



Development of a Long-term Mining Production Planning Model Considering Working Spaces for In-pit Crushers

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Abstract

Designing and planning in open-pit mining encompass a series of processes that commence with the preparation of a block model. Subsequently, upon designing the final scope, it culminates with the timing and sequencing of mining blocks, with the aim to maximize the pit's value within specific technical and operational constraints. Mathematical programming methods have proven suitable for optimizing mine production scheduling. Previous studies have addressed various aspects, including the timing of deployment and periodic relocation of in-pit crushers. Nevertheless, significant challenges remain in integrating the in-pit crusher problem with production planning. This paper introduces a new mixed-integer linear programming model for long-term open-pit mine production planning, incorporating constrained pit deepening to enforce predominantly lateral progression throughout the planning horizon. To achieve this, the number of active benches in each time period was reduced, thereby decreasing the need for equipment movement between working benches. Furthermore, with the horizontal progression of the pit, more workspace became available for deploying in-pit crushers, reducing equipment movement costs between benches and overall transportation costs, ultimately lowering the mine's operational expenses. Finally, the proposed model was implemented at the Miduk copper mine. The results demonstrated that the proposed model successfully achieved the expected objectives, resulting in a 52.45% improvement in reducing the number of active benches and regarding execution time reduction, the model showed a 53.32% improvement.

1. Introduction

Open-pit mining design and planning encompass a structured sequence of activities starting with the development of a block model representing the mineral deposit. Following the determination of final pit boundaries, the process advances to production planning, which involves scheduling and sequencing the extraction of mining blocks [1]. The fundamental objective is to optimize the pit's Net Present Value (NPV) while satisfying various technical and operational limitations.

Production planning in open-pit operations requires establishing an efficient extraction sequence for blocks within the designated pit limits to enhance net cash flow while adhering to system constraints [2]. Given the impracticality of

simultaneous extraction of all materials within the pit boundaries, a phased extraction approach is implemented across a defined time frame to maximize the time value of money and overall profitability. This complex optimization challenge must reconcile operational and physical restrictions while pursuing the dual goals of maximizing block economic value and project NPV [3].

The planning process is categorized based on time horizons. Long-term production planning, spanning 10 to 20 years, focuses on creating comprehensive advance maps for all blocks within the final pit limits and plays a pivotal role in determining the mine's economic viability, particularly as operations progress into deeper, lower-grade zones [4]. Medium-term planning,

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covering 5 to 10 years, addresses specific operational aspects such as ore quality variations, hydrological conditions, geotechnical considerations, or equipment replacement strategies. Short-term planning, which deals with immediate operational periods ranging from one month up to five years, provides detailed execution plans that must align with the broader objectives of medium and long-term planning frameworks [5].

Two principal methodologies govern production planning in open-pit mining. The parametric approach, while not always yielding optimal solutions, remains widely adopted in industry-standard software due to its adaptability to the problem's scale and complexity [6]. In contrast, mathematical modeling techniques, enabled by advances in computing technology, employ sophisticated methods such as linear programming, mixed-integer linear programming, dynamic programming, and graph theory to systematically address production scheduling challenges in open-pit mining operations [7].

The studies conducted by previous researchers have been categorized into two main sections for analysis. The first section is dedicated to articles focusing on production planning. This includes studies that simultaneously address the topics of production planning and in-pit crushers. These studies emphasize the coordination between production planning and the use of in-pit crushers, proposing solutions to enhance efficiency, reduce operational costs, and improve the overall performance of mining operations. This categorization not only facilitates a more comprehensive review of prior research but also helps identify emerging research trends and areas for future focus in this domain.

The second section involves a detailed analysis of articles specifically related to in-pit crushers. These studies explore various technical aspects, such as design, placement, and optimization of in-pit crusher systems, as well as their impact on the efficiency of open-pit mining operations. They provide valuable insights and practical information in this field.

Mathematical programming has been effectively used by various researchers to address long-term planning problems in open-pit mining. In 1969, Johnson first used linear programming (LP), which led to formulation by Gershon [8]. Gershon presented a formulation for the time-constrained production scheduling problem based on Johnson's research [9]. Denby et al. used genetic algorithms for simulating the design and

production planning problem in open-pit mining [11]).

A MILP model that considers equipment access and mobility constraints proposed by Dimitrakopoulos and Ramazan. They considered two concentric inner and outer windows around each block. This optimization model extracts each block along with its neighboring blocks in the smaller inner window. If blocks within the inner and outer windows were not extracted, their tonnage was considered as "deviation," which was then minimized along with the deviation costs in the objective function. The resulting model reduces the movement of equipment in each bench [12].

A comprehensive history of mathematical programming models used in open-pit production planning has been presented by Osanloo et al. [3] for open-pit optimization and by Newman et al. for optimization in underground mine planning. Gaupp [13] proposed various strategies to accelerate the solution time of production planning problems by reducing the number of decision variables, adding cuts to strengthen the formulation, and using Lagrangian relaxation techniques.

Pourrahimian et al. proposed two MILP (Mixed Integer Linear Programming) formulations to address drilling sequence scattering within scheduling periods [14]. Their first model - a block-based approach building on Ramezan and Dimitrakopoulos [15] - enforced constraints requiring the extraction of a working block alongside at least 40% of its surrounding blocks within the same period. The second model integrated concepts from Caccetta and Hill [6] and Boland et al. [16], grouping blocks into "mining cuts" based on spatial location, rock type, and grade distribution before applying the scheduling framework. The authors demonstrated that this mining cut-based approach yielded more practical production plans.

Bley et al. introduced the technique of reducing decision variables using the branch-and-cut [17]. They used the integer linear programming formulation of Caccetta and Hill (2003) for the production scheduling problem and transformed the spatial structure of extraction sequence constraints into a Precedence-Constraint Knapsack Problem (PCKP).

Cullenbine et al. formulated the problem of block extraction sequencing using integer programming and presented an innovative approach called sliding time window to reduce computational time. In this model, the earliest and latest extraction times of blocks are calculated based on the overlying and underlying blocks.

Then the Lagrange relaxation method was used to solve it [18].

Sattarvand introduced an algorithm based on Ant Colony Optimization (ACO) [19], and Shishvan and Sattarvand presented another algorithm based on ACO in 2015 [20]. They claimed that the efficiency of the ant algorithm in solving the problem of sequential block extraction has a direct relationship with the defined parameters for the algorithm.

Gholamnejad et al. proposed a model for long-term planning in open-pit mines using integer programming [21]. The computation time required is very high, which poses challenges for larger-scale problems.

