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A Deviation-Minimization Approach to Short-Term Underground Mine Schedule Optimization

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Abstract

Production forecasts derived from the medium-term schedule represent the best path forward for underground mining operations to achieve corporate and operational goals. Unforeseen circumstances, such as equipment breakdown, can cause significant deviations from established production forecasts in the short term. Such situations require timely mitigation of the effects of the deviations in order to stay as close as possible to the medium-term plan. This paper presents a deterministic mathematical formulation for short-term scheduling that addresses this challenge. The formulation is able to make up for deficits resulting from operational disruptions by minimizing deviations from medium-term production goals and medium-term activity start dates. We demonstrate this in a case study by simulating disruptions involving reduction in ore extraction capacity and development advance rate. Aside from the rescheduling capability, this formulation can help mine planners conduct analysis on the impact of various disruptions on the schedule. The formulation can help identify those conditions or disruptions that are more detrimental to the achievement of forecast targets, or otherwise. The formulation also affords mine planners the flexibility to prioritize one production goal over the other, depending on operational conditions at the mine. In the future, we seek to incorporate in the formulation respirable dust, diesel particulate matter, and ventilation constraints in order to create more realistic schedules and enhance miners' health and safety.

Keywords Underground mine planning · Production scheduling · Mine optimization · Short-term scheduling · Operations research

1 Introduction

Mining remains a relevant industry as it is essential to the production of goods, services, and infrastructure that improve our quality of life. The industry provides all materials that cannot be grown or extracted as liquid or gas [24]. In the USA, the average person requires over 40,000 pounds of minerals per year to maintain their standard of living [49]. Aside from enhancing quality of life, mining is an economic driver that supports local businesses and contributes tax revenue to government entities. Mining is the process of extracting naturally occurring minerals from the earth's crust using surface or underground methods. Surface mining methods are employed when the orebody is exposed or close to the surface. They are relatively cheaper than underground mining methods and account for about 70% of global mineral production [20]. Underground mining methods are employed when the orebody is deep seated or significantly vertical such that surface mining methods are uneconomic and/or unsafe. In both surface and underground mining, a good mine plan is required for the safe and profitable extraction of minerals. A significant aspect of mine planning is the production schedule, which guides miners as to what portion of the orebody to mine at a given time. The literature on production scheduling

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in surface mining is well established, unlike in underground mining [26, 36, 38]. We thus focus on underground production scheduling in this paper by considering both existing and emerging methods for production schedule optimization.

In underground mine planning, production scheduling is the sequencing of mining activities, i.e., development, production, and remediation, needed to achieve clearly defined goals in order to generate revenue, while adhering to precedence and resource constraints. Scheduling results in the determination of activity start dates for the operation with a scheduling fidelity corresponding to the desired planning horizon, i.e., long-, medium-, or short-term planning [28, 30]. Long-term production schedules establish the overarching goals, e.g., portions of the orebody that can be economically extracted, life-of-mine production, annual production targets, and capital project goals, for the operation based on corporate policy. Utilizing this information, the medium-term schedule determines the sequence of activities at a finer fidelity, e.g., monthly or quarterly, for up to a period of 5 years while adhering to production constraints [11, 30]. The prescribed sequence of activities from the medium-term schedule helps mine planners determine a production forecast for the operation. Short-term production schedules inform the day-to-day operations of the mine which can include defining active working areas, immediate equipment needs, ventilation requirements, and material consumption. They are developed based on the forecast from the medium-term schedule, and current operational conditions, e.g., ground conditions and equipment availability. Thus, they define an extraction sequence by specifying activity start dates at a very fine fidelity, i.e., hourly, by shift, or daily, over a time horizon spanning several weeks to months and typically not exceeding 2 years [4]. They focus on the effective utilization of resources, e.g., equipment and labor, to achieve shift, daily, or weekly production targets [48].

Considering that the production forecast from the medium-term schedule represents the best path forward for the operation to achieve the corporate or operational goals, e.g., contract requirements, market demand, and corporate objectives, mine planners strive to develop short-term schedules that closely match the forecast [11]. Notwithstanding, unforeseen circumstances, such as equipment breakdown and the downstream impact of geological and commodity price uncertainty, can cause significant deviations from established production forecasts in the short term. Situations such as these require timely mitigation of the effects of the deviations in an attempt to stay as close as possible to the medium-term plan and realize the overarching long-term economic and operational potential of the mine.

