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A Generalized Mathematical Model for Integrated Production Planning in Drift-and-Fill Mining Operation

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Abstract

Drift-and-fill mining is a variation of cut-and-fill mining method. Drift-and-fill mining method refers to the excavation of several parallel drifts in ore. Excavation of a new drift could start when its adjacent drifts are backfilled or not excavated. The amount of ore material and its grade depends on the excavation sequence of drifts. As the number of drifts increases, one will need a model to optimize the drift excavation and backfilling sequence. This paper introduces a mathematical model to determine the optimal drift-and-fill sequence while the safety constraints, excavation, and backfilling capacities and their dependencies are satisfied. The model seeks to minimize the deviations from some predefined goals, and it handles the long-term and short-term constraints in separate and integrated scenarios. An application of the model is presented based on the data available from a lead/zinc underground mining project. There are 91 drifts in the selected level. Based on the monthly planning horizon, the integrated model leads to the slightest deviations in both the mining rate and average grade, and the deviation from the predetermined annual goals is negligible. For the case where long-term and short-term plans are determined separately, the deviation is approximately 10%.

1. Introduction

Along with the growth in population and civilization, the mineral demand is increasing. To fulfill the demand, and because of the scarcity of high-grade and near-surface deposits, the mining industry tends to extract the mineral resources by underground mining operations if feasible. Mining of such deposits is very sensitive to an appropriate mining plan. A production plan determines the quality and quantity of material that should be extracted during the life of a mine. The primary goal of a mining plan is to achieve the highest Net Present-Value (NPV) for the given technical constraints [1-3].

Underground mining plans are developed through a sequential process. First, a stope layout or stope boundary is determined. The stope boundary depends on the mining method and its specific economic, geometric, and operational constraints [4, 5]. Subsequently, a detailed development network layout is designed with the aim of cost minimization, and finally, the production schedule is determined. Stope layout and production scheduling are important issues in underground mining plans. These plans are affected by geologic and economic uncertainties [6].

Mine production planning is a complex optimization problem. Production planning is determined for different time horizons (i.e., long-term and short-term planning), and typically, they are conducted as two separate phases. Mine planning begins with creating a long-term plan that defines the annual production operation throughout the mine life while the NPV of the operation is maximized and the technical constraints are satisfied. The next stage involves creating a short-term plan. The aim is to provide a practical guide to implement the activities according to the long-term plan. In short-term planning, considering the operational constraints, emphasis is placed on

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following the long-term goals. Short-term planning aims to provide a constant amount of minerals to the processing plant, where the deviations in quality and quantity of mill feed are minimized. Any significant and sudden change in feed disrupts the mill balance and recovery [7]. Hence, a separate definition of long-term and short-term production plans will lead to a locally optimal solution. However, achieving a globally optimal solution is possible by integrating these plans and considering the interactions between short-term and long-term activities.

Production planning methods are divided into mathematical and search-based methods. In most cases, mathematical models (although mathematically optimal) suffer from complexity and are hard to implement. In contrast, search-based heuristic and meta-heuristic methods can produce a practically acceptable solution (but not necessarily optimal). Javed [8] used linear programming to minimize the deviations from predetermined cost and production goals in a room and pillar mining activity. He considers several constraints, including workforce, operational, extraction capacity, plant capacity, and ventilation [9]. Trott [10] presented a mixed integer programming model intending to maximize the NPV in a sublevel copper mining project. The proposed model consists of five binary variables representing extraction, drawing, backfilling, and the lead time to start extraction after a backfill. Moreover, two decision variables define the tonnage and filling capacity of the stopes. The major drawback of this model is the simultaneous mining of neighboring stopes. Continuing Trott's work, Nehring [11] built a model by adding new constraints to avoid simultaneous mining of neighboring stopes. They studied the model performance by comparing it with a manually generated plan. The results showed that the net present value has improved by 11%.

Little et al. [12] used mixed-integer programming to optimize underground stopes boundary and production scheduling to maximize the NPV. They evaluated the problem in two scenarios. In the first scenario, they maximized the NPV of the operation by simultaneously satisfying the constraints related to the design of the stopes and the production schedule. In the latter scenario, the two problems are solved separately. First, the optimal stope boundary is determined. Then, considering the production constraints, the appropriate stope sequencing is determined. The results showed an increase in NPV for the simultaneous scenario. A mixed integer linear programming model is developed for maximizing the NPV and long-term planning in block-caving. The model considers several constraints, including the mining capacity, draw rate, extraction priority, number of draw points in each period, and the maximum number of active draw points [3].

O'Sullivan and Newman [13] used integer programming to maximize the amount of metal production over the mine life of an underground lead/zinc project. They considered the earliest starting time for extraction of panels and a heuristic method for decomposition and reduction of the solution time. Treblanche and Belli [14] have also used the concept of the earliest time to start and the latest time to finish an activity to reduce the solution time.

Huang et al. [15] presented a robust mixed integer linear programming formulation for underground cut-and-fill mining. The objective function is to maximize the NPV of the operation while meeting all mining and processing constraints. The new model is validated with two case studies (The case studies contain 12 time periods and 40-120 stopes), and the results show a 9% to 17% improvement in NPV. The main drawback of this model is that the sizes of the stopes are equal, which may produce unreliable results in cases where the sizes of the stopes are variable.

Foroughi et al. [16] used an integer programming model to maximize the NPV of a sublevel stoping operation by simultaneous optimization of long-term planning and the stope boundary. Application of the model in an iron ore deposit resulted in a 16% increase in the NPV compared to the case where the stope boundary and the production schedule are determined separately. Shenavar et al. [17] introduced a new mathematical model to maximize the NPV of a sublevel caving operation. This model considers technical and operational constraints such as production capacity, geometric constraints, access constraints, and mining advance direction. Also, the stope boundary was determined using the floating stope algorithm, and the unnecessary blocks were removed to reduce the number of decision variables. Sari et al. [18] proposed a heuristic clustering approach to identify rich blocks and prioritize their extraction to maximize profit. The proposed approach was compared and validated with the results of a rigorous model on a small example [19]. Heuristic algorithms are also applied for problem size reduction and running time improvement [20, 21].

