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A Practical Model for Short-Term Open-Pit Mine Production Scheduling Based on Goal Programming Approach

Saeideh Qaedrahmat, Javad Gholamnejad*, and Ali Dabagh

Department of Mining and Metallurgical Engineering, Yazd University, Yazd, Iran

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Abstract

The scheduling of short-term production in open-pit mining requires determining an optimal extraction sequence for blocks to fulfill multiple goals over a short-term monthly, weekly and daily planning horizon. These goals include meeting required limits on ore grade, production tonnage, waste removal, and slope constraints. One of the key objectives of Short-Term Production Scheduling (STPS) is to ensure a stable and continuous supply of ore to the processing plant, while minimizing operating costs through measures such as reducing unnecessary equipment movements and variation in feed quality. However, one of the major obstacles to the operational feasibility of STPS is the limited working space available for equipment, as well as the excessive equipment movement between benches within each scheduling period. To tackle these challenges, this paper employs an Integer Goal Programming (IGP) with a new constraint that limits active benches per period, enhancing the practicality of production schedules. Unlike previous GP-based STPS models, it improves operational feasibility by ensuring extraction continuity and minimizing equipment movement. The model was tested on a copper deposit using GAMS software. The results show that by applying this new constraint, the average number of active benches per month was reduced from 14 to 10)36% reduction) and the number of extraction periods per bench from 6 to 4 (33% reduction) without violating the existing constraints such as ore grade, tonnage, or slope. This approach improves equipment efficiency, reduces fuel consumption, reducing equipment relocation costs, promoting operational continuity of extraction and enhances operational feasibility in real conditions.

1. Introduction

To design and plan open pit mining, a 3D orebody model is used to divide the deposit into blocks. Each block is assigned metal values and geometallurgical characteristics using geostatistical modeling. This 3D model, along with technical and economic data, is input into mine planning process. Mine production planning is typically structured into long-term, medium-term, and short-term horizons, each serving distinguished strategic, tactical, and operational objectives within the overall mine planning framework [1]. Long-Term Production Scheduling (LTPS) involves making strategic technical decisions such as the pit limit, profit, and capital investment. The goal of this phase is to maximize the operation's Net Present Value (NPV) while adhering to operational and geometrical constraints annually. Medium-Term Production Scheduling (MTPS) determines the annual block sequence while managing resource constraints such as production level and haul equipment. STPS focuses on the operational implementation of long- and medium-term plans, generating detailed extraction schedules that achieve production targets while ensuring consistency with operational constraints across shifts, days, weeks, or months [2]. The objectives of STPS, can be summarized as follows [3]:

- meeting the quantity and quality requirements;

Corresponding author: j.gholamnejad@yazd.ac.ir (J. Gholamnejad)

- maximizing the utilization of mine equipment such as shovels, trucks, etc.;
- minimizing the deviation from medium- and long-term plans;
- minimizing the shovel movement for each mining period;
- ensuring that sufficient ore is exposed for the next period;
- producing short term plans that can be practically applied, i.e., ore and waste blocks are accessible for shovels and trucks, and equipment have enough room to extract the blocks;
- optimizing short-term plans over multiple periods.

Although in STPS the overall equipment capacities can be taken into account, the detailed equipment scheduling (which equipment, where, and when to use) is not considered. Alarie and Gamache [4] introduced a fourth level of production scheduling called very STPS that aims to dispatch trucks to shovels/loaders during the shift.

One of the major challenges commonly encountered in Short-Term Production Planning (STPP) models is the non-uniform mineral extraction across benches and time periods. This problem often arises due to insufficient working space for equipment maneuvering during each planning interval, which not only increases operational costs and reduces profitability, but also disrupts the continuous supply of ore to the processing plant—ultimately rendering such plans infeasible in practice.

Accordingly, this study aims to develop an optimized monthly production scheduling framework by employing a Goal Programming (GP) approach that overcomes these limitations and yields more practical and executable mine plans.

The subsequent sections of this paper will be organized as follows:

Section 2 provides an overview of the GP Approach, including its mathematical formulation and historical development.

Section 3 reviews a selection of studies published between 1990 and 2025 that address short-term production planning in open-pit mines.

In Section 4, the materials and methods used in this study will be detailed. Specifically, the problem definition will be presented along with the notations of variables and the Integer Programming (IP) formulations that were employed to address the problem. Furthermore, new constraint, namely the working benches constraint, will be introduced, which have been investigated and integrated into the Base model for each scheduling period.

In Section 5, the results obtained from the suggested model will be showcased through a comprehensive comparative mining case study. By contrasting it with the conventional approach, the strengths and advantages of the proposed model will be highlighted. The data will be analyzed, the outcomes will be compared, and a thorough evaluation of the model's performance in relation to the traditional one will be presented.

Lastly, in Section 6, a concise summary and conclusion will be provided, outlining the main findings and implications of the study. The significance of the proposed model in solving the addressed problem will be emphasized, and its potential applications and directions for future research will be discussed. After concluding the paper, a comprehensive list of references that served as the basis for the study will be included**.**

2. Goal Programming

Linear Programming (LP) approach can handle STPS problems. However, classical LP models have a single objective function that must be minimized or maximized subject to the constraints given [5, 6]. In open pit mines STPS, multiple objectives need to be considered, such as ore and waste production rate, processing capacities, and ore quality. Scheduler must take all these objectives into account while making decisions since these objectives often have conflicting requirements. Combining these objectives into a single objective function is challenging. To address this issue, the GP method can be utilized.

GP is one of the more popular Multi-Criteria Decision-Making (MCDM) techniques where the criteria are known as goals. In GP method, the unwanted deviations (under and/or over) from the target levels are minimized in the goal achievement function/objective function to achieve a satisfactory solution. GP was first used by Charnes, Cooper and Ferguson in 1955 [7] although the actual name first appeared in a 1961 [8] text by Charnes and Cooper.

Charnes and Cooper [9] suggested the GP model with m goals, p system constraints, and n decision variables using Equations 1 to 4:

$$\text{Minimize } Z = \sum_{i=1}^{m} P_i(\mathrm{w}_\mathrm{i}^{+}.\mathrm{d}_\mathrm{i}^{+} + \mathrm{w}_\mathrm{i}^{-}.\mathrm{d}_\mathrm{i}^{-}) \tag{1}$$

Subject to:

Goal constraints:

$$\sum_{j=1}^{n} a_{ij} X_j - d_i^+ + d_i^- = b_i \qquad (2)$$

$$for\ i = 1,2, \ldots, m$$

System constraints:

$$\sum_{j=1}^{n} a_{ij} X_j \begin{bmatrix} \leq \\ = \\ \geq \end{bmatrix} b_i \qquad (3)$$

$$for\ i = m+1, \ldots, m+p$$

$$d_i^+, d_i^-, X_j \geq 0 \qquad (4)$$

Where:

Z - Objective function which is summation of all deviations,

a_{ij} - The coefficient associated with variable j in the i^{th} goal,

x_j - The j^{th} decision variable,

b_i - The value of RHS (Right Hand Side)

d_i^- -The negative deviational variable represents the shortfall from the i^{th} goal,

d_i^+ - The positive deviational variable represents the excess from the i^{th} goal.

