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Short-Term Production Planning Optimization in Open-Pit Copper Mines: An MILP Model Integrating Comminution Modeling and Feed Quality Control

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Abstract

Optimizing short-term production in open-pit copper mines is crucial for maximizing economic returns and ensuring operational stability, yet is frequently challenged by inherent geological variability. This work presents a novel Mixed-Integer Linear Programming (MILP) framework designed to address these challenges by directly integrating critical geometallurgical parameters, specifically rock hardness (SPI index) and clay content, into the short-term production planning process. The simultaneous integration of these key geometallurgical feed quality attributes within an operational MILP model distinguishes this work from previous approaches and effectively bridges geological data analytics with operational decision-making, aligning economic objectives with enhanced metallurgical performance. Utilizing real operational data from the Sarcheshmeh Copper Mine, the framework was validated over a 186-day period. It achieved optimal production conditions on 137 days (73.6% of the duration), realizing a maximum Net Present Value (NPV) of $132,000. Key outcomes included a significant 21% reduction in concentrate grade variability and a 15% decrease in flotation reagent consumption, achieved through the simultaneous control of SPI and clay content. Advanced statistical methods were employed to identify critical relationships. While the model demonstrates scalability for porphyry copper mines globally, its successful implementation depends on careful parameter customization and alignment with existing infrastructure. This research work underscores the substantial value of data-driven, integrated optimization techniques in enhancing both profitability and process stability within mineral processing circuits.

1. Introduction

Short-term production planning optimization in open-pit copper mines is crucial, as daily extraction decisions directly influence the actual production volume and the quality of the feed entering the processing plant. In short-term planning, which typically spans from weekly to a few months, it is essential to determine the tonnage and composition of materials sent to the plant [1]. This process must ensure that production and economic targets are achieved, while effectively managing fluctuations in feed quality.

For example, studies have shown that increased hardness and clay content can significantly reduce crushing performance and flotation recovery [2]. At the operational level, managing the supply chain (from extracted blasted fragments to the feed particle size) to maintain stable plant performance requires precise daily and weekly planning [3, 4].

However, short-term mine planning has received less research attention than long-term planning. There is a pressing need for more advanced methods to integrate geological and operational data effectively.

The Sarcheshmeh Copper Complex, located 65 km southwest of Kerman city at an average elevation of 2,600 meters in the Central Iranian Volcanic Belt is one of the largest porphyry copper deposits in the world. It contains approximately 1.2

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billion tonnes of sulfide ore, with an average grade of about 0.7% copper (Cu) and 0.03% molybdenum (Mo), along with valuable by-products of gold and silver. Owned by IMIDRO and operated by NICICO, commercial production began in 1975 with a concentrator capacity of 14 million tonnes per annum (Mtpa). Today, the integrated open-pit mine, concentrator, smelter, refinery, and tailings management facility processes over 20 Mtpa, yielding approximately 730,000 tonnes of copper concentrate each year.

This paper begins with a review of the relevant literature. The methodology section then outlines the data collection and preparation processes, statistical analyses, and the Mixed-Integer Linear Programming (MILP) framework. Key findings from optimization and statistical analyses are subsequently presented. These results are interpreted in the discussion section. Finally, the paper concludes with a summary of the findings and recommendations for future research.

2. Literature Review

Short-term production scheduling in open-pit mining plays a crucial role in aligning operational decisions with strategic objectives, while ensuring a consistent supply of ore to processing plants. Traditional deterministic models often fail to adequately capture the dynamic and uncertain nature of geological conditions and equipment performance. To address these limitations, stochastic scheduling models have been developed, allowing mine planners to more effectively account for uncertainties in grade, hardness, and equipment availability. Research has demonstrated that these models improve compliance with production targets and enhance the stability of both ore feed quality and quantity [5-10].

To realistically represent daily operations within computational constraints, continuous-time shovel allocation models have garnered attention in short-term planning horizons, providing efficient truck routing and loading dynamics [10,11]. Additionally, hierarchical multi-objective algorithms—particularly those employing super-period aggregation—allow planners to generate diverse and balanced schedules with minimal parameter tuning [12, 13]. The joint optimization of extraction sequencing and fleet management further enhances operational cost reductions and improves equipment utilization rates [14].

Recent reviews emphasize that achieving short-term efficiency and sustainability necessitates an integrated perspective of the mining value chain—from drilling and blasting to haulage and processing—while ensuring alignment with long-term objectives [15,16]. The incorporation of stockpiling, ore blending strategies, and semi-mobile in-pit crushing and conveying (IPCC) systems into scheduling models has demonstrated the ability to stabilize product specifications and enhance profitability [17-22]. Furthermore, hybrid frameworks that connect block sequencing with medium-term hierarchical models effectively address the temporal disconnect between tactical and operational plans [23, 24].

Parallel to advancements in scheduling frameworks, Mixed-Integer Linear Programming (MILP) has emerged as a dominant tool for integrating complex constraints. MILP models have been utilized to optimize cut-off grades across multiple processing routes [25] manage fleet allocation while prioritizing fuel consumption and grade control [26], and synchronize strategic and operational planning layers [27-29]. Robust MILP formulations have also been adapted for underground and cave mining scenarios, further demonstrating their flexibility and value in dynamic extraction environments [30, 31].

A significant advancement in recent literature is the integration of geometallurgical indices into mine planning. These indices encompass spatially variable parameters such as ore hardness, comminution energy, and mineralogical complexity, all of which impact plant performance. For instance, at the Sarcheshmeh copper mine, Bond Work Index (BWI) values have been recorded to range from 5.67 to 20.21 kWh/t, with lithological and alteration zones playing a crucial role in driving this variability [32]. By incorporating these indices into scheduling through stochastic or maximin programming approaches, planners can redefine pit limits, adjust cut-off grades, and enhance mill reconciliation while maximizing net present value (NPV) [33-35].

In this context, machine learning has significantly enhanced the predictive capabilities of mine planners. By modeling variables such as ore hardness, power draw, and particle size distributions, machine learning-based models have improved throughput forecasting accuracy by as much as 10.6% compared to traditional linear regression methods [36]. This advancement has resulted in more reliable weekly production forecasts, thereby reducing the risk of shortfalls by up to 7%. Furthermore, comprehensive geometallurgical frameworks now advocate for continuous multi-domain data collection—encompassing geological, geochemical, and geomechanical attributes—followed by the application of clustering algorithms to define performance-relevant ore domains [37–40].

The significance of geometallurgy in planning is further reinforced by studies highlighting its impact on energy and processing efficiency. For instance, adjusting the feed properties to Semi-Autogenous Grinding (SAG) mills—such as increasing the >200 mm particle fraction or targeting softer ores—can reduce energy consumption by up to 40% and boost throughput by nearly 20%. At Sarcheshmeh, SAG Power Index (SPI) data show that the SAG circuit alone consumes approximately 44.65% of total plant energy, with new predictive models substantially improving energy forecasting accuracy [41-46]. These operational insights underscore the importance of feed consistency in reducing costs and environmental impacts**.**

In parallel, environmental geometallurgy has emerged as a complementary domain. For example, applying a clay cap to mine waste has been shown to dramatically reduce pyrite oxidation and associated acid mine drainage [47]. However, limitations in geometallurgical testing remain a concern; for instance, non-standardized Bond Work Index protocols can introduce substantial variability in grindability estimations, compromising downstream modeling accuracy [48]. Additionally, recent findings suggest that trace-element variations in pyrite can significantly influence surface chemistry and flotation dynamics—factors rarely considered in block models or scheduling [49-51].