Many mining operations work continuously, e.g., 365 days per year, 24 hours per day. Short-term schedules thus require rapid adjustments to accommodate the changing conditions associated with equipment breakdowns, labor shortages, and extreme weather, for example. The ability to efficiently integrate new information into a model and produce a revised, high-quality schedule would help to minimize the negative impacts of these operational challenges and better achieve the desired operational performance. To accomplish this, mines have added technology that allows for the collection of data reflecting operational conditions. Advances in operational technology (OT) systems enable real-time or near real-time tracking and monitoring of a myriad of operational data points using fleet management systems, GPS equipment tracking, and real-time production rates [33]. Improved integration of such data into the mine planning processes can significantly help to mitigate production uncertainty and risks by maintaining flexibility in the overall mine plan [25]. The improved coupling between operations and planning departments has been possible with the implementation of Short-Interval Control (SIC) systems at operations. The SIC process, traditionally applied at manufacturing facilities, can provide mine engineering and management personnel with real-time data to guide decision-making [18].

Responding effectively to such changing operational conditions often requires the short-term planner to evaluate a multitude of options, which can be a cumbersome and time-consuming process. In this paper, we attempt to formalize the process of determining an acceptable solution to the operational issue with a deterministic mathematical formulation, by balancing schedule changes against the longer-term forecast goals. In practical terms, the formulation includes minimizing deviation from medium-term production goals and deviation from the medium-term activity start dates subject to the modified set of operational constraints. We achieve this by introducing penalties for the respective deviations. Aside from incorporating scaling factors by which mine planning engineers can assign priorities to the aforementioned deviations, this formulation makes it possible to prioritize one production goal over the other, depending on operational conditions and considerations at the mine. This is to contribute to a more flexible and realistic short-term scheduling of underground mining operations. We also simulate realistic operational scenarios by modifying production goals in the short term and assessing solutions to determine impact and viable options while minimizing deviations from the medium-term plan.

1.1 Background

Operations Research techniques have been widely applied to aid decision-making at mining operations since the 1960s, starting with the introduction, formalization, and subsequent proliferation of the Lerchs-Grossman algorithm [27]. Since then, researchers have developed a number of mathematical models to describe and solve a varied set of problems, using linear, integer, and mixed-integer programming. However, given the historic popularity of open pit mining over underground mining and certain technical challenges, Operations Research applications in open pit mining have advanced faster and farther, and underground mining has only seen major advances made in the last 2 decades. In general, the unique characteristics of underground mining make it more challenging to optimize underground production schedules, relative to optimizing production schedules in open pit mining [34, 38]. Underground mining operations are more heterogeneous and, contingent on geotechnical considerations and the selected mining method, require decisions to be made as to which section of the orebody to extract next [11]. These decisions come with greater degrees of freedom when compared to the case of open-pit mining. In open pit mining, the direction of extraction is more predictable because the pit keeps expanding laterally and getting deeper as mining progresses. Furthermore, the stopes extracted in an underground mine may vary significantly in shape, unlike blocks in an open pit mine which are more homogeneous. The underground extraction sequence is distinctly characterized by activity precedence, where certain types of activities must precede others.

Early applications of Operations Research tools involved evaluating alternative schedules and making decisions regarding extracted ore [36]. For instance, Williams et al. [50] develop a model that minimizes production fluctuations among multiple production faces of a copper mine. Most early implementations utilized simulation and linear programming techniques for underground production scheduling until the mid 1990s, when mixed-integer programming (MIP) techniques were introduced. While simulation fails to guarantee optimality, linear programming precludes the use of integer decision variables. These variables are required for determining optimal start dates of activities, facility siting, and enforcing activity precedence. Thus, the use of MIP models and, subsequently, integer programming (IP) models improved the representation of operational procedures in underground mining. In one of the first implementations of MIP for this problem, Trout [48] determines the time periods for the extraction and backfilling of stopes in a cluster of base metal mines. Carlyle and Eaves [7] build upon Trout's work by incorporating additional activities, i.e., development drilling and stope preparation, in their model for a platinum and palladium underground mine. The model is used by mine planners for routine economic analysis and tactical planning. These and subsequent models have focused on solving long- and medium-term scheduling problems with improved solution time amid increasing complexity over the years. For instance, Smith et al. [45] improve solution time by using aggregation techniques to reduce the number of variables in the model. A common objective has been to maximize the net present value or minimize the overall cost of operations over the long or medium term [7, 22, 37, 45, 48].