It is not possible for both shortfall and excess of a goal to happen at the same time. Therefore, one or both of these variables must have a value of zero; i.e., $d_i^+ \times d_i^- = 0$

P_i - Priority factors of the i^{th} goal.

w_i^+ And w_i^-- The non-negative constants $w_i^+$and w_i^-represent the relative weight assigned to the positive and negative deviation variables in the GP formulation. These weights can be any real numbers, with greater weights assigned to variables with greater importance in minimizing their respective deviation.

There are two types of variables used in GP formulation - decision variables and deviational variables. In addition, two kinds of constraints are used: system constraints (which are strict like in traditional linear programming) and goal constraints. The goal constraints use expressions of the original functions with target goals, set priorities, and positive and negative deviational variables.

The GP approach has been widely used for optimizing STPS of open pit mines, with previous studies incorporating constraints such as quality, quantity, mining reachability, mining precedence, bench front smoothing constraints—where the working front is required to be continuous and practically feasible in mining operations [10]—, costs minimization, and more into the formulation.

3. literature survey

In the study conducted by Chanda [11], the GP Approach was utilized for STPS in the crushed stone industry, with a specific focus on managing stockpile to ensure optimal inventories for various products, such as limestone powder used in the chemical industry. The objectives of the model were to establish a relationship between demand and inventory, manage capacity constraints, and adhere to overtime constraints. The objective function aimed to minimize deviations from the predetermined goals, considering assigned priority factors. The decision variable in this model was determined as the quantity of product i produced during period t.

Youdi et al. [12] proposed a two-step approach for STPS optimization in surface mines. In the first step, medium- to short-term plans were obtained using binary GP, while in the second step, a CAD technique and systems simulation were applied to generate practical and flexible short-term plans. The objective function in the GP model aimed to minimize the deviation of each objective between actual and expected values based on respective priorities. The model incorporated operational and geometrical constraints directly into the GP formulation, including quality and quantity, mining reachability, mining precedence, and bench front smoothing constraints, to ensure that the optimization results were practical and realistic.

Chanda and Dagdelen [13] presented a linear GP model for STPS optimization in a coal mine, specifically for the blending problem. Their production objective was to supply coal with uniform grades (ash, sulfur, and BTU) and tonnage according to plant requirements. In the objective function, they utilized two optimization criteria: maximizing total profit and minimizing the weighted sum of deviation of grade and tonnage from their target values. They solved the linear GP model with the simplex method and the optimal solution determined where to mine and at what rate to achieve production goals. The optimal solution was then used as the basis for generating practical short-term plans utilizing interactive graphics.

Smith and You [14] and Smith [15] introduced a multi-period GP scheduling and inventory control model for a surface phosphate operation. The model aims to minimize the variance of plant feed characteristics, namely phosphate and silica, through a combination of mine production scheduling and inventory stockpile modeling. The model uses two types of decision variables: continuous variables representing the tonnage mined from a block or stockpile and zero-one variables used to indicate if the block is mined in the period or not. The major constraints of the model include ore body block characteristics, blending, mining precedence relationships, inventory stockpile precedence, inventory control, and equipment capacity constraints. The model assumes that the quality characteristics of stockpiles are not known and should be treated as a variable. To address this, the model includes nonlinear combined equations that are used for inventory control. These nonlinear equations were then linearized using Separable Programming and the resulting model was then solved using CPLEX's mixed integer optimizer.

Smith [5] presented a multi-period Mixed Integer Programming (MIP) model that utilized GP approach for constructing short-term production schedules. The objective function of the model was set to minimize the sum of deviation targets multiplied by their corresponding penalty weights. The constraints in the model contain slope constraints, ore quantity and quality constraints, reserve constraints, and stripping constraints. Additionally, the model incorporated block accessibility constraints, which ensured that the blocks on a given bench were mined from the face inwards, and sinking cut constraints, which guaranteed that a single continuous block was mined from a bench without any free faces. This approach enabled the optimization of short-term production scheduling while considering multiple constraints in an open pit mining operation.

Esfandiari et al. [16] introduced a non-linear 0–1 GP model for open-pit mine optimization that uniquely incorporates mineral processing criteria into the block selection process. Unlike conventional models focused solely on economic value or tonnage, this approach integrates beneficiation constraints—such as concentrate recovery and processing efficiency—into the decision-making structure. The model uses binary variables to determine whether or not each block should be extracted, subject to mining precedence and processing limitations. A small-scale case study demonstrated that incorporating processing parameters leads to more practical and technically feasible mining plans, especially when mineral processing constraints significantly affect the economic return of extracted ore.

Sattarvand and Niemann [17] Delius developed a simulation-based optimization model to support short-term production planning in open-pit mining operations. The model relies on a binary linear programming (0-1 LP) formulation to determine the optimal sequence of blocks to be extracted during a given planning period, typically three months. Input data to the model include detailed block model attributes such as ore and waste volumes, grades, and the number of predefined pushbacks. At each iteration, the model identifies a subset of blocks that optimally satisfy production targets, balancing ore and waste quantities in line with operational constraints. The primary objective function aims to minimize the deviation from the targeted average ore grade in extracted blocks. Simultaneously, in the case of waste removal, the model prioritizes the exposure of blocks with the highest potential ore grades, thereby improving access for subsequent extraction phases. The model incorporates key constraints including block count limits, geometrical constraints (e.g., bench width and block accessibility), and grade blending requirements. Upon solving, the software iteratively updates the block selection and continues until cumulative ore and waste production targets are achieved. By integrating a detailed block-based simulation with mathematical programming, this approach improves the alignment of short-term plans with practical mine operation requirements, enhancing both efficiency and ore feed consistency.

Jafari et al. [18] present an operational mathematical model based on integer programming for short-term production planning of open-pit mines. This short-term production planning model has been expanded to ensure that before mining each block, not only must the upper 9 blocks be removed, but also 2 or 3 blocks in front of that block at the same level must be extracted.

Ben-Awuah et al. [19] proposed a mixed-integer GP model for short-term production scheduling in oil sands surface mining. The model integrates ore extraction sequencing with waste and dyke material allocation, considering multiple objectives such as meeting production targets, minimizing deviations, and reducing dyke construction costs.
By including binary and continuous decision variables, the model simultaneously manages production and waste placement under operational constraints. The results showed that the model achieved realistic and implementable mining schedules, maintained a practical ore-to-waste ratio

(1:1.5), and maximized NPV over the mine life. This study shows the effectiveness of GP in optimizing complex surface mine operations where both production efficiency and environmental constraints must be considered.

Kumral [20] introduced a hybrid optimization framework that combines GP with Simulated Annealing (SA) to address a modified five-period open-pit production scheduling (5-OPPS) problem under grade uncertainty. The proposed model simultaneously resolves block sequencing and ore–waste classification (cut-off grade) decisions, which are typically interdependent and critical to short-term mine planning. Initially, the GP formulation minimizes deviations in mining and processing capacity constraints, while generating a feasible extraction sequence that satisfies precedence and reserve constraints and achieves a target NPV. Subsequently, the SA algorithm improves upon this initial solution by iteratively adjusting: the timing of block extraction, and the classification of blocks as ore or waste, selecting a randomly subset of blocks. This two-phase hybrid strategy was applied to a real-world gold mining operation. The results demonstrated that SA substantially make better the initial GP-based schedule, achieving improved NPV and better alignment with operational goals.