While previous studies have employed Mixed-Integer Linear Programming (MILP) for various mine planning optimizations and others have highlighted the importance of integrating geometallurgical indices, a common limitation is the lack of simultaneous integration of multiple critical, interacting geometallurgical parameters specifically within short-term production scheduling. For instance, while the effects of rock hardness (like SPI) and clay content on processing are known, they are often addressed separately or in long-term contexts, rather than as combined, direct inputs for daily or weekly operational schedules.

Unlike previous models, this study introduces a novel Mixed-Integer Linear Programming (MILP) framework that simultaneously integrates geometallurgical constraints, such as ore hardness (SPI) and clay content, directly into short-term production scheduling. This approach optimizes both economic objectives and feed consistency within a unified decision-making process.

3. Methodology

This section provides a detailed description of the methodology used for optimizing short-term production planning in the Sarcheshmeh Copper Mine. The methodology includes three main phases:

(1) data collection and preprocessing.

(2) statistical analysis and mathematical modeling.

(3) optimization and MILP model solving. All formulas used in each phase are presented below.

3.1. Data collection and pre-processing

a. Data Collection

The data used is sourced from various origins, including geological block models and processing plant data. These data include variables such as clay content, SPI index, pyrite percentage, feed tonnage, grades of various elements (copper, molybdenum, etc.), and other operational parameters.

b. Outlier removal using boxplot

To eliminate outliers, the boxplot method is employed. First, the first quartile (Q1) and the third quartile (Q3) for each variable are calculated using Equation (1):

$$IQR = Q_3 - Q_1 \tag{1}$$

Then, values outside the range defined by Equation (2) are then excluded.

$$x < Q_1 - 1.5 \times IQR \quad or \quad x > Q_3 + 1.5 \times IQR \tag{2}$$

This ensures the input data used for analysis are of high quality, reducing statistical noise.

c. Data normalization

Min-max normalization was applied to rescale all variables to a common range [0,1]. This step was particularly important before conducting multivariate analysis (e.g., PCA), where differences in variable scales could bias the computation of distances and principal components. It also ensured comparability in regression models and sensitivity studies.

To mitigate the effects of scale differences among variables, min-max normalization, as described in Equation (3), is employed.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3}$$

Where $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the variable, respectively.

3.2. Statistical analysis and mathematical modeling

a. Correlation and regression analysis

To understand the relationships between key variables, a correlation matrix is computed. Linear regression models were employed to quantify the impact of individual variables (e.g., SPI and clay content) on response variables such as feed tonnage and concentrate grade. The general form of these linear regression models is presented in Equation (4):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{4}$$

Where:

Y is the target output (concentrate grade)

X_i are the input variables

β_i are the regression coefficients

ε is the error term

b. Principal Component Analysis (PCA)

PCA was used to reduce data dimensionality and uncover latent structures among highly correlated geometallurgical variables. Given that variables such as SPI, BWI, and clay content may exhibit multicollinearity, PCA helps extract uncorrelated principal components that preserve most of the variance, allowing for clearer interpretation and more stable regression modeling.

PCA is used for dimensionality reduction and eliminating multicollinearity. It transforms the data into a new space defined by principal components $Z_{1,2,\ldots,}Z_k$, which capture the maximum variance.

4. Findings and Performance Evaluation

4.1. Optimization using MILP

In this section, the MILP framework is presented to determine the extraction sequence with the objective of maximizing the Net Present Value (NPV). The proposed MILP model was used to schedule and sequence the extraction of mining units throughout the life of the open-pit mine [52]. The objective function of the MILP model maximizes the project's NPV for the open-pit section by delivering a consistent and near-optimal tonnage and grade required by the processing plant.

The constraints of the proposed MILP model control the mining capacity, processing capacity, processing plant cutoff grade, and precedence relationships (for pit extraction). The mining capacity is a function of the ore reserve and the processing capacity based on the designed operations. Processing capacity constraints determine the ore production schedule in each period and ensure that the material delivered from the mine meets the targeted tonnage for the plant. Based on the processing plant's cutoff grade, grade constraints are defined for blending from each extraction option within the upper and lower grade limits for operational feasibility.

The details of the proposed integrated MILP model are further explained below.

The MILP framework represents an evaluation method based on an optimization approach called Competitive Economic Evaluation (CEE). The CEE optimization strategy is an unbiased and impartial approach that offers equal opportunity for each mining unit to be selected for extraction (or not). The CEE process evaluates each ore reserve extraction unit and makes an economic decision on whether the unit should be selected for open-pit mining.

In summary, the strengths of the MILP framework presented in this study include:

1- Unbiased optimization approach–ensuring competitive economic evaluation;

2- Inclusion of average grade constraint (mean feed grade delivered to the processing plant);

3- Inclusion of average clay content constraint (mean clay content in the feed);

4- Inclusion of average SPI constraint (mean SPI of feed delivered to the processing plant);

5- Integrated production scheduling for the open-pit extraction scenario;

6- Consideration of key mining aspects, including operational preparations;

7- Realistic, practical, and scalable approach for large-scale mining operations.

To implement the relationships and apply the constraints in the mathematical model, as well as to solve it, it is essential to first define the indices and sets, decision variables, parameters, and binary parameters. Table 1-4 provides the definitions of these elements.

Table 1. Definition of indices and sets

No.	Index	Symbol
1	Index for scheduling periods in the model	$t \in \{1, \ldots, T\}$
3	Row index of mining blocks along X-axis	$i \in \{1, \ldots, I\}$
4	Row index of mining blocks along Y-axis	$j \in \{1, \ldots, J\}$
5	Row index of mining blocks along Z-axis	$k \in \{1, \ldots, K\}$
6	Index representing block position in the model	i, j, k
7	Number of mining units in one bench for open-pit	$js \in \{1,\ldots,JS\}$

Table 2. Symbols Used in the model for sets

Row	Set	Set Symbol
1	Set of all open-pit mining blocks in the model	$\bar{\mathrm{B}} = \{1, \ldots, \bar{\mathrm{B}}\}$
2	Set of all open-pit mining blocks in horizon L in the model	$\bar{\mathrm{B}}_{\mathrm{L}} = \{1, \ldots, \bar{\mathrm{B}}_{\mathrm{L}}\}$
3	For each open-pit mining block (i, j, k), a set $\Delta_{\mathrm{i,j,k}}(\mathrm{S}) \subset \bar{\mathrm{B}}$ exists that defines the predecessor blocks which must be mined before block (i, j, k). In this set, s is the total number of blocks in $\Delta_{\mathrm{i,j,k}}(\mathrm{S})$.	$\Delta_{\mathrm{i,j,k}}(S)$
4	Set of immediate predecessor variables (S) in the model	$\mathrm{S} =\{1, \ldots, S\}$
5	For each horizon, a set $\bar{\mathrm{L}}_{\mathrm{i,j,k}}(\mathrm{S}) \subset \bar{\mathrm{B}}$ defines the total number of mining blocks available for open-pit extraction in that horizon. In this set, s is the total number of blocks in $\bar{\mathrm{L}}_{\mathrm{i,j,k}}(\mathrm{S})$.	$\bar{\mathrm{L}}_{\mathrm{i,j,k}}(S)$

Table 3. Symbols Used in the model for parameters.