Advances made over the last few decades in operations research techniques and computational power have enhanced the solution of large-scale and complex underground production scheduling problems. Notable is the casting of underground production scheduling as a Resource-Constrained Project Scheduling Problem (RCPSP). The RCPSP is an OR framework that schedules activities subject to precedence and resource constraints while minimizing the makespan, i.e., the time difference between the start of the first activity and finish of the last activity [1, 21]. The RCPSP belongs to the class of non-deterministic polynomial-time (NP)-hard problems. The standard RCPSP model cannot cover all real-world scenarios; thus, researchers have proposed variants and extensions of the RCPSP in the literature. One group of the extensions considers alternative objectives, and the majority of the RCPSP-based underground schedules fall under this group. Variants considered for this group in the literature include objectives based on net present value (NPV), cost, resource leveling, time-based requirements, and limitations on rescheduling [8, 21, 47, 51]. The first two variants are common in underground production scheduling and have mainly been used in solving long- and medium-term scheduling problems. For instance, Maybee [31], Fava et al. [16], and Sharma [44] generate schedules that improve NPV over the medium and long term. They solve their models using the Schedule Optimization Tool (SOT) [41] that makes use of genetic algorithms and heuristics. O'Sullivan and Newman [39] solve a variant of the NPV-based objective problem by focusing on maximizing metal production. Using an optimization-based heuristic, they generate schedules that maintain feasibility for three different mining methods and that can be evaluated for several end-of-life-of-mine scenarios. Brickey [5] develops and solves a model with a similar objective that incorporates ventilation requirements. The author solves the model for a 2-year horizon at a daily fidelity using the OMP Solver [40], which utilizes the Bienstock-Zuckerberg algorithm [3] and a toposort heuristic [9] to rapidly develop solutions. King et al. [23] use a similar approach to solve scenarios of the open-pit-to-underground transition problems while maximizing NPV. Using a sliding time window heuristic [13], Lopes [29] expedites solutions for scheduling large real-world instances of a RCPSP-based model for underground stoping and cut-and-fill operations. In their work, Huang et al. [22] develop a more flexible (expandable) model for scheduling ore extraction and development activities for cut-and-fill mining.

OR-based research in short-term underground scheduling has been sparse, compared to long- and medium-term underground scheduling. The available literature reports of two main frameworks for developing short-term schedules. These are the flow-shop and RCPSP-based frameworks. The former is mainly used for equipment allocation while the latter is used for activity scheduling. The formulation we present in this paper is based on the latter framework.

In flow-shop scheduling, all works or jobs are set up to have the same processing route, i.e., a job can only be processed in a fixed sequence across different machine types [15]. In underground flow-shop problems, the working faces, i.e., active mining areas, represent the jobs, and the mining equipment represent the machines. Gamache et al. [17] adopt the flow-shop approach in solving an underground mine dispatch problem. The authors utilize the shortest-path algorithm to simultaneously dispatch, route, and schedule bi-directional mining vehicles in an underground mine. Using dynamic programming, Beaulieu and Gamache [2] develop an enumeration algorithm that determines the optimal route and schedule for bi-directional underground mining vehicles in the shortest time. The schedule avoids conflicts on the haulage network by taking into account the displacement modes of the vehicles, i.e., either forward or in reverse. Using a similar approach, Song et al. [46] develop a flow-shop model for scheduling mobile mining equipment that improves working efficiency and reduces the working time of an underground gold mine. The model utilizes four enumeration algorithms, i.e., sequencing, grouping, machine set, and machine sharing, to determine the schedule with the shortest makespan. In recent years, researchers have extended the flow-shop to incorporate mine workers as resources, i.e., both machines and workers are assigned specific mining tasks and are scheduled simultaneously [42, 43].