Morin et al. [22] presented a discrete event simulation model for planning drift-and-fill operations in the presence of an underground pre-concentration system. The results showed that the system productivity varies with reliability while it is improved with pre-concentration. Mohseni et al. [23] presented a classification system to predict unplanned dilution in the cut-and-fill mining method.

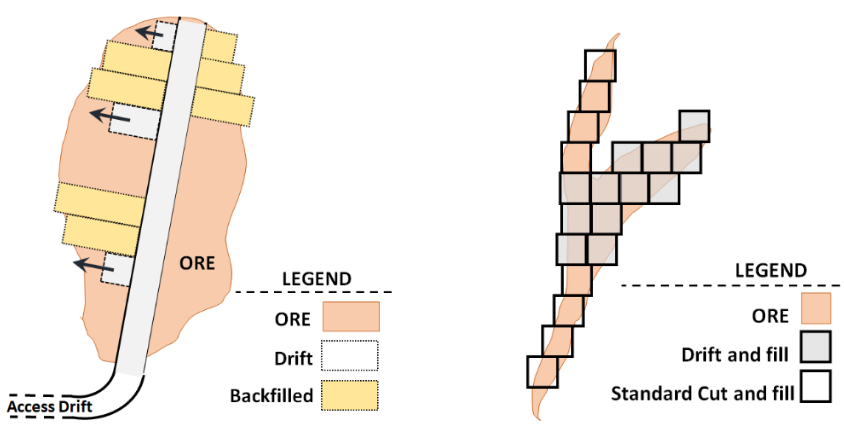
Manriquez et al. [24] consider a bench-and-fill mine and try to improve schedule adherence by creating a hybrid simulation model for short-term production. In each iteration, a short-term schedule is created using a mixed integer linear programming model that is simulated later using a discrete-event simulation model. The model considers the operational uncertainties of equipment by the simulation process. The drawbacks of this work include: (a) the optimization model is stope-based while the schedule of cuts inside the stopes is ignored, and (b) the model is developed for vertically inclined orebodies. Hence, the model will generate an infeasible stope sequence for cut and fill mining projects in massive orebodies. Brickey et al. [25] formulated a daily production planning model to optimize tactical schedules and supervisory decisions based on resource availability. They try to control the resource and equipment availability to follow a given stope sequence. The point is that the objective function seeks the maximum NPV while the production deviations are ignored. Some researchers studied the effect of specific constraints like machine allocation and ventilation in underground production scheduling [26-28].

According to the literature, limited studies have been carried out on integrated production planning for different time horizons. In 2012, Nehring et al. investigated the connection between short- and medium-term planning and its effects on NPV. Furthermore, they presented a short-term planning model intending to minimize the deviations in metal production and medium-term planning intending to maximize the NPV. Their model is applied in a sublevel stoping operation, which includes 65 stopes [7]. Campeau et al. [29, 30] described a new model for optimizing short- and medium-term planning of underground mines. They proposed a mixed integer programming model with flexible time discretization to accurately represent operational constraints. The results show that the integrated formulation makes it possible to create practical solutions. An application of the model in a gold project is used to schedule equipment, rock support, and similar activities.

Since the studies on simultaneous long- and short-term planning are limited, and the globally optimal solution can only be achieved if these two plans are combined, this paper attempts to develop an integrated mathematical model. Moreover, the model is developed for the underground drift-and-fill mining method. The model is applied in an underground lead/zinc operation. A general description of the drift-and-fill mining method is provided in section 2. The model definition and formulation are introduced in section 3. Section 4 contains a case study, and the conclusions are derived in section 5.

2. Drift-and-fill mining

In the cut-and-fill mining method, the excavated area is filled back with some material to facilitate the excavation of the remaining ore. The fill material acts as a support for the area. The drift-and-fill mining method is a variation of the cut-and-fill mining method, where, several parallel drifts are excavated in ore except it is used for thick ore reserves (Figure 1).



a) Plan view of a massive deposit **b) Vertical section of a vein deposit**

Figure 1. Application of drift-and-fill to (a) massive and (b) narrow vein orebodies (from [31])

Drift-and-fill mining refers to excavating several parallel and regularly spaced drifts in the ore reserve and backfilling the completed drifts before mining adjacent drifts [31]. Generally, the layout of drift-and-fill mining is similar to a conventional room and pillar where the ore grade is valuable enough to justify the backfill of rooms for pillar mining.

In this method, as the first drift is excavated to the end of the orebody or its specified length, the drift is sealed for backfilling. The next drift is driven adjacent and parallel to the first drift. This process continues until the ore reserve is mined out. As mining of the first level is completed, the second level is started below the first level. For safety reasons, the drifts in different levels are excavated perpendicular (Figure 2).

There are two variations of the drift-and-fill mining method. Their main difference is the mining direction. Overhand drift-and-fill follows a bottom-up mining direction, while the underhand variation has a top-down direction [31]. This method is very flexible in massive or narrow flat-lying orebodies. The ore recovery is almost maximum, while the exposure to unsupported ground and the risk of subsidence are minimal [32-34]. This method is applied in high-grade orebodies with poor or variable ground conditions, where high selectivity and control are needed. This method is suitable in massive deposits if sublevel stoping is not feasible [35].