Long-term plans generated by formulas mainly organize the scattered block extraction into several consecutive benches that are practically executable. The displacement of equipment beyond the limit of pit slope in each planning period is limited to a minimum. Considering that transportation accounts for a significant portion of mining costs, a small change in transportation can have a significant impact on the value of a block. There is a high correlation between reducing transportation costs and increasing the value of the block [22].

Previous research attempted to develop models for mining production planning (short-term or long-term) considering issues such as some of the uncertainties and factors, including risk, sequential block extraction, etc. However, reducing equipment movements between benches and concentrating equipment in a single bench, as well as reducing horizontal and vertical displacement for equipment, except in rare cases, have not been adequately addressed. Yet, this is one of the factors that carry out significant costs on mining operations.

Considering the fact that transportation costs account for half of the mining costs, a small change in transportation costs can have a significant impact on the blocks value. There is a strong correlation between the reduction of transportation costs and the increase in block value [23]. The relocation of the primary crusher within the pit is solely performed to reduce transportation costs. Changes in block values will certainly alter the sequence of block extraction. In general, for two mineral blocks with the same metallic content, the block that is closer to the in-pit crusher holds greater value. As a result, it will have a higher extraction priority. On the other hand, the revenues obtained from changing the transportation system may significantly affect the ultimate pit limit [24].

In a study conducted by Nehring et al., the effects of using IPCC systems on production planning and the sequencing of block extractions and pushbacks were well demonstrated by comparing production planning when using truck-shovel transport systems and mobile and semi-mobile in-pit crushing systems [25].

Among the key issues addressed in the field of production planning are challenges related to various uncertainties, such as price fluctuations [26], stockpile limitations [27], access space constraints [21], production capacity [28] and processing plant operations [29]. However, research on the optimization of In-Pit Crushing and Conveying (IPCC) systems remains relatively limited. While some studies have focused on determining the optimal location of in-pit crushers [30], others have expanded their scope to include system capacity [31], availability [32], and the timing of system implementation [33]. Despite these efforts, a comprehensive understanding of how in-pit crushers impact production planning and how to optimize their integration into mining operations remains an area requiring further exploration [34].

By 2016, advancements in technology and methodology led to the determination of the optimal location for the in-pit crusher. This was achieved through the application of various approaches, including heuristic methods, computer modeling, hub location models, and Markov chain models.

Paricheh et al. also considered the possibility of relocating the IPCC system within a long-term plan. They believed that the location of the crusher has a long-term nature, and decisions regarding its placement and the timing of its relocation should be evaluated over an extended period [35].

Radlowski examined the in-pit crusher system as an option for open-pit mines. Simulations were conducted for both the shovel-truck transportation system and the IPCC system, and the results from these simulations, along with feasibility study data, were used as inputs for economic comparisons. Cash flow analysis revealed that the IPCC system would achieve a return on investment within four years and would have overall costs 30% lower compared to the shovel-truck system [36].

Changzhi examined the optimal point at which the shovel-truck system transitions to the IPCC system. He considered the relocation of an in-pit crusher system and the impact of changing its location on cost variations. However, this researcher addressed the issue only briefly, and certain parameters critical to optimization were not

taken into account [37]. Konak et al. examined the effects of pit geometry and the necessity of mine access to the optimal pit location, which is primarily based on minimizing haul distances [38].

Turnbull and Cooper, and Morrison and Laurell, in the same year, evaluated the IPCC system and focused on potential options for drilling, transportation, and dumping. They categorized these options based on the system's applications. They believed that when the average truck cycle time exceeds 25 seconds, the IPCC method becomes cost-effective. Additionally, it was mentioned that the IPCC system is far more suitable for new operations and those under development compared to stable existing operations. Furthermore, a specific type of IPCC, deemed highly suitable for specialized mining applications, was also studied [39].

Atchison and Morrison conducted a study focusing on the critical factors to assess when determining the appropriateness of various IPCC systems. These factors encompass system productivity, the interplay between drilling, blasting, and the sequencing of bench operations, as well as mobility. They also highlighted the importance of flexibility to accommodate changes in reserves, scalability, and the system's compatibility with other components [40]. Rahmampour et al. proposed a method for locating an in-pit crusher within open-pit mines. In this study, the process of determining the optimal position for the placement of the in-pit crusher system was modeled as a hub location problem [35].

Paricheh and Osanloo carried out a comprehensive study aimed at identifying the optimal placement of an in-pit crusher while accounting for uncertainties in operational and production costs. Their analysis was grounded in the application of a stochastic facility location model, providing a robust framework for addressing these challenges [41]. Yarmuch et al. assessed the placement of the crusher system in the Chuquicamata open-pit mine in Chile, employing a Markov chain approach. This method incorporated equipment failures to evaluate the production capacity of crusher systems [42].

Builes introduced a model based on mixed-integer linear programming to address the challenge of determining the optimal location for an in-pit crusher and conveyor system. His research utilized a dynamic facility location model, taking into account economic and operational factors alongside the mine's long-term production planning [43]. Abbaspour and his team conducted

a comprehensive study to design optimal solutions for the placement and relocation of in-pit conveyor and crusher systems in open-pit mines. Their approach leveraged the transportation problem methodology to enhance system efficiency [44].

Shamsi and Nehring conducted a study to determine the optimal depth at which the transition from the shovel-truck system to the IPCC system becomes most effective. In their research, the conclusion of each mining phase was identified as a potential point for replacing the transportation system [45].

Shamsi et al. also introduced a mixed-integer programming model to pinpoint the optimal location and timing for relocating the in-pit crusher. Their study compared production planning scenarios for waste and ore using both the shovel-truck system and the IPCC system over the mine's lifespan. The system delivering the highest NPV was ultimately recommended as the optimal material handling solution [46].

Kamrani and his team assessed the feasibility of using semi-mobile in-pit crusher systems through a two-stage mathematical model. Their research emphasized minimizing transportation costs and highlighted the advantages of this innovative approach [47]. Abbaspour et al. carried out a comparative analysis of shovel-truck systems and in-pit crusher systems in open-pit mines. Employing system dynamics modeling, they conducted a technical evaluation to identify the most efficient transportation method [48].

Findlay and Dimitrakopoulos focused on stochastic optimization techniques for the long-term planning of mining complexes that incorporate IPCC systems [49].

Finally, Kamrani et al. developed two advanced models for long-term mine planning, integrating road networks and conveyor systems. Their work provided a comparative analysis of the IPCC system and the shovel-truck system, emphasizing the benefits of integrating these networks [50].