The available literature for underground short-term scheduling provides methodologies that are similar to those for underground long- and medium-term scheduling. Nehring et al. [35] provide a MIP model that simultaneously schedules production and provide machine allocations for sublevel stoping operations. The model minimizes deviation from targeted ore production. Using a MIP formulation, Campeau and Gamache [6] develop a RCPSP-like model to create an activity schedule in the short term at weekly fidelity based on medium-term objectives. The model maximizes ore tonnage and prioritizes solutions that finish tasks earlier by discounting the ore tonnage over time. The authors demonstrate that scheduling activities in a preemptive manner, i.e., where activities can be stopped once started and restarted at a later date, provides more realistic and quality solutions than otherwise. Manríquez et al. [30] improve adherence to short-term production schedules by developing a simulation-optimization framework that incorporates operational uncertainty. The framework is iterative, and in each iteration, a short-term schedule is generated using MIP, followed by a discrete-event-based simulation of the generated schedule. The simulation serves to evaluate the generated schedule and provides useful feedback to generate a new and better schedule in subsequent iterations. Adherence indices utilized in the model to assess solution quality include activity lateness, tardiness, earliness, start, and completion periods, along with material movement.

In this paper, we propose a deterministic mathematical formulation for short-term underground production scheduling that is based on the rescheduling variant of the RCPSP structure [21]. Past researchers have taken a makespan-minimization approach to describe similar problems in other domains, rescheduling activities in response to unexpected disruptions which result in delays, reductions in resource availability, and interruptions [8, 14]. We contribute to the scarce literature in the subject area by addressing the short-term scheduling problem as an adjustment of the activity start dates of an already optimized schedule, i.e., the medium-term plan. We utilize this approach to accommodate unforeseen circumstances such as changes in production rates, activity costs, and revenues. Incorporating this formulation into existing workflows would help mine planners assess different options as deviations arise.

We do not opt for the more popular NPV-based scheduling considering that the planning horizon for short-term scheduling is a small fraction of the timeline compared to medium- and long-term scheduling. Generating short-term schedules based on value maximization may lead to situations where the operations cannibalize the future of the forecast to feed the present. Campeau and Gamache [6] emphasize this concern in their work by stating that at the short-term level of planning, which is usually less than 6 months ahead, most of the economically influential decisions would have been made. Equipment quantity and the amount of resources available would have already been fixed, and mining methods and mine layout would have already been decided. Thus, at the short-term level, there are few possible variations in planning that could affect the overall economics of the operation.

2 Methodology

We develop a formulation for short-term underground production scheduling that provides operationally realistic and flexible decision-making options for the mine planning engineer. We achieve this by building a two-component objective function for the formulation that minimizes deviation from the medium-term plan while striving to achieve monthly forecast goals, e.g., ore production. The proposed formulation thus considers two types of deviations: (i) activity start time deviations from the medium-term plan (activity deviations) and (ii) deviations from forecast target values for operational goals (goals deviations). Activities that are scheduled in the short term to start at a time close to their medium-term start date are not penalized in the objective function. Activities that get scheduled much earlier or much later than their medium-term start date incur an earliness or tardiness penalty, respectively, in the objective function. The formulation also checks against overachieving or underachieving forecast goals by imposing corresponding penalties on the objective function. The farther the achieved goals are from the forecast values, the greater the penalty imposed. By this approach, we are able to obtain activity schedules at a fine fidelity, e.g., shift, half-shift, hourly, that achieve, or are as close as possible to, forecast targets and also follow the medium-term plan.

In developing this formulation, our goal has been to incorporate flexibility for easy adaptation by other operations (mines employing different underground mining methods and having fluctuating operational conditions). We have thus incorporated scaling factors by which mine planning engineers can assign priorities to the two primary components of the objective function, i.e., activity deviations and goals deviations. We have also made it possible to prioritize one goal over the other, depending on operational conditions and considerations at the mine. This is to contribute to a more realistic scheduling in underground mining operations and provide engineers the ability to adjust the model to meet changing priorities. The objective function also controls bias (skewness) by normalizing penalties from the two terms to be in the range 0–1. In this way, both activity deviations and goals deviations are brought to a similar scale prior to solving the model. We create schedules from the model at a 12-hour shift fidelity (time period). We further incorporate sets of consecutively coarser time periods, known as multi-time periods, in the model [10]. A multi-time period can represent a week or a month. The flexibility we incorporate in the model makes it possible for a mine planner to adjust the scheduling fidelity and the multi-time period fidelity according to the needs of the operation. The model assesses goals deviations over each multi-time period rather than over each time period (shift) because shift-to-shift operational performance can vary significantly due to heterogeneity and uncertainty associated with underground mining activities. Implementing goals deviation penalties over the multi-time period (weekly or monthly) allows flexibility in the schedule at the shift-to-shift level while still meeting weekly or monthly forecast targets. The proposed formulation is an improvement upon an existing formulation by Chowdu [12]. We make improvement by incorporating more realistic penalty functions for minimizing activity and production goal deviations. Activity earliness and tardiness are penalized with exponentially increasing values as deviations increase, while goal penalties are only imposed if certain predetermined production target levels are not met, or are exceeded.