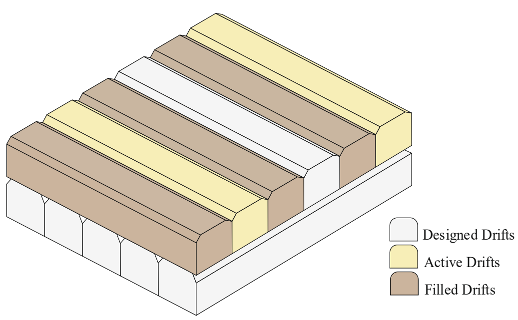


Figure 2. Underhand drift-and-fill mining method

In underhand drift-and-fill, when the first level is completed, a strong crown pillar of cemented fill will be created beneath which the mining operation continues safely [31]. Peng et al. [36] conducted a numerical study assessment of the stability and failure of drifts from the perspective of deformation, stress, and plastic zone. Ran [37] shows that in terms of the RMR system, a drift width is normally less than 5 meters in ‘‘fair” rock masses. Hu et al. [38] and Keita et al. [39] studied the backfill and sill pillar behavior in a drift-and-fill operation.

According to Figure 1, an access drift is excavated along the axis of a deposit. After that, some parallel production drifts are excavated using the access drift. The excavation sequence of drifts is critical. When a drift is mined out, the void is filled with some cemented waste material as soon as possible. Excavation of new drifts depends on the condition of its surrounding drifts. In addition, to maintain ground stability, there must be a safe distance between the active drifts, which limits the number of active drifts and their respective locations.

The NPV of the operation depends on the grade and tonnage of material (i.e., metal content) that is mined annually. In addition, if the variation of ore grade and tonnage in drifts is considerable, then the amount of periodically mined ore material and its grade depends on the excavation sequence of drifts.

Considering the safety requirements, capacity constraints, and variations in metal content in drifts, determining the optimal sequence is challenging for massive deposits. In addition, as the drift number increases, one will need a model to optimize the drift excavation and backfilling sequence.

3. Research method

This section attempts to formulate a binary programming model for production planning of a drift-and-fill operation. The model must consider mining and backfilling rates in each drift while the logical and safety constraints are satisfied. It must determine the optimal mining sequence of drift while deviations from production targets are minimized and safety issues are met. However, the model considers the earliest and latest possible times to drift and backfill to improve the tractability of the model by controlling the number of decision variables. The problem is formulated using the linear programming framework in MATLAB R2021b.

3.1. Model formulation

As stated, the drift-and-fill mining method is suitable for massive and narrow vein deposits. This paper deals with the case of applying the drift-and-fill mining method for massive ores where the number of drifts is considerable. In the drift-and-fill mining method, the deposit is divided into several levels based on the drift height, and an access drift is excavated in the middle of each level (Figure 1-a). The access drift divides each level into two rows of production drifts (i.e., rows a1 and a2, in Figure 3). The lengths of production drifts are determined based on the extent of the orebody at each level. According to Figure 3, there are 91 drifts in the level.

The production drifts are divided into several cuts. These cuts are excavated according to the mining rate or face advance rate. Figure 3 shows the plan view of a mining level representing the rows, drifts, and cuts.

When all the cuts of a drift are mined out, the backfilling operation will start. The time required to complete the backfilling operation depends on the drift length, backfilling capacity, and the time the backfilled material needs to reach its required strength. It means that as long as the backfilling operation is not complete, the cuts in adjacent drifts are not minable. Therefore, a precise drift sequence is needed for a safe mining operation with a constant ore supply.

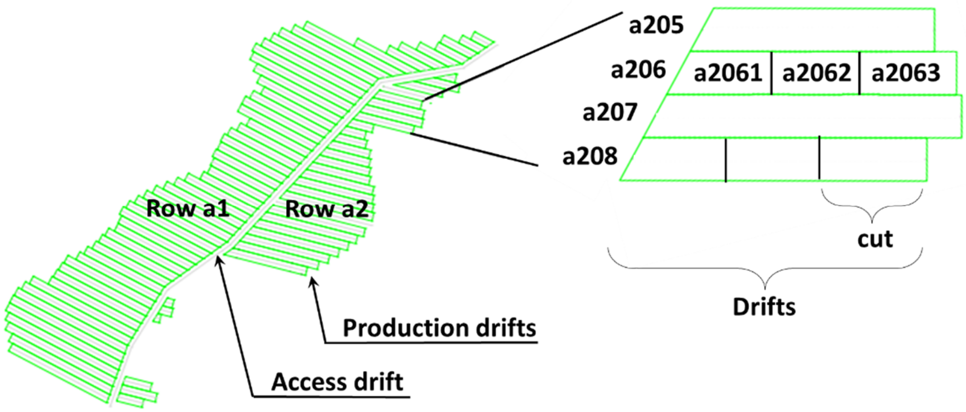


Figure 3. The plan view of the mining level showing the rows, drifts, cuts and their numbering

When discussing production planning in underground mines, there are many constraints, such as production requirements, ventilation, geotechnics, machinery, ore access, and support of underground workings. Each of these constraints is related to different planning horizons. For example, resource constraint is a long-term planning constraint. Access and ventilation are medium-term planning constraints, and machinery-related issues are among the constraints of operational planning or tactical schedules. Hence, these constraints should be considered under the requirements of the planning horizons. In that regard, two binary programming models are presented in this paper. Each model is suitable for a particular planning horizon, and respective constraints are considered for each case.