The use of in-pit crushers significantly affects the sequencing of extraction and pushback development [51]. The strategic positioning of in-pit crushers is fundamentally constrained by active extraction operations, as their placement is prohibited within or above actively mined zones [25]. This restriction stems from both operational safety requirements and the necessity to maintain stable wall slopes [52]. Consequently, the crusher cannot process material located directly beneath its current position, rendering underlying blocks inaccessible without equipment movement [53]. Optimal system placement is therefore critical to

prevent interference with ongoing extraction activities on lower bench levels [54]. This operational reality necessitates meticulous planning of crusher repositioning and conveyor belt extensions to maintain access to ore deposits situated beneath previous crusher installation sites [55].

These spatial constraints underscore the importance of incorporating in-pit crusher operational parameters as a key consideration in open-pit mine production planning [56]. Isolated approaches to production scheduling and In-Pit Crushing and Conveying (IPCC) system design frequently yield suboptimal solutions that may prove operationally impractical [57]. Consequently, the integration of IPCC system dynamics with extraction planning emerges as a crucial operational strategy [35], as this synergy directly governs critical mining parameters including extraction sequences [58], stripping ratios [59], operational adaptability [60], and ultimately, project economics [61].

Given the aforementioned reasons and the importance of the subject, this study aims to reduce equipment mobility by decreasing the number of active benches per time period while expanding the pit horizontally to increase available working space for the in-pit crusher, ultimately leading to reduced mining operational costs.

The incorporated model constraints restrict vertical pit advancement, enforcing predominantly lateral pit expansion. Consequently, equipment movement between working benches is significantly reduced. These implemented constraints account for available operational space limitations of the in-pit crusher system, thereby minimizing equipment movement between active benches and ultimately reducing both haulage costs and overall mining operational expenditures.

In the continuation of the article, the proposed model along with its limitations, variables, and symbols will be explained, and then the model will be applied to a case study. For comparative analysis, the model presented in this study denoted by the symbol (NM), was evaluated alongside a conventional model (denoted as TM) that explicitly omits Constraints 14 through 18. It should be noted that TM constitutes the original formulation proposed by Dimitrakopoulos and Ramazan [12].

2. Materials and Methods

The fundamental objective of optimization problems lies in determining extremal solutions, whether minimizing or maximizing target

functions [62]. This field, formally designated as mathematical programming [63], systematically evaluates feasible solution spaces to identify optimal outcomes against predefined performance criteria. Contemporary scientific practice has witnessed the ubiquitous adoption of optimization methodologies, with their utilization expanding exponentially across diverse disciplines in both scope and importance [64].

The mining engineering domain has particularly benefited from mathematical optimization paradigms [65]. As established in prior discussions, these techniques provide critical enhancements to production planning frameworks, facilitating net present value optimization [66], operational cost minimization [67], waste stream reduction [3], and ore dilution mitigation [68].

Within the spectrum of analytical decision-support tools, linear programming emerges as the predominant approach for open-pit mine planning applications due to its capability to handle continuous variable domains [69]. Discrete decision variables necessitate integer programming formulations [70], while hybrid systems requiring both discrete and continuous variables are effectively modeled through mixed-integer linear programming frameworks [71].

The presented programming model is of the type integer linear programming. In this model, the objective is to maximize the current NPV of the entire project in the long-term open-pit mine production planning. Various constraints have been considered in this regard. The integer programming model is further described below.

3. The Presented Model

Based on the discussions in the previous sections and the studies conducted on the parameters for designing and planning open-pit mine production, a mathematical model for long-term production planning is presented using integer linear programming. In this model, the objective function is to maximize the current NPV, and additional constraints are added to the previous models in order to achieve the mentioned objectives in the previous sections. The different parts of the model are described below.

3.1. Objective Function

In long-term production planning, the main objective is usually to maximize the current NPV of the entire project in the time horizon. However, other objectives such as minimizing risk [72], maximizing reserves [73], minimizing costs, etc.,

can also be considered. In order to formulate the objective function, the profit and costs need to be examined first.

The profit obtained from block i in period t is equal to the revenue from selling the final product

$$v_{ijkt} = \begin{cases} T_{ijk}^o * (g_{ijk} * R^p * P - c^{OP}) & \text{if } g_{ijk} \geq g_c, \forall i, t \\ 0 & \text{if } g_{ijk} < g_c \end{cases} \quad (1)$$

v_{ijkt} : Revenue from selling block ijk in period t

g_c : Cutoff grade

g_{ijk} : Grade of block ijk

R^p : Processing plant recovery

P : Price per ton of metal

c^{OP} : Processing cost per ton of ore

T_{ijk}^o : Tonnes of mineral in block ijk

Extraction costs include the costs of main operations such as drilling and blasting, loading, and hauling. The costs are estimated separately for ore and waste. The extraction cost for each block is calculated as follows:

Extraction cost = Drilling and blasting cost + Loading cost + Hauling cost

$$C = C_{ijk}^{DB} + C_{ijk}^L + C_{ijk}^T \quad \forall i \quad (2)$$

Profit (V_{ijkt}): The profit obtained from extraction, processing, and selling block ijk in period t is equal to the revenue minus the cost.

$$V_{ijkt} = v_{ijkt} - C \quad (3)$$

Net Present Value:

$$NPV = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T \frac{V_{ijkt} \times x_{ijkt}}{(1+d)^t} \quad (4)$$

Finally, the objective function is defined as NPV maximization.

$$Max Z = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T \frac{V_{ijkt} \times x_{ijkt}}{(1+d)^t} \quad (5)$$

in block i minus the extraction costs. A cutoff grade is used to determine whether a block is considered waste or ore. If the grade of a block is below the cutoff grade, it is considered waste. The revenue for such blocks is zero.

Where:

ijk - the indices are related to the row, column and level of blocks in the model, and the block counters are in the x , y and z directions, where k decreases with depth.

$$i = 1, 2, \dots, I$$

$$j = 1, 2, \dots, J$$

$$k = 1, 2, \dots, K$$

I , J , and k : respectively represent the number of blocks in the block model in the x , y , and z directions.

t - the time period for mine production planning

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

T - the number of periods in which the blocks are scheduled

V_{ijkt} - the profit from extracting, processing, and selling block ijk in period t

x_{ijkt} - a binary variable that is 1 if block (i, j, k) is extracted in period t and 0 otherwise.

d - discount rate

3.2. Constraints

In this section, all constraints applied in the model are described. All constraints are considered linear.