L'Heureux et al. [21] proposed a Mixed-Integer Programming (MIP) model for short-term production planning in open-pit mining, with the objective of minimizing total operational costs associated with shovel relocation, drilling, and blasting. The model determines which blocks should be extracted in each scheduling period. To enhance computational efficiency, four solution strategies—branch-and-cut, moving window, simplex, and Large Neighborhood Search (LNS)—were implemented and evaluated. Among these, the LNS approach proved the most effective, as it significantly reduced the problem size and improved solution time without compromising result quality.

Matamoros and Dimitrakopoulos [22] introduced a stochastic integer programming model for short-term production scheduling in open-pit mining. The objective function of this model is to minimize the total cost of extraction while reducing the deviation from production goals, and it considers operational aspects such as the direction of extraction, minimum width, and maximizing the use of the fleet, and uncertainties in orebody characteristics. The model simultaneously optimizes block extraction sequences and fleet allocation decisions, integrating constraints related to blending requirements, equipment capacities, and operational considerations. By incorporating stochastic scenarios for ore grades and equipment availability, the model provides more reliable and cost-effective schedules compared to traditional deterministic approaches. Application of the model to a multi-element iron mine demonstrated improved fleet utilization and reduced variability in production results.

Upadhyay and Askari-Nasab [23] proposed a GP model to optimize the allocation of trucks to shovels in open-pit mining operations. The model addresses multiple conflicting objectives, including maximizing production tonnage, minimizing deviations from target ore grades, and reducing truck idle times. By incorporating these objectives into a single framework, the model provides a balanced solution that aligns with operational goals. A case study demonstrates the model's effectiveness in enhancing productivity and operational efficiency in mining operations.

Mohtasham et al. [24] developed a linear GP model to optimize truck allocation in open pit mining operations. The model considers multiple conflicting objectives simultaneously, including minimizing truck idle time, maximizing productivity, and steady ore feed delivery. It introduces decision variables related to truck assignments for different shovels and destinations, subject to operational constraints such as truck availability, displacement time, and required production tonnage. A real-world case study is used to demonstrate the model's performance, and results show that the proposed method provides an efficient allocation strategy that improves overall system productivity while reducing idle times. This study confirms the practical applicability of GP for multi-objective truck dispatching problems in surface mining operations.

Upadhyay and Askari-Nasab [25] developed a dynamic shovel allocation model for short-term production planning in open-pit mining operations. Utilizing a Mixed-Integer Linear Goal Programming (MILGP) approach integrated with discrete-event simulation, the model aims to optimize shovel assignments to mining faces over a planning horizon. Key objectives include maximizing production rates, meeting ore grade and tonnage targets, and minimizing shovel movements to enhance operational efficiency. The model accounts for equipment capacities, face availabilities, and blending requirements, providing near-optimal solutions that align with strategic mine plans. This integrated simulation-optimization framework offers a practical tool for improving short-term scheduling decisions in dynamic mining environments.

Ben-Awuah et al. [26] extended the classical One-Period Production Scheduling (1-OPPS) problem by integrating short-term production scheduling with in-pit waste dumping planning for oil sands mining operations. The proposed framework is formulated as a GP model, aiming to simultaneously maximize the NPV of the operation and minimize waste dump construction costs, while also controlling deviations from operational targets. In addition to standard precedence and production capacity constraints, the model incorporates strict blending requirements and geometric constraints associated with dump organization. To reduce computational complexity, a pre-processing phase is introduced to define a Unified Pit Limit (UPL) and aggregate blocks into mining cuts at each bench level. This reduction in decision variables allows the exact GP-based formulation to be solved efficiently. The model was implemented in a real-world oil sands project and compared against an industry-standard commercial mine planning software [27]. Results demonstrated better performance in terms of waste handling efficiency and alignment with operational goals.

Maremi et al. [28] developed a GP framework for oil sands mine planning that incorporates the impact of Organic Rich Solids (ORS) on bitumen recovery. The model introduces Automated Production Targeting (APT) constraints and limited-duration stockpiling to optimize annual production capacities. Two scenarios were analyzed: one using standard processing recovery rates and another adjusting recovery based on ORS content. Results indicated that neglecting ORS effects can lead to overestimations of net present value by approximately 3.46%. The framework provides a robust tool for planners to determine annual production tonnages with minimal periodic variations, enhancing the realism and implement ability of mine plans.

Quigley and Dimitrakopoulos [29] developed a stochastic optimization model for short-term production scheduling in open-pit mining, aiming to minimize operational costs while explicitly accounting for geological and equipment performance uncertainty. The model determines the optimal block extraction sequence and allocates mining equipment under constraints such as fleet capacity, operational readiness, and blending targets. Blocks are clustered into groups, each with defined tonnage and grade characteristics, and the model optimizes equipment positioning and shovel-truck cycle times accordingly. While the approach offers improved fleet utilization and more stable production outcomes compared to deterministic models, one notable limitation is that grade blending—a critical component of short-term scheduling—was not incorporated into the optimization process. The model's application to a large copper mining operation demonstrated its capacity to reduce variability in production while maintaining alignment with operational goals.

Salman et al. [30] introduced a new block aggregation method for short-term planning in open-pit mining operations involving multiple processing destinations. The primary objective is to reduce computational complexity in mine planning by clustering adjacent blocks with similar attributes—such as geochemical grades, rock types, and geometallurgical parameters—while honoring operational constraints. The proposed heuristic algorithm ensures that the resulting clusters maintain mineable shapes, controlled sizes, alignment with mining direction, and homogeneity in rock type and processing destination. By integrating these constraints, the method facilitates more efficient and practical short-term production schedules. Application of the algorithm to two different datasets demonstrated its effectiveness in generating reasonable block clusters that meet predefined aggregation requirements, thereby enhancing decision-making in complex mining scenarios.

Martins and Souza [31] proposed a lexicographic goal programming (LGP) model for short-term production planning in open-pit mining. The model addresses multiple objectives hierarchically, including minimizing deviations in ore grade and particle size distributions, controlling the stripping ratio, and reducing haulage distances. By prioritizing these goals lexicographically, the model ensures that higher-priority objectives are satisfied before considering lower-priority ones. The LGP approach effectively generates feasible and balanced production schedules that align with operational constraints and strategic targets, demonstrating its utility in complex mining environments.

Mohtasham et al. [32] developed a Chance-Constrained Goal Programming (CCGP) model to optimize truck-shovel allocation in open-pit mining operations under uncertainty. The model incorporates four primary objectives: maximizing production, minimizing deviations in ore grade, minimizing deviations in tonnage to ore destinations, and minimizing fuel consumption. By introducing chance constraints, the model accounts for uncertainties in loader production rates, ensuring that these objectives are fulfilled with specified confidence levels. Implemented on an open-pit copper mine case study, the model evaluated 11 scheduling scenarios across different confidence levels, demonstrating its capability to produce feasible and efficient truck allocation plans even under high uncertainty. This approach highlights the effectiveness of CCGP in handling multi-objective optimization problems in mining operations where uncertainty is a significant factor.