No.	Parameter	Parameter Symbol
1	Revenue from the sale of final product from open-pit block (i, j, k) in period *t*, minus the mining and processing cost for ore	$\bar{\mathrm{R}}^{\mathrm{t}}_{\mathrm{i,j,k}}$
2	Cost of removing all materials from block (i, j, k) as waste in open-pit mining during period *t*	$\bar{\mathrm{U}}^{\mathrm{t}}_{\mathrm{i,j,k}}$
3	Average grade of elements in the ore section of block (i, j, k) by open-pit method	$\bar{\mathrm{G}}_{\mathrm{i,j,k}}$
4	Ore tonnage in block (i, j, k) (mineralized materials) by open-pit method	$\bar{O}_{\mathrm{i,j,k}}$
5	Waste tonnage in block (i, j, k) (non-mineralized materials) by open-pit method	$\bar{W}_{\mathrm{i,j,k}}$
6	Upper limit of acceptable average grade for open-pit mining in period *t*	$\bar{\mathrm{G}}^{\mathrm{t}}_{\cap}$
7	Lower limit of acceptable average grade for open-pit mining in period *t*	$\bar{\mathrm{G}}^{\mathrm{t}}_{\cup}$
8	Upper limit of acceptable average clay content for open-pit mining in period *t*	$\overline{clay}^{\mathrm{t}}_{\cap}$
9	Upper limit of acceptable average SPI for open-pit mining in period *t*	$\overline{SPI}^{\mathrm{t}}_{\cap}$
10	Upper limit of accessible open-pit extraction in period *t*	$\bar{M}^{\mathrm{t}}_{\cap}$
11	Lower limit of accessible open-pit extraction in period *t*	$\bar{\mathrm{M}}^{\mathrm{t}}_{\cup}$
12	Processing recovery rate	R
13	Sale price of the mineral product	Ƥ^{t}
14	Selling cost of the mineral product	Ç^{t}
15	Overhead cost per ton of ore for mining and processing in period *t*	B^{t}
16	Cost per bench or horizon for mining one ton of rock in open-pit method in period *t*	$\bar{H}^{t}_{L}$
17	Discount rate	DR
18	Cost of mining one ton of rock by open-pit method in period *t*	$\bar{H}^{t}$
19	Desired tonnage of ore to be sent to the processing plant in period *t*	$\bar{N}^{t}_{1}$
20	Penalty cost for positive deviation or oversupply of ore sent to the processing plant from target levels	$\hat{Z}^{t}_{1}$
21	Penalty Cost for negative deviation or undersupply of ore sent to the processing plant from target levels	Z^{t}_{1}
22	Clay content of ore sent to the processing plant by open-pit method in period *t*	$\overline{clay}_{\mathrm{i,j,k}}$
23	SPI of ore sent to the processing plant by open-pit method in period *t*	$\overline{SPI}_{\mathrm{i,j,k}}$
24	Penalty cost for positive deviation or sending ore with higher grade than target to the processing plant	$\hat{Z}^{t}_{2}$
25	Penalty cost for negative deviation or sending ore with lower grade than target to the processing plant	Z^{t}_{2}
26	Cost of processing one ton of ore in period *t*	C^{t}_{P}
27	Processing cost of ore in block (i, j, k) in period *t* using open-pit method	$\bar{\varphi}^{t}_{i,j,k}$

One of the most widely used optimization models is the mathematical programming model, which has garnered significant attention. These models aim to optimize an objective function while reflecting real-world constraints through mathematical relationships such as equations, inequalities, and logical expressions. A typical mathematical programming model consists of four main components:

1. Parameters
2. Decision variables
3. Constraints
4. Objective function

The goal is to either maximize or minimize the objective function within the defined constraints.

While classical operations research models often assume continuous decision variables, many real-world problems involve discrete decision variables. These are referred to as integer programming models, categorized as follows:

- Pure Integer Programming: All decision variables must be integers.
- Binary Integer Programming: All decision variables are binary (0 or 1), representing yes/no decisions.

- Mixed Integer Programming (MIP): Some variables are integers while others are continuous.

These various types of models fall under the broader category of Mixed Integer Programming (MIP), as illustrated in Figure 1.

Table 4. Symbols used in the model for decision variables.

No.	Decision variable	Symbol
1	Continuous variable representing the portion of block (i, j, k) to be extracted as ore and processed in period t through open-pit mining.	$\bar{\mathrm{x}}^{\mathrm{t}}_{\mathrm{i,j,k}} \in [0, 1]$
2	Continuous variable representing the portion of block (i, j, k) extracted in period t through open-pit mining. This fraction of y includes both ore and waste.	$\bar{y}^{\mathrm{t}}_{\mathrm{i,j,k}} \in [0, 1]$
3	Binary integer variable; equals 1 if block (i, j, k) or all mining units at a bench are extracted via open-pit method in period t, otherwise 0.	$\bar{\alpha}^t_{i,j,k} \in \{0, 1\}$
4	Binary integer variable controlling the extraction precedence of a block. If block (i, j, k) has started or begins extraction in period t, equals 1; otherwise 0.	$\bar{\beta}^t_{i,j,k} \in \{0, 1\}$
5	Equals 1 if the tonnage of ore sent from the open-pit section to the processing plant exceeds the target feed tonnage; otherwise 0.	$\bar{\eta}^t_1 \in \{0, 1\}$
6	Equals 1 if the tonnage of ore sent from the open-pit section to the processing plant is below the target feed tonnage; otherwise 0.	$\bar{\eta}^t_2 \in \{0, 1\}$
7	Equals 1 if the ore grade sent to the processing plant exceeds the desired grade limit; otherwise 0.	$\bar{\eta}^t_3 \in \{0, 1\}$
8	Equals 1 if the ore grade sent to the processing plant is below the desired grade limit; otherwise 0.	$\bar{\eta}^t_4 \in \{0, 1\}$

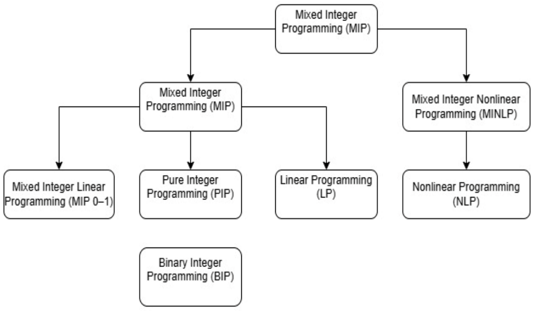

Figure 1. Classification of Mathematical Programming Models

In the current model, an integrated MILP (Mixed-Integer Linear Programming) framework is used to determine the scheduling and extraction sequence of mining units (blocks) over a six-month period of open-pit mine life.