3.2.1. Grade combination constraints

Grade combination constraints are important as they regulate the quality of input feed to the plant and control the grade of each block's mineral value.

For these constraints, upper and lower bounds are considered.

$$\sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (g_{ijk} - AG_{max}^t) \times OT_{ijk} \times x_{ijkt} \leq 0 \quad \forall t \quad (6)$$

$$\sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (g_{ijk} - AG_{min}^t) \times OT_{ijk} \times x_{ijkt} \geq 0 \quad \forall t \quad (7)$$

g_{ijk} - Average grade of block ijk

AG_{max}^t - Maximum average grade of ore sent to the processing plant in period t

AG_{min}^t - Minimum average grade of ore sent to the processing plant in period t

OT_{ijk} - Tonnes of ore in block ijk

3.2.2. Processing capacity constraints

Processing capacity constraints impose upper and lower limits on the amount of ore that can be processed in each period. If the processing plant has a minimum tonnage requirement, the lower bound can be used for extraction scheduling.

$$\sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (OT_{ijk} \times x_{ijkt}) \leq PU_t \quad \forall t \quad (8)$$

$$\sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (OT_{ijk} \times x_{ijkt}) \geq PL_t \quad \forall t \quad (9)$$

PU_t - Maximum processing capacity in each period, t

PL_t - Minimum amount of ore that must be processed in period t

3.2.3. Mine capacity constraints

$$9x_{ijkt} - \sum_{r=1}^t (x_{i-1,j-1,k+1,r} + x_{i-1,j,k+1,r} + x_{i-1,j+1,k+1,r} + x_{i,j-1,k+1,r} + x_{i,j,k+1,r} + x_{i,j+1,k+1,r} + x_{i+1,j-1,k+1,r} + x_{i+1,j,k+1,r} + x_{i+1,j+1,k+1,r}) \leq 0 \quad \forall i, j, k, t \quad (12)$$

r - Time period index, $r = 1, 2, \dots, t$.

3.2.5. Storage constraints

This constraint indicates that each block cannot be extracted more than once. Furthermore, this equation enables the simultaneous determination of the ultimate pit limit and production schedule, formulated as follows:

$$\sum_{t=1}^T x_{ijkt} \leq 1 \quad \forall i, j, k \quad (13)$$

Capacity constraints impose upper and lower bounds on the tonnage of ore that can be extracted in each period. The waste-to-ore ratio can also be controlled with the lower bound of extraction capacity (ML_t).

Total extraction capacity constraints:

$$\sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K T_{ijk} \times x_{ijkt} \leq MU_t \quad \forall t \quad (10)$$

$$\sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K T_{ijk} \times x_{ijkt} \geq ML_t \quad \forall t \quad (11)$$

ML_t, MU_t - Upper and lower bounds for mining capacity to tonnage in time period t

T_{ijk} - tonnage in block ijk .

3.2.4. Block precedence constraints

Precedence constraints restrict the extraction of a block only if a specific set of blocks has been completely extracted in the previous period or in the same period. There are several methods to enforce the precedence constraints, including the 1:5 slope pattern, the 1:9 pattern, and the 1:5:9 pattern. In this model, the precedence constraints for a 1:9 pattern are enforced as follows:

3.2.6. Vertical movement restrictions of equipment

These restrictions were presented by Gholamnejad et al. [21] in their model. Using these constraints, the researchers minimized the average number of working benches.

The relevant constraints can be written as follows:

$$\frac{\sum_{i=1}^I \sum_{j=1}^J x_{ijkt}}{I \times J} \leq y_{kt} \leq \sum_{i=1}^I \sum_{j=1}^J x_{ijkt} \quad \forall t, k \quad (14)$$

$$\frac{\sum_{t=1}^T \sum_{k=1}^K y_{kt}}{T} \leq \eta \quad (15)$$

η - An integer represents the maximum average number of benches that are allowed to be extracted in each period specified by the designer.

y_{kt} -is a binary variable that is equal to 1 if at least one block is extracted inside the k th bench in period t and 0 otherwise. In fact, $\sum_k y_{kt}$ Indicates the number of benches extracted in a timing period (t).

A bench is considered active only if a block from that bench is extracted in a specific scheduling period; therefore, the left-hand side of constraint 15 represents the average number of benches extracted in a certain timing period.

3.2.7. Maximum vertical depth extractable in each time period and restriction of horizontal movement of equipment

Considering the changing shape of the pit over time, the crushing system must be relocated periodically. These relocations are not only time-consuming but also increase project costs. One of the key factors in cost reduction is minimizing transportation expenses. The relocation of the primary crusher within the pit is primarily aimed at reducing transportation costs. This relocation can alter the extraction sequence of the blocks. Additionally, changing the transportation system can influence the ultimate pit limit and increase mining revenues. The installation and relocation of the in-pit crusher also present challenges. The crusher requires adequate working space and proper access to function effectively. Relocating and reinstalling it at different intervals is not only costly but also causes interruptions in mining operations.

Furthermore, installing the crusher inside the pit means that a portion of the mineral reserve becomes inaccessible—effectively blocked—due to the need for foundation and workspace for the crusher setup. Therefore, in open-pit mine production planning, it is crucial to account for the constraints related to workspace of the in-pit crusher and its impact on production scheduling. Among these constraints are limiting the number of active benches, reducing the advance depth per time period, and minimizing equipment movement between working benches. By applying these restrictions, the advance is primarily horizontal, ensuring access to the crusher installed in a suitable location for extended periods.

This approach not only reduces transportation costs but also significantly lowers mine operating expenses. Consequently, after collecting and analyzing data from previous models, a constraint has been added to the model that primarily limits pit advance in the horizontal direction while reducing vertical pit advance. This modification ensures consistent operational focus across different time periods and significantly reduces equipment movement between working benches. The resulting strategy not only contributes substantially to cost reduction but also improves the efficiency of semi-mobile in-pit crushing system. To better understand the necessity of applying new constraints regarding the in-pit crusher's workspace conditions, refer to Figures 7 and 8. These figures clearly illustrate the difference between two scenarios: one without workspace constraints and the other with these constraints applied.

Unconstrained Scenario Analysis (Figure 1)

Figure 1 illustrates the extraction sequence for a hypothetical ore deposit using a semi-mobile in-pit crushing system. In this scenario, no constraints are imposed on the crusher's working space, allowing both vertical and horizontal pit advancement to proceed freely. Extraction begins on the eastern side of the deposit and gradually progresses westward. Under these conditions, blocks with the highest economic value are extracted first. However, to maintain an optimal haulage distance for trucks to the crusher, the initial pit depth is limited.