Bakhtavar et al. [33] developed a fuzzy cognitive-based GP model for sustainable waste rock management in open-pit mining. The model prioritizes in-pit dumping to reduce environmental impact, hauling costs, and addressing operational challenges. Fuzzy cognitive mapping is used to evaluate trade-offs between competing goals. Application of the model to a limestone deposit demonstrated that internal dumps, despite longer haulage, offer more sustainable outcomes. Sensitivity analysis confirmed the model's adaptability to dump capacity constraint.

Shamsi et al. [34] developed a short-term production scheduling model for open-pit mining with the goal of minimizing deviations from predefined production targets in terms of ore tonnage and grade. The study applied a LGP approach to account for operational constraints such as processing plant capacity, ore blending requirements, and slope limits. By adjusting penalty weights for deviations, the model ensures alignment with both quantitative and qualitative production objectives. Application of the model in a case study demonstrated reduced variation from target plans and improved steady in ore delivery to the processing plant.

de Carvalho and Dimitrakopoulos [35] introduced an integrated framework for short-term production planning in industrial mining complexes, aiming to simultaneously optimize shovel allocation and grade control decisions. The model employs an actor-critic reinforcement learning approach, wherein an agent learns to assign shovels to mining areas based on operational requirements and grade control objectives. A spatially constrained clustering method defines diglines and material destinations, while a discrete-event simulator forecasts material flow from benches to processors. Application of the model to a copper mining complex demonstrated a 27% improvement in cash flow compared to a non-adaptive baseline approach, highlighting the effectiveness of integrating reinforcement learning techniques into mine planning processes.

Habib et al. [36] presented a mixed-integer programming (MIP) model for short-term production planning in open-pit mining, focusing on shovel allocation in the context of Semi-Mobile In-Pit Crushing and Conveying (SMIPCC) systems. The model aims to minimize material handling costs and maximize revenue by optimally assigning shovels to mining faces over a 12-month horizon, considering constraints such as plant requirements, allowable tonnage variation, and IPCC relocation schedules. A case study on an iron ore mine demonstrated the model's effectiveness, showing that incorporating SMIPCC can lead to significant cost savings and improved alignment with strategic production targets compared to traditional truck-shovel systems.

Noriega et al. [37] introduced a real-time truck dispatching system for open-pit mining operations, utilizing a Deep Reinforcement Learning (DRL) framework based on the Double Deep Q-Network (DDQN) algorithm. The primary objective of this model is to optimize the allocation of haul trucks to shovels, aiming to achieve production targets, maintain desired ore feed grades, and minimize operational costs. The system is trained using a discrete-event simulation that captures the dynamic and stochastic nature of mining operations, including uncertainties in equipment performance and haulage cycles. A case study conducted on an iron ore deposit demonstrated that the DRL-based dispatching system effectively learned robust policies, leading to improved compliance with production targets and enhanced operational efficiency compared to traditional dispatching methods.

Deressa, et al. [38] published a comprehensive review in the Arabian Journal of Geosciences focusing on advanced bench design and the technical challenges associated with stability and productivity in open-pit mining operations. The primary objective of the study is to emphasize the significance of effective mine planning and design, highlighting key factors such as rock mass properties, bench geometry, stability considerations, blast design, and other operational elements that directly impact efficiency and safety. The authors underscore the importance of integrating geomechanically understanding into bench design, noting that historically, this integration has been underestimated, leading to operational challenges. The review delves into the optimization of bench design, which requires a careful balance of economic, geomechanical, and operational factors, including bench height, slope angle, blasting design, and equipment considerations. Numerical modeling is highlighted as a crucial tool for simulating interactions between rock behavior, bench design, and mining processes, providing insights into stress distribution, material displacement, and potential failure mechanisms. Furthermore, the incorporation of machine learning techniques in open-pit mine planning is discussed as an innovative solution for design optimization. In conclusion, the paper proposes strategies for improving stability and productivity through integrated blasting protocols, advanced monitoring technologies, and machine learning for design optimization. The authors suggest that future research should focus on enhancing safety and productivity by refining modeling techniques and deepening the understanding of mine planning and design for sustainable mining operations.

Several studies have employed GP for optimizing STPS in open-pit mines by incorporating a variety of constraints to enhance the realism and operational applicability of the models. These constraints include mining precedence relations, bench front smoothing cost minimization, and other operational requirements.

Overall, GP has proven to be an effective multi-objective optimization framework for STPS in open-pit mining, addressing a broad spectrum of goals and constraints. Applications range from stockpile management and material blending to adherence to geometrical and operational constraints, cost control, and environmental compliance.

In this context, the present study introduces a new GP formulation for STPS in open-pit mining. In addition to the conventional constraints typically considered in STPS models, this formulation incorporates a set of linear constraints aimed at reducing the number of active benches during each scheduling period.

Since truck haulage represents approximately 60% of total operating costs in open-pit mining operations [39], reducing the number of simultaneously active benches can significantly decrease long-haul equipment movements between benches, thereby lowering transportation costs and enhancing operational efficiency.

4. Formulation of a Mathematical Model

In the previous section, several short-term production scheduling models were reviewed. However, during simulation experiments under real operational conditions, these models demonstrated major limitations. Specifically, it produced Dispersed block extraction patterns—mathematically valid but practically inexecutable. These schedules increased unnecessary machine relocations, increased fuel consumption, equipment wear, and higher operational cost and failed to guarantee the steady of ore feed. Such inconsistencies risk supply interruptions to the processing plant and lead to suboptimal utilization of mining resources. These deficiencies highlighted the need for an extension to the model that accounts for the spatial coherence of operations—specifically, by limiting the number of simultaneously active benches. To address these challenges, the present study was enhanced by introducing a new constraint that limits the number of active benches in each scheduling period. This case serves two purposes: first, to validate the model's performance under real mining conditions, and second, to evaluate the operational benefit of adding the active bench constraint. This additional constraint helps generate more contiguous block sequences and thereby significantly reducing unnecessary lateral movement of mining equipment. The enhanced model uses GP to minimize deviations from tonnage and grade while penalizing them proportionally. The model's indices, parameters, and variables are defined in this section and the mathematical model is explained, including its objective function and physical and technical constraints. It is important to note that this model has also served as the foundation for short-term production planning in the mine analyzed in this study. It should be noted that the model's generality is not affected by this case study's specific location.

4.1. Indices and Parameters

i, j, k: Block indices ($i=1, 2, \ldots, I; j=1, 2, \ldots, J; k=1, 2, \ldots, K$)

t: A production planning period where ($t=1, 2, \ldots, T$)

e: Total number of blocks within the extraction cone of block (i, j, k).

l: Index related to e block within the extraction cone of block (i, j, k).

m: Index of the neighboring blocks of block i, including ($i-1, i, i+1$).

n: Index of the neighboring blocks of block j, including ($j-1, j, j+1$).