The objective function aims to maximize the Net Present Value (NPV) of the open-pit mining project. The amount of ore processed is controlled by the continuous decision variable $\bar{x}^t_{i,j,k}$, and similarly, the material extracted is controlled by the continuous variable $\bar{y}^t_{i,j,k}$. These variables ensure compensation for any deficit in ore extraction over the mine's life.

The model includes constraints on mining capacity, processing capacity, cutoff grade of the processing plant, geotechnical slope, and extraction precedence relations. Mining capacity is a function of ore reserves, processing capacity, and mining fleet limitations. Processing constraints ensure that the Run-of-Mine (RoM) meets the plant's required throughput in each period. Based on the cutoff grade, blending constraints are imposed to keep the ore grade within acceptable upper and lower target bounds.

The economic value of a block (mining unit) is a function of the total recovery of minerals within the block, revenue from the sale of the final product, extraction costs, processing costs, and refining and selling expenses. The economic value of a block in open-pit mining is denoted by $B\bar{E}V^t_{i,j,k}$ and is defined by Equation 5.

The revenue generated from the sale of the final product from a block extracted in period *t* using the open-pit method is expressed as $\bar{R}^t_{i,j,k}$ in Equation 6.

The processing cost of ore within the block in period *t* using the open-pit method is denoted as $\bar{\varphi}^t_{i,j,k}$ and presented in Equation 7.

Similarly, the extraction cost of all materials within the block in period *t* using the open-pit method is represented by $\bar{U}^t_{i,j,k}$ in Equation 8.

The objective function of the MILP model, as shown in Equation 9, maximizes the Net Present Value (NPV) of the mining project.

$$B\bar{E}V^t_{i,j,k} = \overline{(R}^t_{i,j,k} - \check{\text{Ṫ}}) - (\bar{\varphi}^t_{i,j,k} + \bar{U}^t_{i.j.k}) \tag{5}$$

$$\bar{R}^t_{i,j,k} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} \bar{O}_{i,j,k} \times \bar{G}_{i,j.,k} \times R \times (\text{Ᵽ} - \text{Ç}) - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} \bar{O}_{i,j,k} \times B \tag{6}$$

$$\overline{\upvarphi}^t_{i,j,k} = \bar{O}_{i,j,k} \times C^t_P \tag{7}$$

$$\bar{U}^t_{i.j.k} = \left(\bar{O}_{i,j,k} + \bar{W}_{i,j,k}\right) \times \bar{H}^t \tag{8}$$

$$\max Z=\sum_{t=1}^{T}\left[\begin{array}{c}\left(\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(\frac{\left(\bar{R}_{i\,j\,k}^{t}-\check{\mathrm{T}}\right)}{(1+DR)^{t}}\times\bar{x}_{i\,j\,k}^{t}-\frac{\left(\bar{\varphi}_{i\,j\,k}^{t}+\bar{W}_{i\,j\,k}^{t}\right)}{(1+DR)^{t}}\times\bar{y}_{i\,j\,k}^{t}\right)\right)\\ -\left(\begin{array}{c}\left(\frac{Z_{1}^{t}}{(1+DR)^{t}}\times\bar{\eta}_{1}^{t}\times\left|\bar{N}_{1}^{t}-\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(\bar{O}_{i\,j\,k}\times\bar{x}_{i\,j\,k}^{t}\right)\right|+\frac{\hat{Z}_{1}^{t}}{(1+DR)^{t}}\times\bar{\eta}_{2}^{t}\times\left|\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(\bar{O}_{i\,j\,k}\times\bar{x}_{i\,j\,k}^{t}\right)-\bar{N}_{1}^{t}\right|\right)+\\ \left(\frac{Z_{1}^{t}}{(1+DR)^{t}}\times\bar{\eta}_{1}^{t}\times\left|\bar{N}_{1}^{t}-\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(\bar{O}_{i\,j\,k}\times\bar{x}_{i\,j\,k}^{t}\right)\right|+\frac{\hat{Z}_{1}^{t}}{(1+DR)^{t}}\times\bar{\eta}_{2}^{t}\times\left|\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(\bar{O}_{i\,j\,k}\times\bar{x}_{i\,j\,k}^{t}\right)-\bar{N}_{1}^{t}\right|\right)\\ \left(\frac{Z_{2}^{t}}{(1+DR)^{t}}\times\bar{\eta}_{3}^{t}\times\frac{\left|\bar{N}_{2}^{t}\times\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\bar{x}_{i\,j\,k}^{t}-\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\bar{\mathrm{G}}_{\mathrm{i\,j\,k}}\times\bar{x}_{i\,j\,k}^{t}\right|}{100}+\frac{\hat{Z}_{2}^{t}}{(1+DR)^{t}}\times\bar{\eta}_{4}^{t}\times\frac{\left|\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(\bar{\mathrm{G}}_{\mathrm{i\,j\,k}}\times\bar{x}_{i\,j\,k}^{t}\right)-\bar{N}_{2}^{t}\times\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\bar{x}_{i\,j\,k}^{t}\right|}{100}\right)\end{array}\right)\end{array}\right] \tag{9}$$

The objective function aims to maximize the net present value of ore extraction and processing by summing the discounted block-level profits, which are calculated as revenues minus mining and processing costs. Additionally, penalty terms are subtracted for deviations from the target feed tonnage $\bar{N}_1^t$and grade $\bar{N}_2^t$. The decision variables $\bar{x}_{i\,j\,k}^t$ (tons of ore) and $\bar{y}_{i,j,k}^t$ (tons of waste) dictate the extraction process. Positive and negative deviations are penalized using coefficients $\hat{Z}_1^t$ and $\hat{Z}_2^t$weighted by efficiency factors η, all discounted by $(1+DR)^{-t}$.

The objective function maximizes the Net Present Value (NPV) of the mining project over the mine's lifetime. It includes penalty terms for deviations in both production tonnage and ore grade from the desired levels. By maximizing NPV, the model inherently minimizes these deviations. The choice of penalty weights depends on the company’s priorities higher penalties reduce deviations but may increase computation time and reduce NPV. Conversely, lower penalties may lead to faster computations and higher NPV but at the cost of higher deviation tolerance.

The proposed MILP model includes the following categories of constraints, working simultaneously to schedule open-pit mining operations:

1. Open-pit mining constraints
2. Non-negativity constraints

These are represented in equations (10 to 20), controlling production planning and scheduling:

Equation 10: Limits total material extracted in each period to within the lower and upper bounds of fleet capacity using variable $\bar{y}_{i,j,k}^t$.

$$\bar{M}_{\cup}^t \le \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{k}[(\bar{O}_{i,j,k}+\bar{W}_{i,j,k})\times\bar{y}_{i,j,k}^t \le \bar{M}_{\cap}^t \tag{10}$$

$$\forall\, t\in\{1,\dots,T\}$$

Equation 11: Controls the amount of ore (ROM) sent to the processing plant using $\bar{x}_{i,j,k}^t$, ensuring uniform feed over time within acceptable grade bounds.

$$\bar{P}_{\cup}^t \le \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{k}\left(\bar{O}_{i,j,k}\times\bar{x}_{i,j,k}^t\right) \le \bar{P}_{\cap}^t \tag{11}$$

$$\forall\, t\in\{1,\dots,T\}$$

Equation 12: Ensures grade blending meets the quality specifications of the processing plant in each period.