2.1 Activity Start Time Deviation Penalties

For each activity scheduled in the short term, a penalty is imposed in the objective function based on how much the short-term start date deviates from the production forecast, i.e., medium-term start date. Activities that begin earlier than their forecast date incur earliness penalties while those which begin later than their forecast date incur tardiness penalties. We adopt a symmetric approach to the calculation of earliness and tardiness penalties (Fig. 1). That is, an activity that is early by a certain number of time periods incurs the same penalty as one that is tardy by the same number of time periods. No penalty is assigned if an activity is scheduled to start on the same date as the forecast date. We also incorporate the concept of grace period, i.e., the number of time periods an activity is allowed to be early or tardy without incurring penalty. For the case study presented herein, we impose a grace period of 1 day, i.e., two shifts (Fig. 1). This is essential considering that in medium-term planning, activity start dates are of coarser fidelity, e.g., daily, weekly, and monthly, than in short-term planning. The use of grace periods thus prevents over constraining the problem when considering finer time fidelity, e.g., shift, half-shift, and hourly. Prior to modeling the short-term schedule, we determine the activity deviation penalties for each activity over all the possible start times in the short-term horizon using Eq. 1 (Table 1 provides a description of the symbols utilized).

$$pen_{at} = \begin{cases} 0, & |t-\hat{t}_a| \leq 2 \\ \left(\frac{|t-\hat{t}_a|}{n}\right)^{3f} + \left(\frac{|t-\hat{t}_a|}{n}\right)^{f-1}, & 2 < |t-\hat{t}_a| \leq 28 \\ \left(\frac{|t-\hat{t}_a|}{n}\right)^{f} + \left(\frac{|t-\hat{t}_a|}{n}\right)^{f-1}, & |t-\hat{t}_a| > 28 \end{cases} \tag{1}$$

Equation 1 describes an exponentially increasing penalty function. Assuming a 12-hour shift fidelity, i.e., time period, the difference t - $\hat{t}_a$ measures the earliness or tardiness deviation, in shifts, between an activity's forecast start time $\hat{t}_a$ in the medium-term schedule and the potential start time t in the short-term schedule. Dividing this deviation by the number of shifts in a multi-time period yields an earliness or tardiness deviation expressed in terms of the multi-time period. In this study, a multi-time period is assumed to be a 30-day month, resulting in a total of 60 shifts per month. Equation 1 is made up of three components. The first component ensures that no penalty is assigned when an activity starts within the grace period, i.e., up to 2 shifts before or after the medium-term start date. The second component assigns a more gentle exponentially increasing penalty for activities whose earliness or tardiness is within 2 weeks, i.e., 28 shifts, of their medium-term start date. The third component assigns a steeply increasing exponential penalty to activities whose earliness or tardiness goes beyond 2 weeks. This incentivizes the model to schedule activities close to their forecast start times, i.e., estimated start times in the medium-term plan.