O^r_{ijk}: tonnage of Ore block (i, j, k).

r: Rock type (a characteristic that identifies the type of Rock and can be used to distinguish between the various Rock types present in the mine), ($r=1, 2, \ldots, R$)

W_{ijk}: tonnage of Waste block (*i, j, k*).

UT_{max}^{t}: Upper limit of the total extracted ore tonnage in period *t*.

LT_{min}^{t} : Lower limit of the total extracted ore tonnage in period *t*.

O_{ijk}^{1} - tonnage of Sulfide Ore block *ijk*,

O_{ijk}^{2} - tonnage of oxide Ore block *ijk*,

UO_{target}^{1t} - The desired target of Sulfide ore production for processing plant for each time period t,

LO_{min}^{1t} - Minimum acceptable sulfide ore tonnage that must be processed by mill in period *t*,

UO_{target}^{2t} - The desired target of oxide ore production for leaching operations in period *t*,

LO_{min}^{2t} - Minimum tonnage of oxide ore that must send to the leaching pad in period *t*,

G_{ijk}; Average grade of block (*i, j, k*).

UG_{max}^{t} : Upper limit of the average grade of material sent to the processing plant in period *t*.

LG_{min}^{t} : Lower limit of the average grade of material sent to the processing plant in period *t*.

P_1, P_2, P_3 - The penalty weighting parameters, provides a means of ranking the importance of meeting the different goals,

NAB^t - Maximum number of benches that can be extracted in any time period *t*,

BM - a large positive constant.

4.2. Decision Variables

Three types of variables are used in the proposed model.

- The first group of variables are binary variables in order to identify the extraction time of each block:

$Xijkt$ - Binary decision variable, if block ijk is extracted in period t it gets value of 1, otherwise 0.

- The second group of variables are also binary and used to identify the active benches in each time period:

V_k^t - Binary decision variable, if at least one block in the k^{th} bench is extracted in period *t* is equal to 1, otherwise 0.

- Finally, the last group of variables is deviation variables:

d_t^{o1+}, d_t^{o1-} - Deviation variables of sulfide ore production for processing operations above or below UO_{target}^{1t} for each time period *t,*
d_t^{o2+}, d_t^{o2-} - Deviation variables of oxide ore production for leaching operations above or below UO_{target}^{2t} for each time period *t,*
d_t^{g+}, d_t^{g-} - Deviation variables of cu average grade of sulfide ore sent to the processing plant above or below LG_{min}^{t} for each time period *t.*

4.3. Objective Function

The objective function is typically defined according to operational objective such as maximizing tonnage or minimizing costs. In this study, considering the constraints of the processing plant, the model adopts a GP approach to minimize deviations from predefined production and grade targets. The objective function is formulated as follows: (Equation 5) [5]

$$\text{Minimize Z} = \sum_{t=1}^{T}((P_1 * d_t^{o1-}) + (P_2 * d_t^{o2-}) + (P_3 * d_t^{g-})) \quad (5)$$

In the proposed model, deviation variables represent the extent to which deviates from the stated production and grade targets. They quantify the "underachievement" or "overachievement" of each goal, allowing for the minimization of these deviations in the objective function. These variables are crucial for handling multiple, potentially conflicting, goals in a decision-making process.

The penalty weights P_1 through P_3 are determined based on empirical cost assessments of deviations in ore grade and tonnage, reflecting their actual operational and economic consequences. Specifically, a 1% deviation in ore grade is evaluated for its impact on downstream processes, including metallurgical and concentrate recovery rates, plant throughput, product quality, and final pricing. Similarly, a one-ton deviation in ore production is analyzed in terms of its effect on feed stability, equipment scheduling, and overall operational efficiency.

The monetary costs required to compensate for each type of deviation are quantified and incorporated into the model as penalty weights. Consequently, each deviation is penalized in proportion to its true technical and financial impact, promoting a balanced and practical production schedule. To operationalize this:

- P_1 penalizes deviations in sulfide ore production,
- P_2 penalizes deviations in oxide ore production,
- P_3 addresses deviations below the minimum threshold of low-grade sulfide ore LG^t_{min}.

By minimizing the weighted sum of these deviations, the model seeks a balanced and practical short-term production schedule that maintains alignment with strategic goals and real-world limitations.

4.4. Constraints

Every production planning model incorporates a set of constraints that guide the feasibility and practicality of the proposed solutions. The general constraints of short-term production planning, which are commonly used in most of the models, are described below. However, to align the formulation with the principles of GP, these constraints have been formulated within the structure of GP. It is worth noting that for each constraint, its purpose and what it ensures are also explained.

4.4.1. Reserve Constraint

This constraint ensures that each block in the model can only be extracted once [40]:

$$\sum_{t=1}^{T} X^t_{ijk} \leq 1 \tag{6}$$

$$For\ \ i = 1,2,\dots,I; j = 1,2,\dots,J; k = 1,2,\dots,K$$

4.4.2. Mining Capacity Constraint

This constraint ensures that the total amount of extracted material, including both waste and ore, does not exceed the overall capacity of the available equipment in time period *t*.

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{r=1}^{R} X^t_{ijk} \cdot \left(O^r_{ijk} + W_{ijk}\right) \leq UT^t_{max} \tag{7}$$

$$For\ \ t = 1,2,\dots,T$$

It is possible to limit the amount of waste material removed in each period. To achieve this, a lower bound constraint has been introduced [41].

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{r=1}^{R} X^t_{ijk} \cdot \left(O^r_{ijk} + W_{ijk}\right) \geq LT^t_{min} \tag{8}$$

$$For\ \ t = 1,2,\dots,T$$

4.4.3. Processing Plant Capacity Constraint

The processing capacity constraints regulate the quantity of ore allocated to each processing method by enforcing lower, upper, and/or target bounds. In the present case study, two different processing methods are employed; flotation for sulfide ores and heap leaching for oxide ores:

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} X^t_{ijk} \cdot O^1_{ijk} - d^{o1+}_{t1} + d^{o1-}_{t1} = UO^{1t}_{target}\ \forall\ t \tag{9}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T} X^t_{ijk} \cdot O^1_{ijk} \geq \mathrm{T}.LO^{1t}_{min} \tag{10}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} X^t_{ijk} \cdot O^2_{ijk} - d^{o2+}_{t1} + d^{o2-}_{t1} = UO^{2t}_{target}\ \forall\ t \tag{11}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T} X^t_{ijk} \cdot O^2_{ijk} \geq \mathrm{T}.LO^{2t}_{min} \tag{12}$$

Equation (9) stipulates that, for each time period, the sum of the tonnage of sulfide ore sent to the flotation plant, minus any overproduction, must equal the available processing capacity.

Equation (10) ensures that the cumulative tonnage of sulfide ore delivered to the processing plant over the entire scheduling horizon exceeds a predefined minimum threshold.

Similarly, Equation (11) controls oxide ore, requiring that the tonnage sent to the leaching pad, adjusted for overproduction, must match the available normal capacity in each period.

Finally, Equation (12) guarantees that the cumulative quantity of oxide ore processed over the scheduling horizon meets a minimum planned tonnage.