Equations 13 & 14: Impose limits on clay content and SPI (SAG Power Index) for ore delivered in each period.

$$\bar{G}_{\cup}^t = 0.006 \le \left[\frac{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(\bar{\mathrm{G}}_{\mathrm{i,j,k}}\times\bar{O}_{i,j,k}\times\bar{x}_{i,j,k}^t\right)}{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(\bar{O}_{i,j,k}\times\bar{x}_{i,j,k}^t)}\right] \le \bar{G}_{\cap}^t \qquad \forall\, t\in\{1,\dots,T\} \tag{12}$$

$$\left[\frac{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(\overline{clay}_{\mathrm{i,j,k}}\times\bar{O}_{i,j,k}\times\bar{x}_{i,j,k}^t\right)}{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(\bar{O}_{i,j,k}\times\bar{x}_{i,j,k}^t)}\right] \le \overline{clay}_{\cap}^t = 0.34 \quad \forall\, t\in\{1,\dots,T\} \tag{13}$$

$$\left[\frac{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(SPI_{\mathrm{i,j,k}}\times\bar{O}_{i,j,k}\times\bar{x}_{i,j,k}^t\right)}{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(\bar{O}_{i,j,k}\times\bar{x}_{i,j,k}^t)}\right] \le \overline{SPI}_{\cap}^t = 130 \quad \forall\, t\in\{1,\dots,T\} \tag{14}$$

Equation 15: Defines the relationship between ore extraction and total block tonnage, ensuring $\bar{x}_{i,j,k}^t \le \bar{y}_{i,j,k}^t$.

$$\bar{x}_{i,j,k}^t - \bar{y}_{i,j,k}^t \le 0$$

$$\forall\, t\in\{1,\dots,T\}$$

$$i\in\{1,\dots,I\} \tag{15}$$

$$j\in\{1,\dots,J\}$$

$$k\in\{1,\dots,K\}$$

Equations 16 to 18: Represent precedence constraints for vertical block extraction and enforce geotechnical slope constraints, requiring upper blocks to be removed before the lower ones.

$$\bar{\beta}_{i,j,k}^t - \sum_{t=1}^{T}\bar{\alpha}_{i,j,k}^t \le 0 \tag{16}$$

$$\forall\ S\in\Delta_{i,j,k}(S)$$

$i \in \{1, \ldots, I\}$

$j \in \{1, \ldots, J\}$

$k \in \{1, \ldots, K\}$

$\sum_{t=1}^{T} \bar{\beta}_{i,j,k}^{t} - \bar{\beta}_{i,j,k-1}^{t} \leq 0$

$\forall\, i \in \{1, \ldots, I\}$ (17)

$j \in \{1, \ldots, J\}$

$k \in \{1, \ldots, K\}$

$\bar{\beta}_{i,j,k}^{t} - \bar{\beta}_{i,j,k}^{t+1} \leq 0$

$\forall\, t \in \{1, \ldots, T-1\}$

$i \in \{1, \ldots, I\}$ (18)

$j \in \{1, \ldots, J\}$

$k \in \{1, \ldots, K\}$

Equation 19: Ensures each block is extracted only once during the mine's life.

$\sum_{t=1}^{T} \bar{\beta}_{i,j,k}^{t} \leq 1$

$\forall\, i \in \{1, \ldots, I\}$ (19)

$j \in \{1, \ldots, J\}$

$k \in \{1, \ldots, K\}$

Equation 20: Ensures that if any block is extracted in a given bench, the entire bench is considered for open-pit mining.

$\left(\sum_{i=1}^{I}\sum_{j=1}^{J} \bar{\beta}_{i,j,k}^{t}\right) \times \frac{1}{JS} - \bar{\alpha}_{i,j,k}^{t} \leq 0$

$\forall\, t \in \{1, \ldots, T-1\}$ (20)

$i \in \{1, \ldots, I\}$

$j \in \{1, \ldots, J\}$

$k \in \{1, \ldots, K\}$

Equation 21: Requires that if a given bench is selected for extraction, the bench directly above it must also be scheduled for mining.

$\bar{\alpha}_{i,j,k}^{t} - \bar{\alpha}_{i,j,k-1}^{t} \leq 0$

$\forall\, t \in \{1, \ldots, T\}$

$i \in \{1, \ldots, I\}$ (21)

$j \in \{1, \ldots, J\}$

$k \in \{1, \ldots, K\}$

Equation 22 ensures that the decision variables related to open-pit extraction, processing, and mining benches are non-negative. This inequality further indicates that the binary variables, which control the geotechnical sequencing and extraction operations, must be integer values, specifically binary integers (0 or 1).

$\bar{x}_{i,j,k}^{t}, \bar{y}_{i,j,k}^{t} \geq 0 \; and \; \bar{\beta}_{i,j,k}^{t}, \bar{\alpha}_{i,j,k}^{t}$ (22)

$binery \; integers$

The time variable is flexible and can be defined as year, month, week, shift, or day. In this report, a 6-month period has been considered.

This framework is generally applicable to other open-pit mines but requires customization of parameters, updating of constraints, and adaptation to local infrastructure. Implementing this model in new mines can lead to significant operational improvements; however, its success depends on a thorough understanding of each mine's specific conditions and flexibility in execution.

4.2. Operational Impacts of geometallurgical variables: statistical and optimization results

In this study, the statistical analyses and mathematical models developed reveal the influence of key parameters on the performance of mineral processing units. The main findings are as follows:

Statistical analyses initially show that the SPI index, as a measure of rock hardness, has a direct impact on feed tonnage. Specifically, linear regression models were employed to quantify the impact of SPI (as the independent variable) on feed tonnage (as the dependent variable). As illustrated in Figures 2–4, increasing SPI values correlate with lower feed rates and higher reject generation, highlighting the sensitivity of plant throughput to ore hardness. Additionally, the clay content in the feed was identified as a major determinant of concentrate quality; higher clay percentages were associated with reduced concentrate grades, negatively affecting the final product quality.