Model 1: The long-term model

The model given in Equations 1-5 is formulated to determine the annual drift sequence. Equation 1 represents the objective function that seeks to minimize the annual deviation from the production target. According to this equation, different penalty coefficients are defined for over- and under-production through the periods. Deviations from goals are important in the beginning periods. Hence, one could restrict the allowable deviations by defining a declining penalty coefficient over time. Moreover, by changing these coefficients, the penalties imposed on overproduction and underproduction are treated separately. In this paper, these coefficients are equal and constant through the years.

$$Min\, Z_1 = \sum_{t=1}^{T} \beta_t \overline{y}_t + \delta_t \underline{y}_t \qquad (1)$$

where,

$\overline{y}_t$	is the amount of over production at time t
$\underline{y}_t$	is the amount of underproduction at time t
β_t	is the penalty coefficient for over production at time t
δ_t	is the penalty coefficient for under production at time t
T	is the number of planning periods

Equations 2-4 are equality constraints and calculate the deviation between the planned and the actual annual production according to the drifts mined at that period. The tonnage of material in each drift depends on the cut volume and the specific weight of the ore. The specific weight of ore depends on the ore grade. As the grade of minerals increases, the specific weight of ore increases. In that regard, if high-grade drifts are extracted, the probability of underproduction is minimized. Contrarily, if high-grade drifts are extracted, the probability of overproduction is maximized. Thus, the model must extract a combination of low-grade and high-grade drifts in each period to control the production level and minimize its deviations. In Equation 3, it is clear that the actual annual production is at most equal to the mill capacity.

$$TP_t - TR_t + \overline{y}_t - \underline{y}_t = 0, \forall \; all \; t \quad (2)$$

$$TR_t = \sum_{i=1}^{I} \sum_{k=1}^{K} a_{ikt} T_{ik}, \forall \; all \; t \quad (3)$$

$$T_{ik} = \sum_{j=1}^{J_{ik}} A \times L_{ijk} \times \rho_{ijk}, \qquad \forall \; all \; i,k \quad (4)$$

where,

$\boldsymbol{TP_t}$	is planned production at time t
$\boldsymbol{TR_t}$	is actual production at time t
$\boldsymbol{a_{ikt}}$	is a binary decision variable. It is 1 if the ith drift in the kth row is mined at time t, else, it is zero
$\boldsymbol{T_{ik}}$	is the ore tonnage available at the ith drift on the kth row
$\boldsymbol{A}$	represents the drift cross section area (m^2). It is constant an all drifts.
$\boldsymbol{\rho_{ijk}}$	is the specific weight of ore at the jth cut of ith drift on the kth row (ton/m^3). The specific weight depends on the ore grade and it is different in each cut.
$\boldsymbol{L_{ijk}}$	is the length of the jth cut of ith drift on the kth row in meters. The length of cuts is determined according to the given face advance rate. The cut length is about 10 meters. According to the face advance rate that is 2.5 m/day, each cut will be mined in 4 days.
$\boldsymbol{I}$	is the index showing the number of drifts in the level
$\boldsymbol{J_{ik}}$	is the index showing the last cut of ith drift on the kth row
$\boldsymbol{K}$	is the index showing the number of rows. According to Figure 3, the mining level contains two rows ($K = 2$).

Equation 5 guarantees that the drifts are only mined once in a lifetime. It also forces the model to extract all the drifts of the mining level. In that regard, all the drifts are extracted and backfilled before excavation of the next level.

$$\sum_{t=1}^{T} a_{ikt} = 1, \qquad \forall \; all \; i,k \quad (5)$$

Model 2: The short-term model

The model given in Equations 6-24 determines the monthly drift sequence. In Equation 6, the objective function seeks to minimize the deviation from the production target. It is the same as the objective function given in Equation 1, and the parameters are defined earlier.

$$Min \; Z_2 = \sum_{t=1}^{T} \beta_t \overline{y}_t + \delta_t \underline{y}_t \quad (6)$$

Equations 7-9 are equality constraints and calculate the deviation between planned production and actual production rate in each period according to the cuts extracted at that period. These equations are similar to Equations 2-4, but the difference is that Equations 7-9 are based on the cuts, while Equations 2-4 are formulated based on the drifts. The tonnage of material in each cut depends on the cut volume and the specific weight of ore that is a function of ore grade. As the ore grade increases, the specific weight of the ore increases. Thus, the model must extract a combination of low-grade and high-grade cuts in each period to minimize the production deviations.

$$TP_t - TR_t + \overline{y}_t - \underline{y}_t = 0, \forall \; all \; t \quad (7)$$

$$TR_t = \sum_{i=1}^{I} \sum_{j=1}^{J_{ik}} \sum_{k=1}^{K} a_{ijkt} T_{ijk}, \forall \; all \; t \quad (8)$$

$$T_{ijk} = A \times L_{ijk} \times \rho_{ijk}, \qquad \forall \; all \; i,j,k \quad (9)$$

where,

$\boldsymbol{T_{ijk}}$	is the ore tonnage available at the jth cut of ith drift on the kth row
$\boldsymbol{a_{ijkt}}$	is a decision variable. It is 1 if the jth cut of ith drift in the kth row is mined at time t, else, it is zero

Equation 10 guarantees that any cut in a drift could only be mined once in a lifetime. It also forces the model to extract all the cuts in the given level. In that regard, when all the cuts are extracted and backfilled, it will be safe to extract the next level.

$$\sum_{t=1}^{T} a_{ijkt} = 1, \qquad \forall \, all \; i,j,k \tag{10}$$

Equation 11 controls the mining direction inside a drift and ensures that the cuts are sequenced inside the drift. This constraint ensures that any cut can only be extracted if its preceding cut in that drift is extracted at the same period or earlier. This constraint is not applied to the first cut of any drifts.

$$\sum_{t=1}^{t'} \left(a_{ijkt} - a_{ij+1kt}\right) \geq 0, \quad \forall \, all \; i,j,k,t' \in [1,T] \tag{11}$$

Equations 12 and 13 determine the status of a drift, whether it is extracted or not. If the first cut inside the drift is extracted then the drift status is active until it is backfilled.

$$e_{ikt} - a_{i1kt} = 0, \qquad \forall \, all \; i,k,t \tag{12}$$

$$e_{ikt} \geq e_{ikt-1} \;, \qquad \forall \, all \; i,k,t \tag{13}$$

where,

a_{i1kt}	is a decision variable. It is 1 if the first cut of ith drift in the kth row is mined at time t, else, it is zero
e_{ikt}	is a decision variable. It is 1 if the first cut of ith drift in the kth row is mined at time t or earlier, else, it is zero.