During the first extraction phase, blocks are mined up to Level 4 and transported to a crusher likely located outside the pit. Subsequently, the crusher is relocated to a deeper section within the void created by the extraction of Phase 1 blocks, enabling access to Phase 2 blocks. This process continues, and as the ore deposit expands horizontally, the crusher is repositioned again to facilitate access to new blocks. Ultimately, six extraction phases and five crusher relocations are performed. Given the high cost and time-consuming nature of frequent crusher relocations—as well as the partial loss of mineral reserves due to the need for crusher foundations and working space—minimizing the number of relocations is of paramount importance.

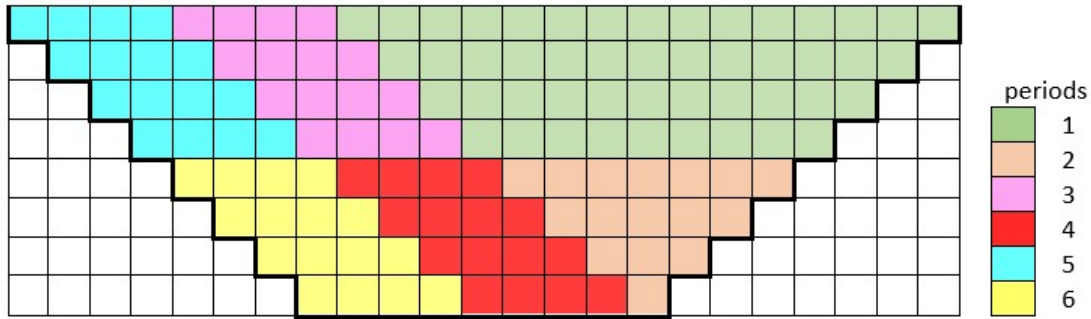


Figure 1. Extraction sequence for the hypothetical ore deposit using a semi-mobile in-pit crusher system without workspace constraints.

Constrained Scenario Analysis (Figure 2)

Figure 2 depicts the extraction sequence with imposed constraints on the in-pit crusher's working space. In this scenario, both vertical and horizontal pit advancement are restricted, and extraction is carried out from two working benches. This approach reduces the number of crusher relocations and enhances operational efficiency.

In the first period, blocks are extracted from two working benches without requiring crusher relocation. In the second phase, blocks are mined from Level 3 while maintaining direct access to the crusher. By the third phase, as haulage distances increase, the crusher is relocated to enable access to deeper levels. These constraints promote horizontal pit progression while reducing the number of active benches per phase. Consequently, operations become more concentrated around the crusher, decreasing relocation, movement and haulage costs.

As shown in the figures, the use of an in-pit crusher significantly influences the extraction sequence and pushbacks. The crusher cannot be placed in an area where active mining is ongoing, as this would block access to underlying blocks.

Therefore, the crusher's position must be carefully selected to avoid interference with extraction operations in lower benches. This needs certain planning for crusher relocation and conveyor adjustments to prevent ore reserve blockages.

Based on the analysis, the new model incorporates constraints on the number of active benches and vertical progression per time period into the base production planning model. These constraints promote horizontal pit advancement while limiting vertical progression. As a result, operational focus is enhanced across different time periods, and equipment movement between working benches is reduced.

Given the costly and time-intensive nature of crusher relocations—along with the loss of mineral reserves due to foundation and workspace requirements—implementing constraints related to in-pit crusher workspace in open-pit mine production planning is critically important. These constraints not only reduce operational costs but also improve extraction efficiency and productivity. Ultimately, by incorporating these constraints, a more optimized production plan can be achieved, enhancing both the economic and technical performance of the mine.

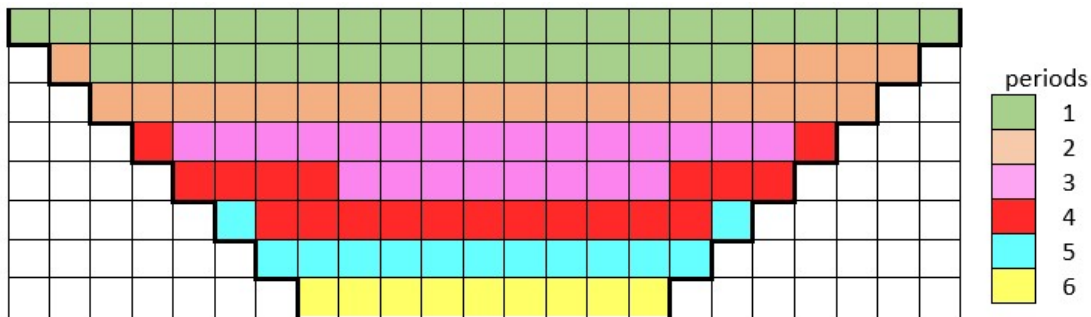


Figure 2. Extraction sequence for a hypothetical ore deposit when using a semi-mobile in-pit crusher system, with the addition of constraints related to the in-pit crusher workspace and limiting vertical and horizontal pit advance

To achieve the goal of maximizing extraction along the horizon and limiting depth progression—such that the pit expands horizontally and avoids excessive deepening—a parameter called the *maximum allowable extraction depth per period (D)* is defined. This parameter serves as a controlling criterion, specifying the permitted depth for extraction in each stage or time period. By imposing this constraint, uncontrolled vertical expansion of the pit can be prevented, shifting the focus instead to horizontal extension and optimal exploitation of mineral reserves. This approach not only contributes to sustainable resource management but also offers significant economic benefits, as previously mentioned.

Therefore, to incorporate in-pit crusher application conditions into production planning, the following constraints have been added to the model:

First, a constraint must be defined to ensure that each block is extracted in only one time period. Thus, each mining block is extracted once and only in a single period, preventing re-extraction. This condition guarantees that once a block is extracted, it is always considered as mined in subsequent periods, avoiding duplicate extraction. In other words, this constraint ensures that the extraction process is irreversible, with each block included in the mine production schedule only once and in a single time period. This contributes to optimizing the extraction process and preventing resource wastage.

$$x_{ijk(t-1)} \leq x_{ijkt} \quad \forall t \in \{2, \dots, T\} \quad (16)$$

As previously mentioned, a parameter called the maximum extractable depth per period (D) is defined. The value of this parameter D is determined based on the designers experience.

According to equation 14, if at least one block from one bench is extracted in period t, then $y_{kt} = 1$.