4.4.4. Grade Blending Constraints

The quality of material varies over the deposit, but the processing plants demand a constant quality with the minimum quality variation. The Blending constraints restrict the combined mill feed grade of all ore blocks from exceeding lower and upper grade limits in any short-term time period [42]:

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} X_{ijk}^{t}\,.\,O_{ijk}^{1}.\,(G_{ijk}-UG_{max}^{t})-d_{t1}^{g+}+d_{t1}^{g-}\;=\;0 \qquad \forall\, t \tag{13}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} X_{ijk}^{t}\,.\,O_{ijk}^{1}.\,(G_{ijk}-LG_{min}^{t})-d_{t2}^{g+}+d_{t2}^{g-}\;=\;0 \qquad \forall\, t \tag{14}$$

These constraints reduce the variation in the grade of raw material sent to the processing plant. This will improve the processing plant efficiency, reduce processing costs, and increase concentrate production.

4.4.5. Slope Constraint

This constraint specifies that all the blocks above the given block, must be extracted before or simultaneous that block. To do this, one or more cone-shaped patterns representing the pit slope angle can be created, for example, 1:5 pattern, 1:9 pattern and 1:5:9 pattern [43] (see Figure 1).

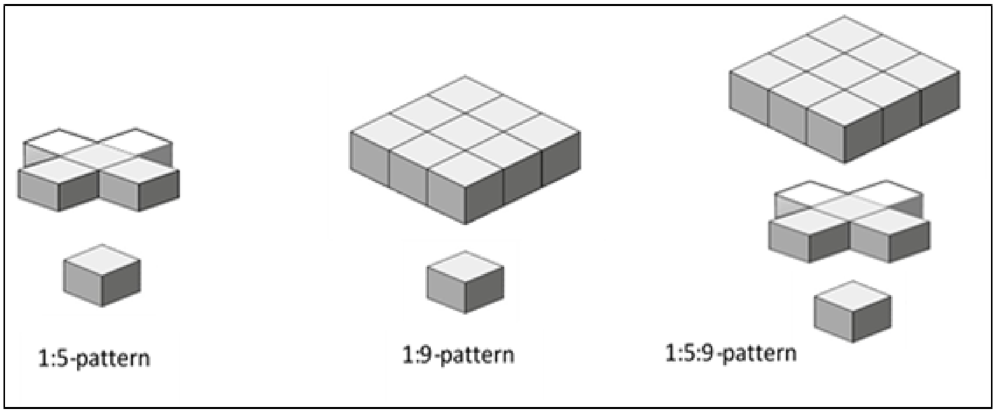


Figure 1. Three Slope pattern to model the precedence relationships

$$eX_{ijk}^{t}-\sum_{l=1}^{t}\sum_{m=i-1}^{i+1}\sum_{n=j-1}^{j+1} X_{m,n,k+1}^{l}\;\leq 0 \tag{15}$$

$$For\; l=1,\dots,e;\; t=1,2,\dots,T; i=1,2,\dots,I; j=1,2,\dots,J; k=1,2,\dots,K$$

4.4.7. Active Benches Constraints

The high number of active benches during each period can result in increasing equipment movements between benches over time, which ultimately increases production costs and can reduces total rock production efficiency. As a result, it is essential to impose constraints that reduce the number of active benches in each period and support smooth mining operations.

$$V_k^t \leq \sum_{i=1}^{I}\sum_{j=1}^{J} X_{i,j,k}^{t} \qquad \forall k,t \tag{16}$$

$$BM \times V_k^t \geq \sum_{i=1}^{I}\sum_{j=1}^{J} X_{i,j,k}^{t} \qquad \forall k,t \tag{17}$$

$$\sum_{k=1}^{K} V_k^t \leq NAB^t \qquad \forall t \tag{18}$$

In traditional LP-based models, mining plans are generated without regard to operational continuity. This results in the activation of multiple benches simultaneously—even in widely separated regions of the pit. To solve this, a new binary decision variable, V_k^t, is introduced. V_k^t is equal to 1 if at least one block in the k^{th} bench is extracted in period t and 0 otherwise. Therefore,

$\sum_{k=1}^{K} V_k^t$ represents the total number of active benches during period t.

Equations 16 and 17 are utilized to determine whether a block is mined within the k^{th} bench during period *t*, which determines whether or not that particular bench is active during that period.

Constraints will ensure that V_k^t is non-negative and the total number of active benches in period *t* is less than or equal to a predetermined value. These constraints limit dispersed block extraction, facilitate the efficient use of truck-shovel systems, and reduce displacement that directly lowers fuel consumption and tire wear.

Equation 18 is enforced to ensure that the number of active benches during that period does not exceed NAB^t.

To enhance operational efficiency and reduce unnecessary equipment movement, a parameter NAB^t, as the number of active benches per period was introduced. This parameter was empirically determined using the trial-and-error method through iterative model runs. The final value was calibrated using sensitivity analyses. This empirically derived value of NAB^t ensures that the model's output is both realistic and implementable in actual mining operations.

5. Case Study: Application of the Proposed Model

The proposed model was applied to a real-world open-pit copper mine. This mine was selected due to its complex operational constraints, which include:

- Stringent grade requirements for the ore delivered to the processing plant in each scheduling period,
- Defined minimum and maximum production capacity limits,
- Equipment relocation challenges; frequent switching between active benches is impractical and costly.

To solve the proposed mathematical model, called as PM (GP-based model), a case study was conducted using data from a section of the deposit scheduled for extraction over a six-month horizon. This mine produces sulfide and oxide ores. Sulfide ores are transported to the processing plant, while oxide ores are directed to the heap leaching pad.

Table 1 presents the key parameters used for the production schedule. In order to investigate the capabilities of the proposed model, the traditional model, called as TM, was also solved in which constraints (16) to (18) are ignored.

Table 1. General information of the presented model

Parameters	Value
Total number of blocks	1,873
I	75
j	74
k	15
Block size (m)	15×15×15
Production periods (month)	1, 2, …, 6
Total rock tonnage	15,930,000
UT_{max}^t (ton/month)	3,000,000
LT_{min}^t (ton/month)	2,500,000
Total sulfide ore tonnage	6,290,000
UO_{target}^{1t} (ton/month)	1,000,000
LO_{min}^{1t} (ton/month)	700,000
UG_{max}^t	0.6%
LG_{min}^t	0.5%
Total oxide ore tonnage	1,070,000
UO_{target}^{2t} (ton/month)	170,000
LO_{min}^{2t} (ton/month)	125,000
Total number of variables	11,238
Total number of constraints	103,239

Table 2 summarizes and compares the scheduling outcomes of the PM and the TM, including total ore tonnage, sulfide and oxide ore tonnages, and the average copper grade across each scheduling period.

As observed in Table 2, all production-related constraints have been satisfied in both models. Additionally, there is no significant difference between the final average grades of sulfide and oxide ores at the end of the six-month planning horizon. However, the ore grades delivered to the processing plant in the PM exhibit noticeably greater uniformity compared to the TM. This consistency is expected to improve processing efficiency and concentrate recovery, ultimately reducing operational costs and increasing revenue at the plant.

Table 3 provides a comparison of the number of active benches per period between the PM and TM models. The results indicate that in the PM, the average number of active benches per period decreased from 14 to 9, representing a 36% reduction. This reduction makes a more continuous and uniform extraction pattern, extends the extraction process laterally across the pit rather than vertically in depth, and enhancing operational continuity and operational feasibility.