Equation 14 ensures that the drift is backfilled right after excavating the last cut of that drift. Equation 15 remembers the status of a backfilled drift through the mine life. In other words, constraint 15 controls the start of the backfilling operation in a drift, while constraint 16 indicates that the drift is backfilled.

$$b_{ikt} + b_{ikt+1} - a_{iJ_{ik}kt} = 0 \quad \forall \, all \; i,k,t \tag{14}$$

$$b_{ikt} \geq b_{ikt-1} \;, \forall \, all \; i,k,t \tag{15}$$

where,

b_{ikt}	is a decision variable. It is 1 if the ith drift in the kth row is backfilled at time, else, it is zero
$a_{iJ_{ik}kt}$	is a decision variable showing the completion of ore in a stope. It is 1 if the last cut of ith drift in the kth row is mined at time t, else, it is zero

If a drift is backfilled, the extraction of neighboring drifts is controlled by Equation 16. This constraint guarantees that the safety pillars remain between two active drifts. It makes sure that if a drift is not backfilled, the extraction of the neighboring drifts will not be allowed. According to this constraint, if the status of a drift is extracted ($e_{ikt} = 1$) and not backfilled ($b_{ikt} = 0$), then it is not possible to extract the neighboring drifts at that period. Otherwise, if the status of a drift is extracted ($e_{ikt} = 1$) and backfilled ($b_{ikt} = 1$), then it is possible to start the extraction of the neighboring drifts at that time or later.

$$e_{ikt} - b_{ikt} + e_{i+skt} \leq 1, \quad \forall \, all \; i,k,t,s \in [1,S] \tag{16}$$

where,

S	is the minimum number of drifts left as pillar between two active drifts

Equations 17-19 guarantee that the drifts located in opposite rows are not mined at the same time. According to the constraints, if the status of a drift is extracted ($e_{ikt} = 1$) and not backfilled ($b_{ikt} = 0$), then it is not possible to extract three neighboring drifts on the opposite row. If the status of drift is extracted ($e_{ikt} = 1$) and backfilled ($b_{ikt} = 1$), then there is no limitation over excavation of neighboring drifts on the opposite row.

$$e_{ikt} - b_{ikt} + e_{i-1k't} \leq 1, \quad \forall \, all \; i,k,t,k \neq k' \tag{17}$$

$$e_{ikt} - b_{ikt} + e_{ik't} \leq 1, \quad \forall \, all \; i,k,t,k \neq k' \tag{18}$$

$$e_{ikt} - b_{ikt} + e_{i+1k't} \leq 1, \quad \forall \, all \; i,k,t,k \neq k' \tag{19}$$

The next constraint is the number of active drifts in each period. In that regard, the number of extracted cuts in a period is controlled by Equation 20.

$$\sum_{i=1}^{I} \sum_{j=1}^{J_{ik}} \sum_{k=1}^{K} a_{ijkt} \leq q_t, \qquad \forall \, all \; t \tag{20}$$

where,

q_t	is the allowable number of active drifts at time t

Equations 21-22 restrict the amount of extracted and backfilled material concerning the loading and haulage capacity and backfilling capacity in each period, respectively.

$$\sum_{i=1}^{I}\sum_{j=1}^{J_{ik}}\sum_{k=1}^{K} a_{ijkt}T_{ijk} \leq T_t^L \quad \forall\, all\ t \tag{21}$$

$$\sum_{i=1}^{I}\sum_{k=1}^{K}(b_{ikt} - b_{ikt-1}) \times T_{ik}^V \leq T_t^f \quad \forall t \in T \tag{22}$$

where,

T_t^L	is the loading and haulage capacity at time t
T_t^f	is the volume to be filled at time t (m^3)
T_{ik}^V	is the volume to be filled in the ith drift in the kth row at time t (m^3)

Equations 23 and 24 restrict the extraction time of the cuts according to the earliest and the latest possible extraction times. The value of ES_{ijk} and LS_{ijk} are defined based the sequence generated by Model 1.

$$\sum_{t=1}^{T} a_{ijkt} \times t \leq LS_{ijk}\ , \quad \forall\, all\ i,j,k \tag{23}$$

$$\sum_{t=1}^{T} a_{ijkt} \times t \geq ES_{ijk}\ , \quad \forall\, all\ i,j,k \tag{24}$$

where,

ES_{ijk}	is the earliest possible time to mine the jth cut of ith drift on the kth row
LS_{ijk}	is the latest possible time to mine the jth cut of ith drift on the kth row

Model 3: The integrated model

In integrated planning, annual and monthly production planning are determined simultaneously. In that regard, the model given in Equations 6-24 is adjusted considering the concept of receding time horizons [40]. The receding time horizons concept involves solving an optimization problem within a set of timeframes. Then, the initial step is stored, and the process is repeated for the remaining periods. In this process, if new data becomes available, it is possible to update the model with the new data. According to the concept, timeframes are defined in Table 1. According to this table, the planning timeframe is composed of 6 short periods that includes 3 periods with a monthly time length and three planning periods with a seasonal time length. The remaining planning periods are yearly based. In this case, the effects of the short-term and long-term constraints are integrated.

Table 1. The planning time intervals in the integrated model

Period	1	2	3	4	5	6	7 to the end
Time length	1 month	1 month	1 month	3 months	3 months	3 months	1 year

3.2. Scenario definition

The presented models are evaluated in two scenarios.