Consider the blocks x_{ijk_1} and x_{ijk_2} with $k_1 < k_2$ and $k_2 - k_1 > D$. Due to the limitation that each block is mined only in one period of time, blocks x_{ijk_1} and x_{ijk_2} must be extracted in two different time periods.

To reduce the amount of computation and decrease the model's complexity, a constraint is added to the model that focuses on the mining benches. This constraint is applied to simplify computational processes and enhance the model's efficiency. Specifically, by concentrating on the mining benches, the model focuses only on the key and impactful sections of the mining extraction

process. This approach not only reduces the volume of data requiring processing, but also significantly decreases the model's runtime. Furthermore, by eliminating redundant factors, the model's accuracy and reliability are improved. Ultimately, this constraint allows the model to deliver more optimal results in mine planning and operation management while using fewer computational resources.

So, we can write:

$$y_{kt} = 0 \quad \begin{matrix} t=1 \\ k > D \end{matrix} \quad (17)$$

$$y_{k_2t} \leq y_{k_1(t-1)} \quad \begin{matrix} \forall t \in \{2, \dots, T\} \\ k_2 - k_1 > D \end{matrix} \quad (18)$$

In this case, for $k_2 - k_1 > D$, block x_{ijk_1} must have been extracted in the time period before block x_{ijk_2} ; in other words, these two blocks are extracted in two different time periods. Thus $y_{k_2t} \leq y_{k_1(t-1)}$.

In this model, by incorporating new constraints, the operational conditions of using in-pit crushers and the associated workspace limitations have been considered. Specifically, applying these constraints reduces the number of active benches in each time period, which decreases the model's computation time. Reducing computation time is a key feature of a professional and efficient model, as it enables faster and more accurate decision-making.

Additionally, by reducing the model's complexity, the depth movement within the pit is restricted, and the movement of equipment between mine benches is minimized. This leads to a greater focus on extraction operations, significantly lowering operational costs. Overall, this improved model not only enhances operational efficiency but also, by reducing complexity and computation time, enables more optimized execution of mining processes.

To validate and evaluate the model's performance, real-world data from the Miduk copper mine was used as a case study. The validation results, including quantitative and qualitative analyses, are presented in detail in the following section.

4. Case Study: Miduk Copper Mine

Miduk Copper Mine is located 42 kilometers northeast of Shahr-e Babak and 132 kilometers northwest of Sarcheshmeh Copper Mine [12]. Its direct distance to Shahr-e Babak is 27 kilometers and to Sarcheshmeh is 80 kilometers. The highest

point in this region is at an altitude of 2842 meters above sea level, and its longitude and latitude are $10^{\circ} 55'$ and $25^{\circ} 30'$, respectively [74]. Figure 3

shows the geographical location of Miduk Copper deposit.

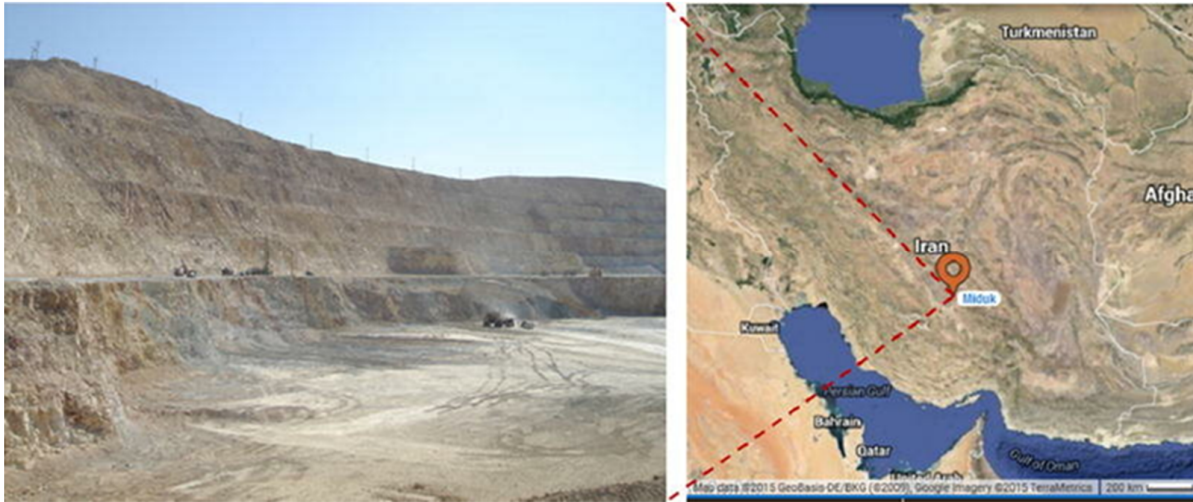


Figure 3. The right-hand figure illustrates the geographical location of the Miduk copper mine, while the left-hand figure presents an image of the mining site. [75]

The Miduk mineral deposit is divided into three zones: oxide, supergene, and hypogene. Iran's Central Metallogenic Belt is one of the most important lines of the Alpine-Himalayan orogenic system related to the Eocene. One of its known belts, along with the Urumiyeh-Dokhtar plutonic volcanic zone, is Miduk Copper Mine.

4.1. Implementing A long-term production planning model for Miduk Copper Mine and analyzing the results:

The proposed planning model has been used for the shovel-truck system at this mine. Due to the limited capacity of the equipment, the mine's lifespan is estimated to be around 29 years, of which 18 years remain. The dimensions of the mining blocks in this mine are $15 \times 2.5 \times 2.5$ in length, width, and height, respectively. In this model, the dimensions of the blocks have been changed to $15 \times 15 \times 15$ to make the model more practical. The total number of benches in the model is 15. To reduce the number of released variables and time required for solving the model, the long-term planning model is executed over six time periods of three years each.

On average, at the Miduk copper mine over the course of a year, the upper limit of extracted sulfide ore tonnage along with waste is 8 million tonnes, and the lower limit is 6 million tonnes, which are then sent to three different destinations depending on the grade: processing plant (including a copper smelter), heap leaching, or dump leaching. The

mine cut-off grade is planned to be 0.2% in production planning. The upper limit of the extraction tonnage from the mine during a year is 35 million tonnes, and the lower limit is 30 million tonnes, corresponding to the production upper limit of 2.5 million tonnes and the lower limit of 1 million tonnes of oxide ore, respectively. In 2017, the cost of mining and processing was \$9.5 per ton of ore, the cost of smelting and refining was \$423 per ton of copper metal, and the selling price of copper metal was \$6,500 per ton. In this model, based on the experience of previous years, a block of completely Sulphide or oxide ore or waste (pure or low-grade) is considered, and there is no block with a combination of ore and waste. Two scheduling models were created to analyze the results obtained from the proposed model in this research: one using the NM model presented in this article and the other disregarding the new constraints added in this paper (constraints 14 to 18) and named the TM model. Information on both scheduling models is presented in Table 1, which provides details for the application of the model to the Miduk mine.