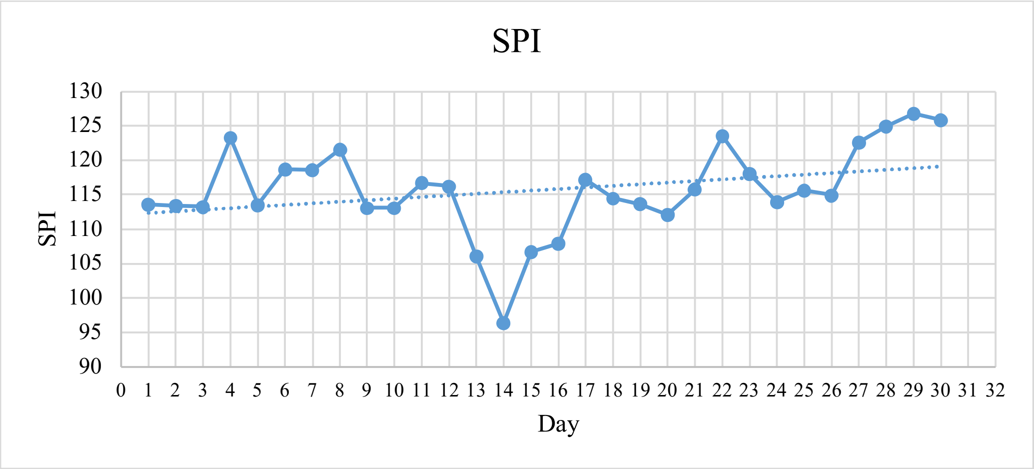

Figure 2. Changes in the SPI Index

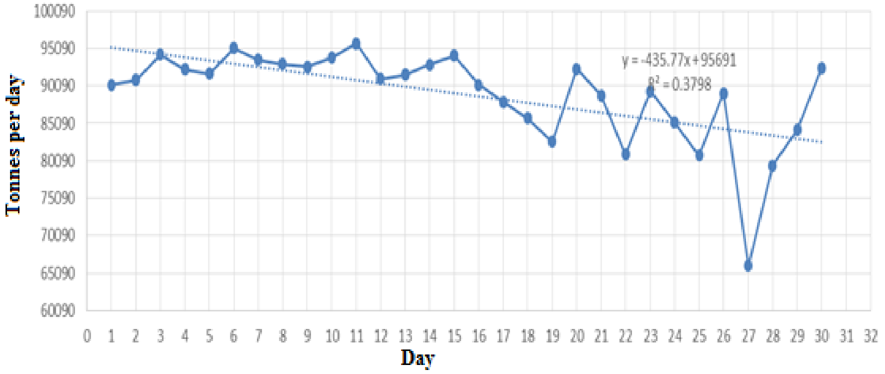

Figure 3. Variations in flotation plant feed

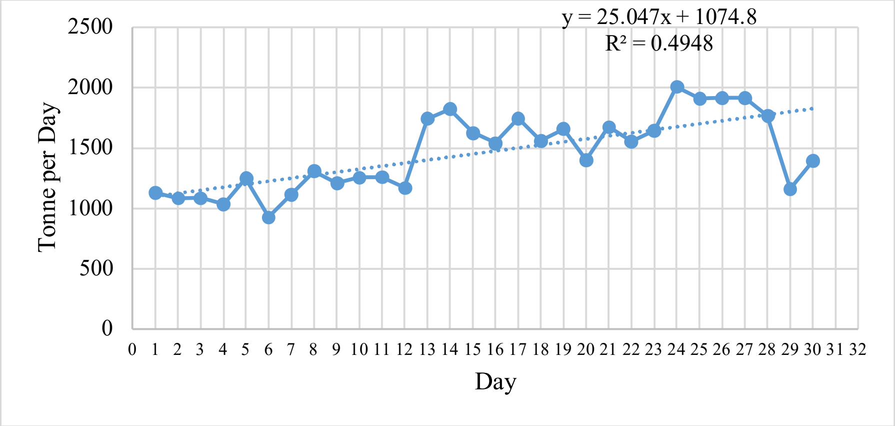

Figure 4. Variations in the amount of reject produced

Using correlation matrices and linear regression models, strong relationships were clearly observed between feed tonnage, clay content, SPI, and concentrate grade (Figure 5). These correlations demonstrate that even small variations in these parameters can significantly impact processing performance. Additionally, the pairwise data plots in Figure 6, which illustrate bivariate scatterplots between key operational variables, visually confirm the strength and direction of these relationships. Notably, there are negative trends between clay content and concentrate grade, as well as positive trends between SPI and reject tonnage.

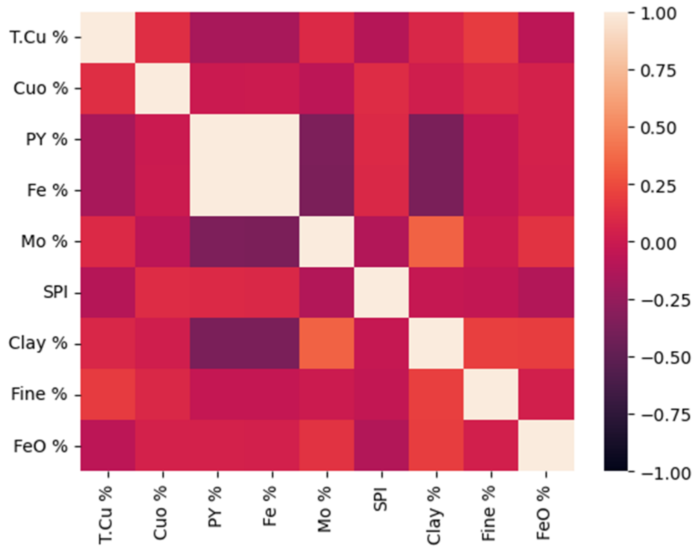

Figure 5. Data correlation

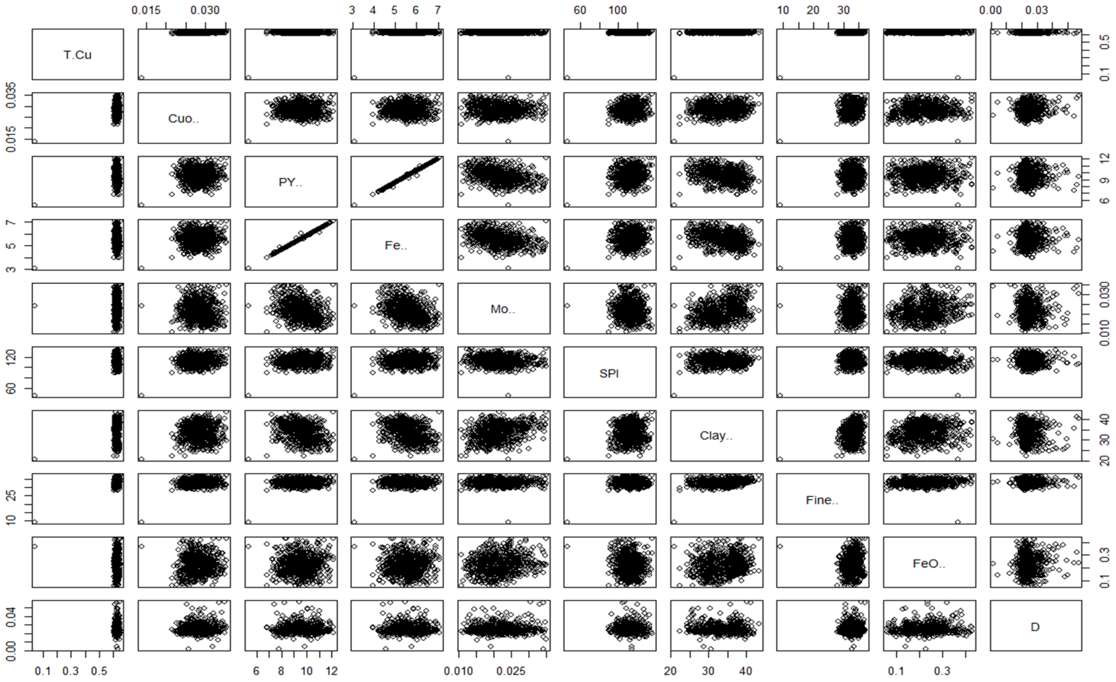

Figure 6. Pairwise data plots

The proposed MILP model, which incorporates technical and economic constraints, successfully determined optimal extraction sequences. For instance, out of a 186-day planning period, optimal conditions were met on 137 days, achieving a maximum Net Present Value (NPV) of approximately $132,000. These results underscore the importance of utilizing accurate and up-to-date data to enhance operational processes.