Table 2. Results of production scheduling using both *PM* and *TM* models

Periods	Total rock		Sulfide ore				Oxide ore			
	mass (mt)		mass (mt)		Ave. grade (%)		mass (mt)		Ave. grade (%)	
	PM	TM	PM	TM	PM	TM	PM	TM	PM	TM
t=1	2.87	2.91	1.13	1.23	0.55	0.52	0.15	0.17	0.34	0.37
t=2	2.50	2.51	1.15	1.31	0.55	0.52	0.15	0.17	0.34	0.34
t=3	2.51	2.55	1.17	1.15	0.54	0.58	0.19	0.17	0.34	0.31
t=4	2.51	2.50	1.19	1.00	0.54	0.55	0.19	0.17	0.35	0.31
t=5	2.71	2.55	0.8	0.89	0.56	0.56	0.19	0.22	0.36	0.39
t=6	2.83	2.91	0.85	0.71	0.55	0.57	0.20	0.17	0.36	0.36
Sum	15.93		6.29		-		1.07		-	
Ave.	-		-		0.55		-		0.35	

Table 3. Comparison of the number of active benches in *PM* and *TM* models

Periods	t=1	t=2	t=3	t=4	t=5	t=6	Ave.
PM	11	6	8	8	10	10	8.83 ≈ 9
TM	13	13	15	13	15	14	13.83 ≈ 14

Table 4 presents a comparison of the number of extraction periods per bench. On average, this value decreased from 6 periods in the TM to 4 periods in the PM, expressing a 33% reduction in the duration of bench-level extraction. This decrease in extraction dispersion contributes to smoother equipment deployment and supports the implementation of bench-level scheduling strategies with fewer disruptions.

Table 4. Comparison of the Number of Extraction Periods per Bench in the PM and TM models

benches	K=1	K=2	K=3	K=4	K=5	K=6	K=7	K=8
PM	3	5	5	3	4	3	5	6
TM	6	6	6	6	6	6	6	6
benches	K=9	K=10	K=11	K=12	K=13	K=14	K=15	AVE.
PM	4	5	3	٣	1	1	2	3.7≈4
TM	6	6	6	6	6	2	3	5.5≈6

Table 5 provides a detailed comparative assessment of the Proposed Model (PM) and the Traditional Model (TM) for short-term production scheduling (STPS) in open-pit mining. The analysis reveals that the PM, through the incorporation of bench-level activation constraints and goal-based deviation minimization, outperforms the TM across multiple operational and production metrics.

The inclusion of the active bench constraint in the proposed short-term production scheduling model led to a 36% reduction in the average number of active benches per scheduling period and a 33% decrease in the number of extraction periods per bench, compared to the traditional model. These reductions are operationally significant and offer several tangible benefits across production, logistics, and equipment performance. A more spatially concentrated extraction pattern reduces unnecessary lateral equipment movements, simplifying truck-shovel coordination and haulage logistics.

From a production target standpoint, the PM exhibits lower deviations from both tonnage and grade targets. Specifically, average deviations from the sulfide ore tonnage and grade targets are reduced by 9% and 75%, respectively, compared to the TM. Such consistency is crucial for downstream processing efficiency and metallurgical recovery.

In terms of qualitative metrics, the PM significantly enhances equipment movement efficiency and operational implementability by limiting unnecessary equipment relocations between scattered benches. The model also delivers lower estimated operational costs, as inferred from reduced bench activations, improved extraction continuity, and more uniform material flow to the plant.

Based on empirical observations and benchmarks from comparable open-pit operations, such consolidation is estimated to yield up to 10–15% fuel savings, as inter-bench haul distances decrease.

From a planning and supervision standpoint, having fewer active benches facilitates better face management, smoother dispatching, and enhanced safety enforcement, particularly in confined operational zones.

Overall, the proposed approach aligns better with the physical and logistical realities of open-pit mining operations. The integration of goal programming, binary decision structures, and empirically calibrated constraints enables a more practical and economically viable scheduling framework. These improvements underscore the model’s potential to serve as a robust decision-support tool for mine planners seeking to bridge the gap between mathematical optimality and field-level feasibility.

Table 4. Overall comparison of the proposed model (PM) and the traditional model (TM) in short-term production scheduling (STPS)

Performance Metric	PM	TM	Improvement (PM vs. TM)
Average Active Benches per Period	10	14	36% Reduction
Average Extraction Periods per Bench	4	6	33% Reduction
Avg. Deviation Sulfide Ore Tonnage from target (Mt)	0.165	0.182	9% Reduction
Avg. Deviation Sulfide Grade from Target (%)	0.005	0.020	75% Reduction
Avg. Deviation Oxide Ore Tonnageb from target (Mt)	0.020	0.012	67% Increase
Avg. Deviation Oxide Grade from Target (%)	0.008	0.027	70% Reduction

Figures 2 and 3 provide a comparative visualization of the TM and PM models on block model.

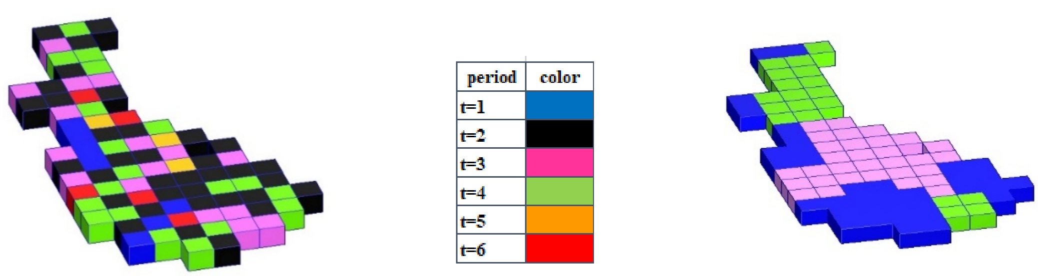
Sub-figure 2-a displays the production scheduling results obtained using the TM (traditional model). As shown, the extraction pattern is highly scattered, leading to operationally infeasible plans. This dispersed distribution of mining blocks results in inefficient equipment movement patterns and prevents the continuous and stable delivery of ore to the processing plant.

In contrast, Sub-figure 2-b illustrates the outcome of applying the PM (Goal Programming-based model) to the same bench. It can be observed that the extraction pattern is significantly more structured and spatially coherent. This improvement minimizes unnecessary equipment movement, increases the practicality of block extraction, and facilitates a steady flow of ore to the processing plant. As a result, overall operating costs are reduced for both the mine and the plant.

An additional key observation when comparing the TM and PM results is the time distribution of mining activity across benches. In the TM, each bench tends to be mined over a larger number of time periods, while in the PM, most benches are extracted within fewer periods. This reflects a smoother extraction sequence, reduced equipment relocation, and fewer active benches in each scheduling period.

As evidenced by these figures, the scheduling pattern generated by the PM appears to be far more practical and operationally executable, whereas the pattern produced by the TM is dispersed throughout the deposit. This implies that implementing the TM-based schedule would require frequent and inefficient movement of mining equipment between benches within each time period.

