of the best-known objective, confirming the adequacy of the chosen runtime.

This research uses MIP for multi-period pit along with DES, integrated through the OPPS to characterize operational dynamics. This approach can provide a decision-support framework that can dynamically optimize both profits and resource flow under uncertainty and reconcile static scheduling with real-world mining conditions. The MIP-DES framework works better than methods that only optimize or only simulate because it considers real operational changes, like equipment delays or ore quality variations, giving more realistic and reliable mine planning results.

6 Conclusion

Mining is more than planning; it involves smart integration. This research proposed a hybrid approach that combines Mixed-Integer Programming (MIP) and Discrete-Event Simulation (DES) to basically change how teams plan an open-pit mine, which is not only economically optimal but also operationally feasible. The hybrid framework implementation using OPPS produced incredible results, including an always low stripping ratio (5.2-6.5), the highest average ore grade (~67%), the shortest haulage cycle times (18-19 mins), and the lowest NPV deviation (-1.5%) against Gurobi and Whittle models. Although the runtime of ~6 hours is longer than heuristic methods, the improved stability and accuracy of results make the framework valuable for large-scale and long-term my planning. These metrics demonstrate OPPS's ability to produce efficient, profitable, and stable my plans. Primary limitations of this research include static simulation inputs without the option of changing in real-time to manage operational interruptions or economic challenges.

Future scope: Future extensions could incorporate real-time sensor feedback and use AI-based adaptive control to continuously update schedules to develop greater resilience and adaptability in a modern open-pit mining context. The suggested MIP-DES framework can benefit from further research in this field. Schedules may be dynamically updated by using real-time sensor and operational data from mining processing and equipment. Then applied to different mines or larger datasets to check if it works well in various conditions and remains reliable for my planning. This makes my planning more adaptable to shifting conditions. The framework's scalability and resilience in various mining contexts may be shown by testing it in many mines or larger-scale operations. Using predictive analytics may assist in foreseeing possible operational disturbances like transport delays or equipment failures, allowing for preemptive scheduling and resource allocation changes to sustain steady output.

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