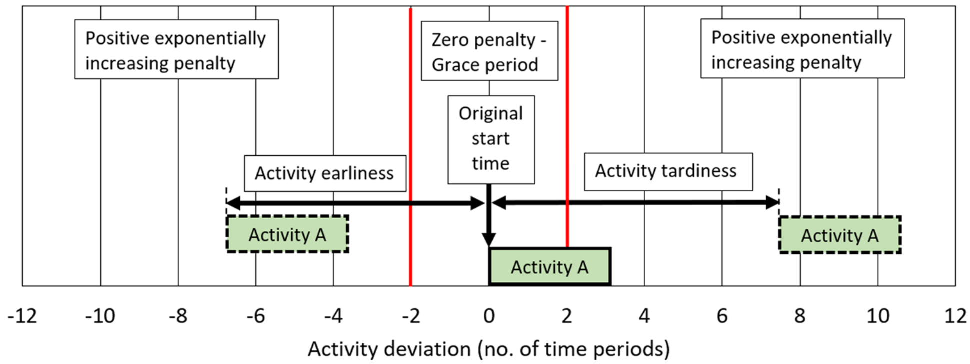

Fig. 1 Activity earliness, tardiness, and grace period. No penalty is imposed if an activity is scheduled within the grace period, i.e., earliness or tardiness within two time periods of an activity's original start time. Scheduling activities beyond the grace period carries an increasingly exponential penalty. It is also possible to impose a skewed penalty scheme, e.g., earliness is less heavily penalized than tardiness

Adopting an exponentially increasing function, instead of a simple linearly increasing function, helps us to better manage penalty assignment to reflect operational situations. That is, based on operational conditions, we segregate the penalty assignment over the time periods in a more continuous and realistic manner. We achieve this by discouraging activity earliness or tardiness that goes beyond 2 weeks by heavily penalizing such and gently penalizing those whose earliness or tardiness is within 2 weeks. Figure 2 shows a graph for the exponential function, assuming a multi-time period of 60 shifts and an exponential factor of 2. An activity with a forecast start time of shift 60 in the medium term, and a scheduled start time of shift 50 in the short term will incur an earliness deviation, i.e., t - $\hat{t}_a$, of 10 shifts. This will result in a penalty of 0.17, assuming a multi-time period of 60 shifts and an exponential factor of 2. In order to ensure that the activity deviation penalties are on a similar scale as the goals deviation penalties, we normalize all pen_{at} values to be in the range 0–1, using Eq. 2.

$$\overline{pen}_{at} = \frac{pen_{at}}{\max_{a,t}(pen_{at})} \; \forall \; a \in \mathcal{A}; t \in \mathcal{T} \tag{2}$$

where

$\overline{pen}_{at}$ = normalized penalty assigned if activity a is scheduled in time period t

$\max_{a,t}(pen_{at})$ = the maximum penalty assigned to activity a

Table 1 Penalty function explained. A time period represents a 12-hour shift in the scheduling horizon, while a multi-time period represents a 30-day month

Symbol	Description
pen_{at}	Penalty if activity a is scheduled in time period t
t	Time period in the short-term schedule
$\hat{t}_a$	Forecast start time for activity a
n	Number of time periods in a multi-time period
f	Exponential factor

2.2 Goal Deviation Penalties

We assign goal deviation penalties based on the multi-time periods. For a given multi-time period, the assigned penalty is determined by the fraction of the goal, i.e., production target, achieved for that period. This fraction can represent under-achievement or over-achievement, either of which we penalize in order to closely stick to the medium-term goals, i.e., ore tonnage and lateral development targets. We define two sets of goal achievement values, i.e., under-achievement and over-achievement. These values are fractions that serve the purpose of adjusting the lower and upper bounds on a given multi-time period goal constraint. The under-achievement values range from 0.80 to 1.00. For each multi-time period, we determine the actual fraction of the goal achieved for that period. We then iterate over the fractions in the set of under-achievement values. When the actual fraction of goal achieved in that multi-time period is lower than a given value, a corresponding penalty is assigned for the deviation. The

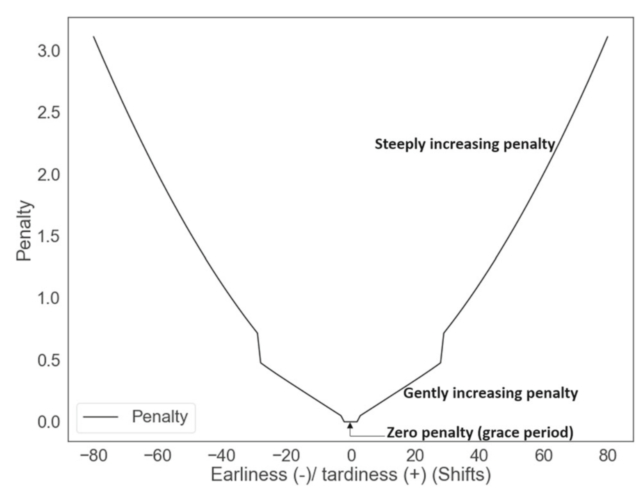

Fig. 2 An example of a realistic penalty scheme. The exponential penalty function discourages activity earliness or tardiness that goes beyond 2 weeks (28 shifts) by heavily penalizing such and gently penalizing those whose earliness or tardiness is within 2 weeks. No penalty is assigned when earliness or tardiness is within 1 day (two shifts) of an activity's original start time. This is termed the grace period

assigned penalties range from 0.00 to 1.00 so as to be on a similar scale as the activities deviation penalties.