Please use the Time New Roman font for all text within figures. If charts or other types of graphs are included, provide editable source files within the main text document. To add text to figures, utilize the "New Drawing Canvas" feature in Microsoft Word. Begin by selecting this option, then insert your figure into the canvas. Subsequently, use the "Text Box" option located in the "Insert" section to

add any necessary notes directly onto the figures (as shown in Figure 1).

When illustrating multiple figures with a single caption, and if these figures are divided into parts (a), (b), (c), etc., as demonstrated in Figure 2, create

a table and place each figure within a separate cell. Then, create a second table directly below the first one and write the caption within it, aligning it precisely beneath the corresponding figures, as illustrated in the example.

Table 1. Model application information for Miduk mine

Description	NM Model	TM Model
Total number of time periods	6	6
Annual discount rate	18 percent	18 percent
Number of restrictions	629,528	100,024
Number of variables	499,591	499,501
Model solving time (seconds)	3.31	7.09

4. Discussion

As mentioned in the previous section, to compare and evaluate the proposed model in this article (NM), the NM and TM models were run for the Miduk copper mine. According to previous studies on optimization models conducted by other researchers, GAMS software was chosen to solve the two models because it is an efficient tool for designing complex applications. The most important use of GAMS is to optimize research models in operations. GAMS software is used to solve linear (LP) and nonlinear (NLP) problems and mixed integer (MIP) problems, and more. GAMS version 24.3.3 and CPLEX Solver were used in a laptop with specifications (RAM 16.0 GB Intel® Core TM i5-1135G7 CPU @ 2.40GHz) to solve these two models.

As the time required to solve the model in modeling and applying the model to problems is very important and as mentioned in the previous sections, one of the most important factors in presenting this model has been reducing the time to

solve the model. Table 1 shows that it takes 7.09 seconds to solve the TM model, while the NM model takes about 3.31 seconds to run, which is a 53.32% decrease, which is very significant. In problems with large dimensions, the time to solve the model is very important, and if the time to solve the problem is too long, the model is often considered impractical. Table 2 and figure 4 summarizes the results of running the two models for easier comparison.

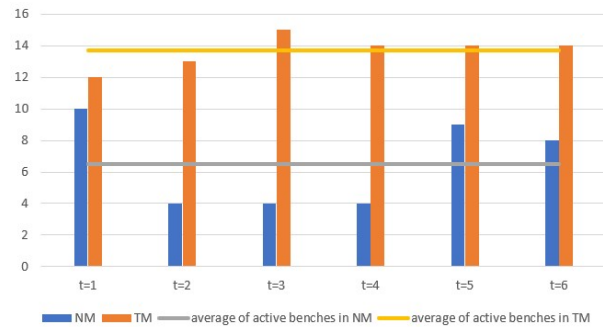


Figure 4. Number of active benches in periods

Table 2. The results of running two models

period	Total operation tonnage		Sulphide ore tonnage		Oxide ore tonnage		waste tonnage		Number of active benches	
	NM	TM	NM	TM	NM	TM	NM	TM	NM	TM
1	2,946,000	2,996,700	1,093,000	1,093,000	266,790	266,790	1,586,210	1,636,910	10	12
2	2,505,300	2,522,100	1,093,000	1,093,000	163,520	163,520	1,248,780	1,265,580	4	13
3	2,502,900	2,505,300	972,510	1,093,000	163,520	163,520	1,366,870	1,248,780	4	15
4	2,505,300	2,505,300	1,093,000	1,093,000	163,520	163,520	1,248,780	1,248,780	4	14
5	2,505,300	2,503,600	1,093,000	1,006,900	163,520	163,520	1,248,780	1,333,180	9	14
6	2,983,200	2,915,000	938,080	903,660	163,520	163,520	1,881,600	1,847,820	8	14
Average	2,658,000	2,658,000	1,047,098	1,047,093	180,732	180,732	1,430,170	1,430,175	6.5	13.67
Total	15,948,000	15,948,000	6,282,590	6,282,560	1,084,390	1,084,390	8,581,020	8,581,050	-	-

As previously mentioned, open-pit mine planning is presented in three-time frames: short-term, medium-term, and long-term planning. Short-term planning considers operational constraints, reserves, equipment, and block access in a way that minimizes deviations from

production. Since short-term planning is based on medium-term and long-term planning, its optimality heavily depends on the optimality of medium and long-term plans. Thus, if the short-term plan is optimal, the long-term plan's objective of maximizing NPV is achieved. To operationalize

a short-term plan, the number of active benches in each time period must decrease, leading to reduced equipment movement and an overall decrease in extraction costs [76]. As shown in Figure 4, The number of active benches was 13.67 for TM model and 6.5 for NM model, representing a 52.45% reduction. This indicates that mining equipment using NM model requires less movement between benches within a specific time frame for mining operations, concentrating all mining activities on fewer benches. Therefore, in NM model, in addition to reducing vertical pit advancement in each time period, efforts are made to increase horizontal pit advancement and reduce the number of active benches in each time period to ensure operational consistency in extraction activities. Figure 5 shows an overview of the blocks and their distribution by color for each period.

By adding constraints to the model, the objective function may remain unchanged or worsen; that is, in minimizing problems, it may

worsen, and in maximizing problems, it may worsen. The total NPVs yielded from models TM and NM are approximately 378.22 million dollars and 358.7 million dollars, respectively, indicating an 5.3% reduction in NPV in NM model. One of the reasons for this is that the objective function in NM model cannot extract more ore from additional benches to meet the tonnage of ore due to the added constraints to the model. This has resulted in restricted vertical movement and a greater focus on horizontal equipment movement. Therefore, although adding constraints to mobility may lead to a reduction in NPV, realized NPV may increase due to a decrease in equipment movement. Since transportation costs in open-pit mines can be more than 60% of mining operations [53], this will enhance efficiency in equipment usage and transportation.

To examine the horizontal scheduling pattern, the number of time periods required for extracting each bench is shown in Table 3.