5. Discussion and Analysis

The results obtained in this study highlight the critical importance of accurately controlling key parameters such as the SPI index and clay content to improve the performance of mineral processing units. An increase in the SPI index, which indicates rock hardness, not only reduces the feed tonnage but also leads to a higher reject rate. Thus, controlling and improving the comminution process is of particular importance.

Regarding clay content, statistical analysis indicates a direct relationship between higher clay percentages and lower concentrate grades. This finding emphasizes that achieving optimal concentrate quality requires continuous monitoring and precise adjustment of clay content in the feed. Moreover, the strong relationships identified between feed tonnage, clay content, SPI, and concentrate grade enable more accurate predictions of processing performance.

The MILP model developed for optimizing extraction sequences successfully provided optimal scheduling in most of the planning periods, ultimately achieving a net present value (NPV) of $132,000. This demonstrates the model’s capability in managing technical and economic constraints and in formulating optimal mining strategies.

Given these findings, the implementation of real-time monitoring systems for tracking key indicators, combined with adaptive algorithms in MILP models, can enhance the flexibility and accuracy of performance forecasting in processing units. Additionally, improving data cleaning and updating procedures creates a foundation for more precise statistical analyses.

Ultimately, these insights emphasize that integrating empirical data, statistical analysis, and advanced mathematical modeling provides an effective toolset for enhancing the economic performance of mining operations. Addressing challenges such as fluctuations in input data and sudden operational changes requires the use of supplementary forecasting techniques and continuous model updates to ensure long-term performance improvements.

The implementation of the proposed Mixed-Integer Linear Programming (MILP) model yielded a comprehensive extraction sequence for the six-month planning period. To illustrate the model's operational output, Figures 7-10 present schematic representations of the scheduled extraction blocks, distinguishing between ore and waste, as well as the boundaries of the mining zones for the first four months of the planning period at the Sarcheshmeh Copper Mine. These figures effectively demonstrate the monthly extraction plan produced by the optimization model.

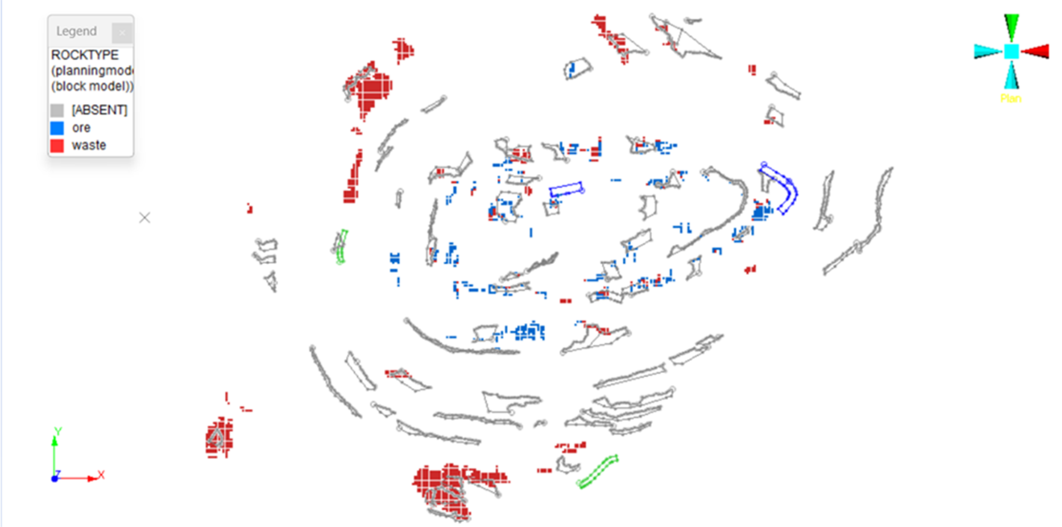

Figure 7. A Schematic of the mirst month’s blocks (ore and waste) and the first-month mining schedule of the Sarcheshmeh Mine (boundary of zones).

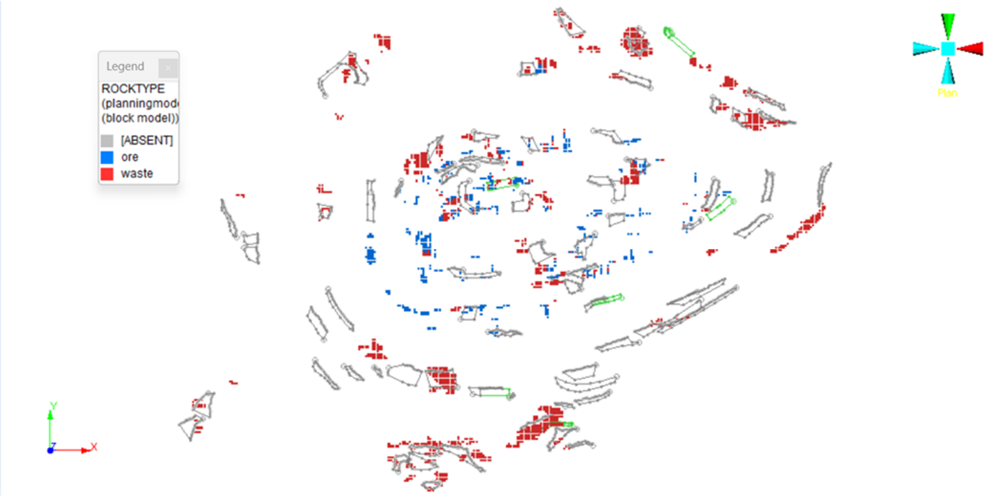

Figure 8. A Schematic of the second month's blocks (ore and waste) and the second-month mining Schedule of the Sarcheshmeh Mine (boundary of zones)