Figure 3 Confirms these findings by showing the extraction outcomes from the TM (a) and PM (b) models across a vertical (z–x) cross-section of the block model. These visualizations clearly demonstrate the effectiveness of the active bench constraint in enhancing operational continuity and reducing the number of periods required to complete the extraction of each bench.



(a), (K=1) (b), (K=1)

Figure 2. Production scheduling results on a single bench of the real block model used in the case study. (a) Scattered extraction layout in the traditional model (TM), (b) structured and continuous extraction in the proposed model (PM)

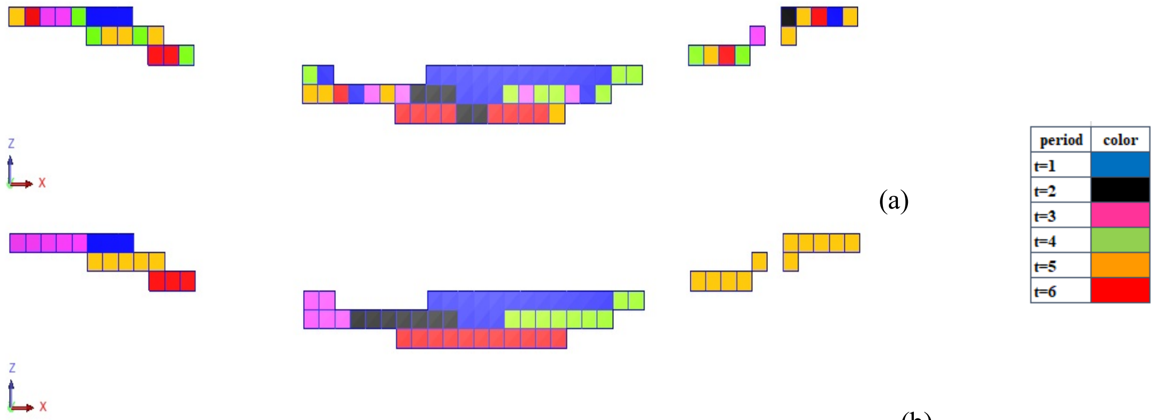


Figure 3. A z–x cross-section view of the block model used in the case study. (a) Scattered extraction layout in the traditional model (TM), (b) structured and continuous extraction in the proposed model (PM)

6. Conclusions

This study developed a mathematical model for short-term production scheduling in open-pit mining, aiming to minimize deviations in ore grade and tonnage while improving operational feasibility. The TM, due to the scattered distribution of selected blocks, posed significant challenges to practical implementation.

To address this limitation, an enhanced model was proposed by incorporating a new constraint that limits the number of active benches in each scheduling period. This constraint was empirically calibrated through sensitivity analyses and real-world simulations to ensure compatibility with actual operational conditions. In addition, penalty weights were introduced into the objective function based on the estimated cost impacts of deviations in grade and tonnage, thereby improving the economic realism of the optimization process.

The proposed model was applied to a real-world copper deposit with a 6-month planning horizon and comparison with the traditional model. The model consisted of 11,238 binary variables and 103,239 linear constraints. The results clearly demonstrated superior performance of the proposed model in terms of operational mining, ore delivery stability, and overall scheduling quality. Key improvements included:

- A 36 % reduction in the average number of active benches, (from 14 to 10 per period);
- A 33 % reduction in the number of extraction periods of each bench, (from 6 to 4 per period);
- Significant decreases in grade and tonnage deviations, resulting in better alignment with production targets;
- Reduced estimated operating costs due to less machine relocation and lower fuel consumption;
- Improved operational continuity in block extraction, leading to smoother equipment movement and more executable schedules.

These results confirm the effectiveness of the proposed approach in enhancing the practicality of short-term scheduling. Future extensions could integrate real-time fleet monitoring data to dynamically adjust NAB^t and further enhance responsiveness in production scheduling and also future work may explore dynamic adjustment of penalty weights based on real-time plant performance and the integration of uncertainty modeling for ore grades and geological variability.

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ارائه یک مدل کاربردی برای برنامه‌ریزی تولید کوتاه‌مدت معادن روباز مبتنی بر رویکرد برنامه‌ریزی آرمانی

سعیده قائدرحمت، جواد غلام‌نژاد*، و علی دباغ

دانشکده مهندسی معدن و متالورژی، دانشگاه یزد، یزد، ایران

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کلمات کلیدی

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جابه‌جایی تجهیزات

چکیده

برنامه‌ریزی تولید کوتاه‌مدت در معدن روباز نیازمند تعیین توالی استخراج بهینه برای بلوک‌ها است تا اهداف متعددی را در یک افق برنامه‌ریزی کوتاه‌مدت ماهانه، هفتگی و روزانه محقق کند. این اهداف شامل برآورده کردن محدودیت‌های لازم در مورد عیار سنگ معدن، تناژ تولید، حذف باطله و محدودیت‌های شیب است. یکی از اهداف کلیدی برنامه‌ریزی تولید کوتاه‌مدت تضمین تأمین پایدار و مداوم ارسال کانسنگ به کارخانه فرآوری و در عین حال به حداقل رساندن هزینه‌های عملیاتی از طریق اقداماتی مانند کاهش جابه‌جایی غیرضروری تجهیزات و تغییر در کیفیت خوراک است. با این حال، یکی از موانع اصلی در امکان‌سنجی عملیاتی برنامه‌ریزی تولید کوتاه‌مدت ، فضای کاری محدود برای تجهیزات و همچنین حرکت بیش از حد تجهیزات بین پله‌ها در هر دوره برنامه‌ریزی است. برای مقابله با این چالش‌ها، این مقاله از یک رویکرد برنامه‌ریزی آرمانی عدد صحیح با یک محدودیت جدید استفاده می‌کند که پله‌های فعال در هر دوره را محدود می‌کند و عملی بودن برنامه‌ریزی تولید را افزایش می‌دهد. برخلاف مدل‌های برنامه‌ریزی تولید کوتاه‌مدت مبتنی بر برنامه‌ریزی آرمانی قبلی، این مدل با تضمین تداوم استخراج و به حداقل رساندن حرکت تجهیزات، امکان‌سنجی عملیاتی را بهبود می‌بخشد. این مدل با استفاده از نرم‌افزار GAMS بر روی یک کانسار مس آزمایش شد. نتایج نشان می‌دهد که با اعمال این محدودیت جدید، میانگین تعداد پله‌های فعال در هر ماه از ۱۴ به ۱۰ (کاهش ۳۶ درصدی) و تعداد دوره‌های استخراج در هر پله از ۶ به ۴ (کاهش ۳۳ درصدی) کاهش یافته است، بدون اینکه موجب نقض محدودیت‌های موجود مانند عیار سنگ معدن، تناژ یا شیب دیواره پیت معدن شود. این رویکرد باعث بهبود راندمان تجهیزات، کاهش مصرف سوخت، کاهش هزینه‌های جابجایی تجهیزات، بهبود عملیات استخراج و افزایش امکان‌سنجی عملیاتی در شرایط واقعی می‌شود.

نویسنده مسئول مکاتبات: j.gholamnejad@yazd.ac.ir (س. قائدرحمت)