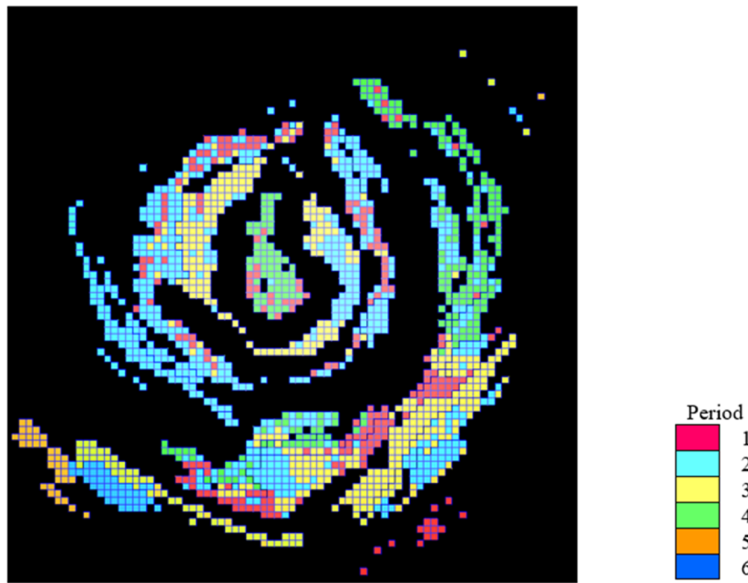


Figure 5. overview of the blocks and their distribution by color for each period

Table 3. The scheduling periods for each bench extraction

bench No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Average
period TM	5	6	6	6	6	6	6	6	6	6	6	6	4	2	4	5.40
NM	3	4	4	2	1	4	4	4	4	2	2	2	1	1	1	2.60

The number of time periods required for extracting each bench decreased from 5.40 in TM model to 2.60 in NM model, representing a 51.85% reduction. For example, the first bench in TM model requires 5 time periods (1, 2, 3, 4, and 5), while in NM model it only requires 3 time periods (1, 3, and 6). Consequently, the extraction of individual benches in NM model involves less

equipment movement compared to the results obtained from TM model.

5. Conclusions

Existing production scheduling models in open-pit mines have sufficiently addressed operational constraints and technical requirements. However,

certain critical aspects—such as optimizing equipment mobility between benches and minimizing the number of active working benches to reduce horizontal and vertical movement—have received less attention. Improving these factors could lead to significant reductions in operational costs. Additionally, accounting for the workspace constraints of in-pit crushers has been increasingly emphasized in recent studies, highlighting its growing importance in production planning.

In this research, by adding constraints to the production planning model, the vertical advance of the pit is limited, allowing the pit to primarily expand horizontally. Consequently, the movement of equipment between working benches is also reduced. Thus, the constraints on the available working spaces for the in-pit crusher are considered, leading to a decrease in equipment movement between working benches and ultimately reducing transportation costs and operational costs of the mine. By reducing the number of active benches in each time periods, the average number of active benches in each scheduling period was reduced by approximately 52.45% in the proposed NM model.

A comparison of scheduling patterns between the TM and NM models reveals that while both models restrict vertical pit advancement, the TM model demonstrates higher complexity and longer solution times than the NM model. Computational efficiency is particularly crucial in mathematical modeling, as increased model complexity and size lead to longer calculation times—potentially rendering models impractical for real-world applications. The proposed NM model addresses this challenge by achieving significantly faster solution times, demonstrating a 53.32% reduction compared to the TM model. This substantial improvement in computational efficiency represents a noteworthy advancement in practical implementation.

In the present study, due to the constraints added to the model, the objective function in the NM model cannot extract more ore from additional benches to meet the ore tonnage requirements. The addition of equipment mobility constraints leads to a 5.3% reduction in the theoretical NPV. Movement in depth is restricted, with greater emphasis placed on the horizontal movement of equipment. However, since haulage costs in open-pit mines can account for 60% or more of a mine's operating costs [53], the realized operational NPV may increase due to reduced mining equipment movement.

By comparing the results of the NM and TM models in the case study, it can be concluded that the proposed model in this paper successfully achieves the expected objectives, including accounting for in-pit crusher workspace constraints by reducing the number of active benches per time periods, minimizing equipment movement between working benches, prioritizing horizontal pit advancement over vertical progression, and reducing model runtime. Furthermore, this model ensures consistent extraction.

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انجمن مهندسی معدن ایران

توسعه یک مدل برنامه ریزی تولید بلندمدت معدن با در نظر گرفتن فضاهاى کارى سنگ شکن هاى درون پیت

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چکیده

طراحی و برنامه ریزی در معدن روباز، مجموعه‌ای از فرآیندهاست که با تهیه‌ی مدل بلوکی از ذخیره‌ی معدنی، آغاز و پس از طراحی محدوده‌ی نهایی، به زمان بندی و توالی استخراج بلوک‌های معدنی، ختم می‌شود و هدف این است که ارزش پیت را تحت برخی محدودیت های تکنیکی و عملیاتی، بیشینه نماید. روش‌های برنامه ریزی ریاضی نشان داده‌اند که برای بهینه‌سازی زمان بندی تولید معدن مناسب هستند. تحقیقات قبلی به موضوعات مختلفی از جمله زمان به کارگیری و جایجایی های دوره ای سنگ شکن درون پیت و ... پرداخته اند. با این وجود همچنان چالش های زیادی در بحث ادغام مساله سنگ شکن درون پیت با برنامه ریزی تولید وجود دارد. در این مقاله یک مدل برنامه ریزی عدد صحیح خطی جدید برای مسئله برنامه ریزی بلندمدت معدن روباز ارائه شد که پیشروی عمقی پیت محدود شده و سبب شد عمدتا در افق پیشروی داشته باشد. بدین منظور تعداد پله های فعال در هر دوره زمانی کاهش یافته و بنابراین میزان جایجایی تجهیزات بین پله های کارى نیز کم شد. علاوه بر این با پیشروی افقی پیت، فضای کارى در دسترس برای به کارگیری سنگ شکن درون پیتی بیشتر بوده و هزینه جایجایی تجهیزات بین پله های کارى کاهش یافته و در کل هزینه حمل و نقل و نهایتا هزینه عملیاتی معدن نیز کاهش یافت. در نهایت مدل ارائه شده برای معدن مس میدوک اجرا شد. نتایج نشان داد که مدل ارائه شده به خوبی اهداف مورد نظر را تامین نمود و از نظر کاهش تعداد پله های فعال باعث بهبود ۵۲.۴۵ درصدی و از نظر کاهش در زمان اجرای مدل، کاهش ۵۳.۳۲ درصد را نتیجه داد.

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کلمات کلیدی

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