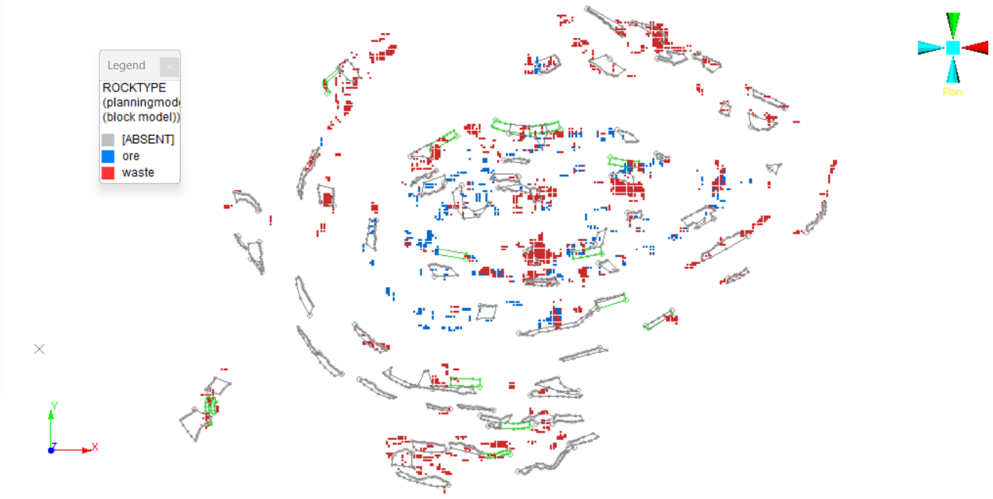

Figure 9. A Schematic of the third month's Blocks (ore and waste) and the third-month mining schedule of the Sarcheshmeh Mine (boundary of zones)

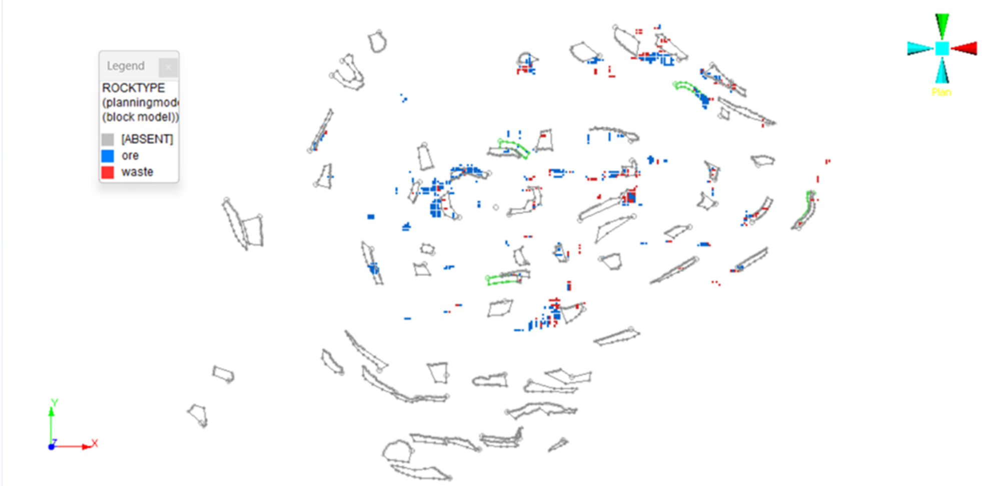

Figure 10. A Schematic of the Fourth month's blocks (ore and waste) and the fourth-Month mining Schedule of the Sarcheshmeh Mine (boundary of zones)

6. Conclusions

The proposed Mixed-Integer Linear Programming (MILP) framework effectively optimizes short-term production planning in open-pit copper mines by integrating geometallurgical constraints, such as the Slope of the Production Index (SPI) and clay content, with economic objectives. The model's application at Sarcheshmeh resulted in significant operational improvements, including reduced concentrate variability and decreased reagent consumption, while maximizing Net Present Value (NPV). Statistical analyses revealed strong correlations between feed quality parameters and processing performance, underscoring the necessity for precise control of ore hardness and clay content. However, the current model does not explicitly address operational uncertainties, such as equipment availability, weather disruptions, or workforce scheduling. To enhance robustness, future research should incorporate uncertainty modeling—such as stochastic Mixed-Integer linear programming (MILP) or scenario-based approaches—to account for variability in equipment downtime, geological conditions, and market fluctuations. Additionally, integrating real-time data from Internet of Things (IoT) sensors and machine learning algorithms could further refine predictive capabilities and improve adaptive decision-making.

Recommendations include:

1. Expanding the model to incorporate dynamic constraints related to equipment reliability and environmental factors.
2. Leveraging digital twin technology for real-time monitoring and scenario simulation.
3. Investigating the impact of additional geometallurgical variables, such as pyrite content and mineralogy, on process efficiency.

By addressing these gaps, the framework can evolve into a more resilient tool, capable of navigating the complexities of contemporary mining operations while ensuring both economic and operational excellence.

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بهینه‌سازی برنامه‌ریزی تولید کوتاه‌مدت در معادن مس روباز: یک مدل MILP با ادغام مدل‌سازی خردایش و کنترل کیفیت خوراک

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برنامه‌ریزی خطی عدد صحیح مختلط (MILP)

چکیده

بهینه‌سازی تولید کوتاه‌مدت در معادن مس روباز برای به حداکثر رساندن بازده اقتصادی و تضمین ثبات عملیاتی بسیار مهم است، اما اغلب با تغییرپذیری ذاتی زمین‌شناسی به چالش کشیده می‌شود. این کار یک چارچوب برنامه‌نویسی خطی عدد صحیح مختلط (MILP) جدید ارائه می‌دهد که برای رسیدگی به این چالش‌ها با ادغام مستقیم پارامترهای مهم ژئومتالورژی، به ویژه سختی سنگ (شاخص SPI) و محتوای رس، در فرآیند برنامه‌ریزی تولید کوتاه‌مدت طراحی شده است. ادغام همزمان این ویژگی‌های کلیدی کیفیت خوراک ژئومتالورژی در یک مدل MILP عملیاتی، این کار را از رویکردهای قبلی متمایز می‌کند و به طور مؤثر تجزیه و تحلیل داده‌های زمین‌شناسی را با تصمیم‌گیری عملیاتی پیوند می‌دهد و اهداف اقتصادی را با عملکرد متالورژیکی بهبود یافته همسو می‌کند. با استفاده از داده‌های عملیاتی واقعی از معدن مس سرچشمه، این چارچوب در یک دوره ۱۸۶ روزه اعتبارسنجی شد. این چارچوب در ۱۳۷ روز (٪۷۳.۶ از مدت زمان) به شرایط تولید بهینه دست یافت و حداکثر ارزش خالص فعلی (NPV) ۱۳۲۰۰۰ دلار را محقق کرد. نتایج کلیدی شامل کاهش قابل توجه ۲۱ درصدی در تغییرپذیری عیار کنسانتره و کاهش ۱۵ درصدی در مصرف معرف فلوتاسیون بود که از طریق کنترل همزمان SPI و محتوای رس حاصل شد. روش‌های آماری پیشرفته برای شناسایی روابط حیاتی به کار گرفته شدند. در حالی که این مدل مقیاس‌پذیری را برای معادن مس پورفیری در سطح جهانی نشان می‌دهد، اجرای موفقیت‌آمیز آن به سفارشی‌سازی دقیق پارامترها و همسویی با زیرساخت‌های موجود بستگی دارد. این کار تحقیقاتی بر ارزش قابل توجه تکنیک‌های بهینه‌سازی یکپارچه و مبتنی بر داده در افزایش سودآوری و پایداری فرآیند در مدارهای فرآوری مواد معدنی تأکید می‌کند.

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