- The first scenario represents Separate Planning (SP)

In this scenario, the long-term and short-term plans are determined separately. In that regard, the long-term plan is determined using the Model 1. When the annual sequence of drifts is identified, a short-term plan is prepared using Model 2, and a monthly production plan is determined. Due to a shorter planning horizon, some constraints may significantly impact the results, including geotechnics, grade control, resource availability, and backfill constraints.

- The second scenario represents Integrated Planning (IP)

In this scenario, the long-term and short-term production planning are determined simultaneously based on the context described in Model 3. As stated earlier, the main difference is the way the time horizons are defined. In this case, the effects of the long-term and short-term constraints are integrated based on the receding time horizons concept. The time horizons are defined in Table 1.

The performance of these scenarios is evaluated in an underground lead/zinc operation. In that regard, these two scenarios are applied, and the results are compared.

4. Results

The performance of the models is presented in an underground lead/zinc operation. The block model of level +2737 is selected for the study. The selected level contains 91 drifts (Figure 3). According to the available mining capacity, the level is excavated in two years. The dimensions of the drifts are 4 meters by 5 meters. As shown in Figure 3, the drift length and ore contents are different. Therefore, the time for excavation and backfilling of a drift differs from others. This complex situation will increase the complexity of the planning process. Therefore, the essence of the presented model is clear. According to the block model, drift location, ore reserve, ore density, and the average grade are calculated for each drift.

Based on the mine design, the face advance rate in drifts is 2.5 meters per day. In monthly plans, the drifts are divided into some cuts with a length of 10 meters. The cut length is equal to the face advance in 4 working days. For example, for a drift with a length of 40 meters, it takes 16 working days to complete cut excavation. The backfilling of this drift requires 12 days. So, the excavation and backfilling of a 40-meter drift is estimated to be about one month.

The maximum number of active drifts in a month is four. In addition, based on the current mine design, at least two drifts are left as pillars between two active drifts. The information is summarized in Table 2.

Table 2. The parameters used to evaluate the models

Para\meters	Un\it	value
Face advance rate	Meters per day	2.5
Number of active drifts	Drifts in month	4
Safety pillars width	Drifts	2
Mine production	Tons per year	138’000
LHD's loading capacity	Tons per day	750
Conveyor capacity	Tons rial per hour	50
Filling capacity	m^3 per day	280

The production goal is to produce about 138kt of ore annually. The loading capacity of LHDs is 750 tons per day, and the conveyor can convey 50 tons of material per hour. Moreover, the filling capacity is 280 cubic meters per day. Based on these assumptions, the models are implemented.

In the first scenario, the long-term and short-term plans are determined separately. Therefore, first, an annual planning is conducted using the Model 1. Figure 4 shows the annual drift sequence. Then, based on the annual sequence, Model 2 is applied to determine the monthly drift sequence for the first period (Figure 5).

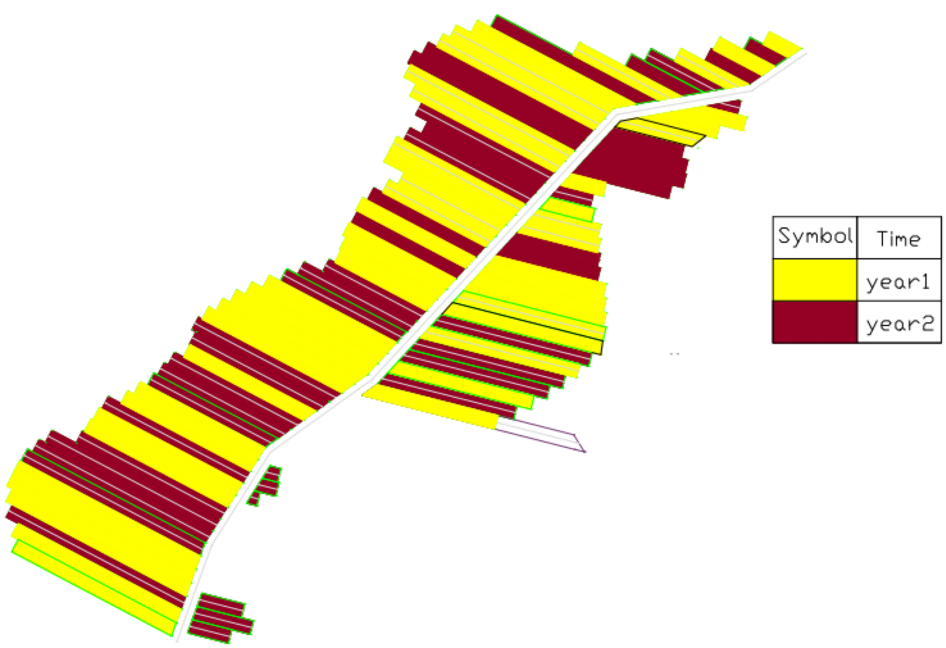


Figure 4. The drift sequence determined by Model 1

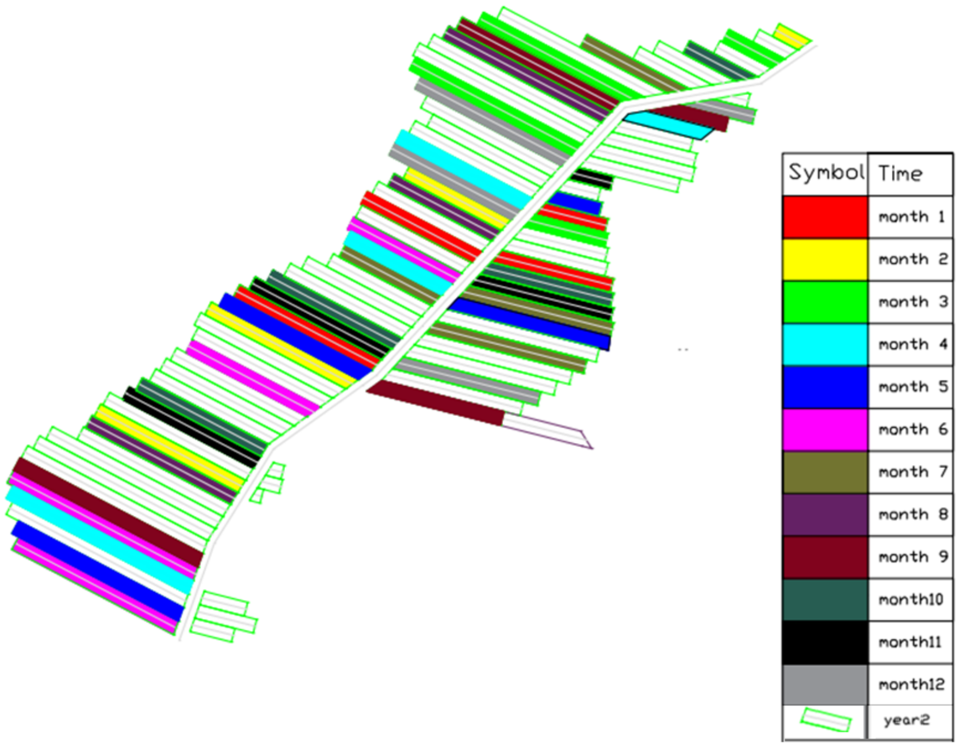


Figure 5. The drift sequence determined by Model 2

In the case of integrated planning (the second scenario), the annual and monthly plans are determined simultaneously. Figure 6 shows the monthly drift sequence that is determined by using Model 3. The figure shows the drift sequence based on the first run of model 3.

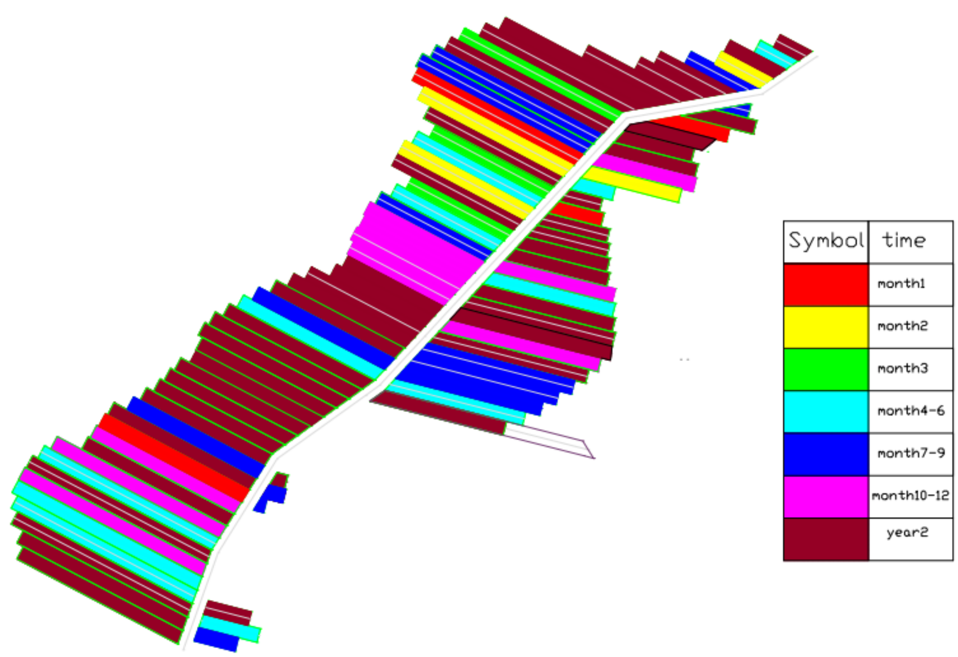


Figure 6. The drift sequence determined by Model 3

As stated, the production goal is to produce 138kt of ore annually, which equals a monthly production of 11.5kt. The deviations incurred in monthly production for both scenarios are calculated. According to the results, the separate plan will produce an annual deviation of 10%, while for the integrated plan, the annual deviation is almost zero.

For a comparison, the annual and monthly deviations for the two scenarios are shown in Figures 7 and 8. According to Figure 7, for the case of SP, the total production in the first year is higher than in IP. Moreover, the difference between the annual productions is much lower for the IP, where the annual and monthly drift sequences are determined simultaneously. According to Figure 8, it can be seen that the IP deviations are softer than in the SP. In addition, the figure shows that the monthly ore content variations are the same for both scenarios. Monthly ore content variations for SP are less than 1%, and it is almost zero for the IP.

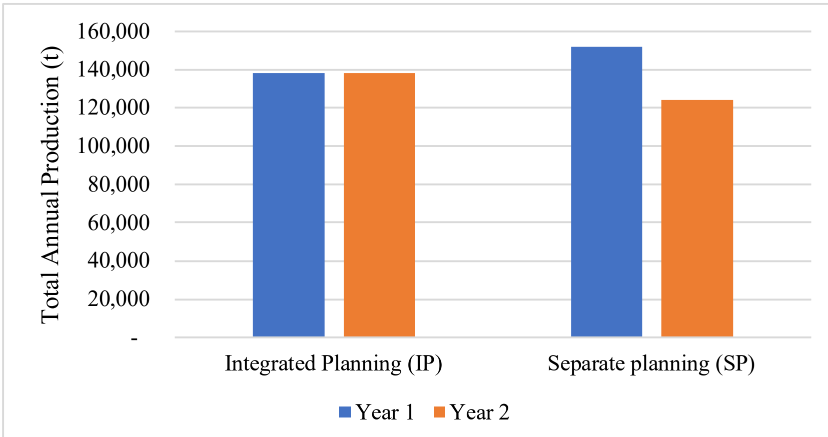


Figure 7. Comparing the target annual production and production resulted from both scenarios

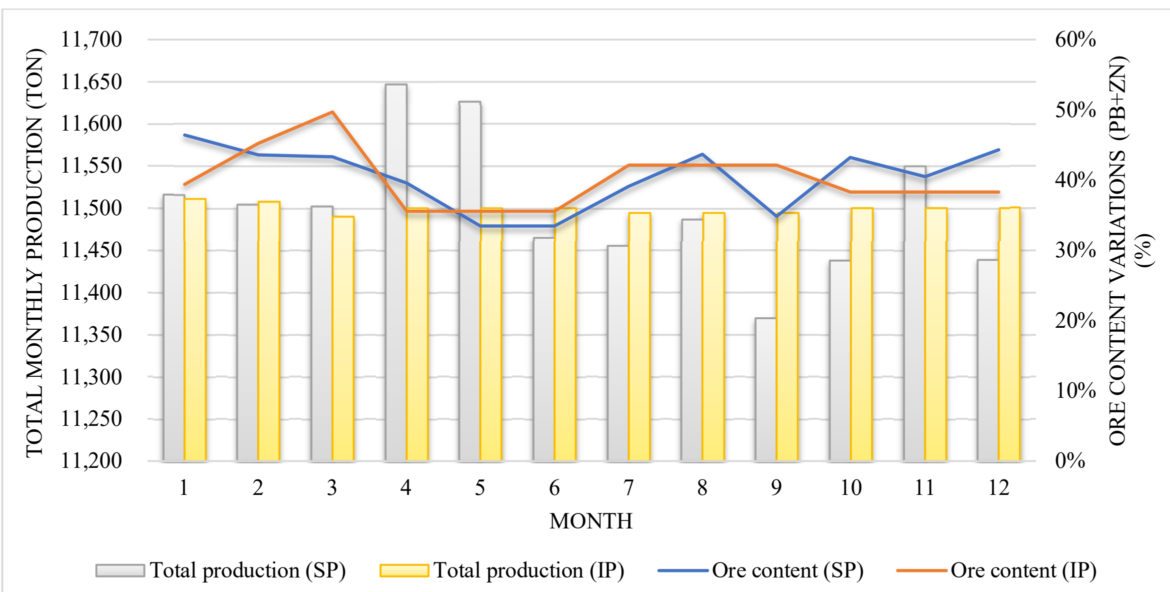


Figure 8. The deviation in total production and ore content in both scenarios

5. Conclusions

Determining the optimal production plan plays a significant role in the design and operation of underground mines. Production planning optimization techniques are not comprehensively used in underground mining because each method has specific limitations. Moreover, production planning in underground mines is normally programmed manually, which is time-consuming and non-optimal. In complex cases having numerous activities, manual planning may not be the choice. In such cases, developing a mathematical model enables the mine planner to compare different mining scenarios to reach an appropriate mining schedule.

This paper formulated a mathematical model to optimize drift excavation sequence in drift-and-fill mining operations. The model considers the advance rate in a drift. In addition, the timing and sequence of drift excavation is controlled by safety requirements. Drift sequencing could be determined on annual and monthly scales. The results show that the integrated model produces a mining schedule with minimal deviations. Comparing the results of separate and integrated plans shows that the lowest deviations belong to the integrated model, where the deviations are negligible. While for the separate model, the deviations are about 10%. Moreover, the monthly ore tonnage variations are almost zero for the IP.

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ارائه یک مدل ریاضی برای برنامه ریزی تولید یکپارچه در روش استخراج کندن و پرکردن با کارگاه‌های تونلی

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چکیده:

روش استخراج کندن و پرکردن با کارگاه‌های تونلی یکی از انواع روش استخراج زیرزمینی است. در این روش، تعدادی کارگاه تونلی به موازات هم و در داخل ماده معدنی حفر می‌شوند. احداث یک کارگاه تونلی پس از تکمیل و پرکردن کارگاه‌های مجاور امکان پذیر است. مقدار و متوسط عیار ماده معدنی استخراج شده در هر دوره، به ترتیب استخراج کارگاه‌ها وابسته است. با افزایش تعداد کارگاه‌ها، برنامه ریزی و تعیین توالی استخراج کارگاه‌ها کاری دشوار خواهد بود. در این مقاله، یک مدل ریاضی برای بهینه سازی توالی استخراج و پرکردن کارگاه‌های تونلی با رعایت محدودیت‌های ایمنی، ظرفیت استخراج و پرکردن، و محدودیت دسترسی ارائه شده است. تابع هدف این مدل بصورت کمینه سازی انحراف از اهداف تولید تعریف شده است که در آن محدودیت‌های بلندمدت و کوتاه مدت در دو حالت مجزا و یکپارچه بررسی شده است. سپس، نتایج بدست آمده از مدل در یکی از طبقه‌های یک معدن زیرزمینی سرب و روی ارائه شده است. در این طبقه، ۹۱ کارگاه تونلی وجود دارد. در افق برنامه ریزی ماهلنه، مدل برنامه ریزی یکپارچه از نظر مقدار تولید و متوسط عیار کمترین انحراف را با اهداف تولید دارد. بعلاوه، مقدار انحراف از تولید در افق سالانه قابل چشم پوشی است. این در حالی است که در مدل برنامه ریزی مجزا، مقدار انحراف از تولید در حدود ۱۰٪ محاسبه شده است.

کلمات کلیدی: بهینه سازی، معدنکاری زیرزمینی، روش استخراج کندن و پرکردن با کارگاه‌های تونلی، برنامه ریزی تولید یکپارچه، انحراف از تولید.