For illustration purposes, consider the following set of values: 0.80, 0.90, and 0.98. Assume the respective penalties for failing to achieve these values in a multi-time period are 0.75, 0.50, and 0.10. Assuming in a given month, representing one multi-time period, the total amount of ore tonnage produced is 42,500 out of a production target, i.e., goal, of 50,000 tonnes, the fraction of achieved ore tonnage will be 0.85, i.e., $\geq$ 85% of the production target. Iterating over the set of under-achievement values results in a total deviation penalty of 0.6, i.e., 0.5 + 0.1, for ore tonnage in that month. Note that no penalty is assigned for the first value since the achieved fraction of 0.85 exceeds that value.

A similar concept is applied to the set of over-achievement values, defined over the range 1.00 to 1.10. In this case, goal over-achievement is penalized. That is, when the actual fraction of goal achieved in a multi-time period is greater than a given value, a corresponding penalty is assigned. Subsequently, for each multi-time period, a cumulative over-achievement or under-achievement penalty is assigned. This is calculated as part of the objective function, and thus implemented during solution of the model, and not a priori like in the case of the activities deviation. The implementation creates a step-wise goal deviation function that increases in magnitude as the goal deviation increases and vice versa. By this approach, the model is incentivized to prevent large deviations from the forecast production targets. From the foregoing, the overall range of goal achievement values considered in the formulation is from 0.80 to 1.10. We do not, however, penalize values between 0.98 and 1.02. This constitutes a $\pm$2% goal deviation margin, and it represents the amount of ore tonnage or lateral development in excess or shortage that can be allowed without significantly disrupting future operational goals. It is analogous to the concept of grace period in the activities deviation function; it helps prevent the model from being over constrained. Strictly requiring the model to achieve the exact target in a given month may over constrain the problem, leading to longer solution times and poor solution quality [38]. The model's flexibility allows a mine planner to define specific fractions for the two sets of goal achievement values, depending on short-term production requirements and operational conditions. Additionally, the planner can define the range over which no penalty is assigned for both over-achievement and under-achievement.

2.3 Mathematical Formulation

We formulate the model as a RCPSP following the rescheduling variant. That is, we formulate the short-term scheduling problem as an adjustment of the activity start dates of the medium-term schedule at a finer fidelity while minimizing

Table 2 Simple sets

Symbol	Description
$\mathcal{A}$	Set of all activities ($a \in \mathcal{A}$)
$\mathcal{R}$	Set of operational resources ($r \in \mathcal{R}$)
$\mathcal{E}$	Set of equipment resources ($e \in \mathcal{E}$)
$\mathcal{T}$	Set of shifts in scheduling horizon (time periods for short-term scheduling) ($t = 1 \ldots \lvert\mathcal{T}\rvert$)
$\mathcal{M}$	Set of all multi-time periods ($m \in \mathcal{M}$)
$\mathcal{G}$	Set of production and development goals ($g \in \mathcal{G}$)
$\mathcal{L}^+$	Set of goal over-achievement values ($l \in \mathcal{L}^+$)
$\mathcal{L}^-$	Set of goal under-achievement values ($l \in \mathcal{L}^-$)

activity and goal deviations. The objective function minimizes these deviations subject to resource and precedence constraints. We include goal deviation constraints to ensure the satisfactory achievement of goals in each multi-time period. The model has three types of decision variables. These include binary variables y_{at}, which determine when an activity starts; binary variables x^+_{gml}, which turn on goal over-achievment penalties; and binary variables x^-_{gml}, which turn on goal under-achievement penalties.

We obtain the data used in the model from the medium-term mine plan. From this, we deduce the sets of activities, resources, goals, and predecessors (listed in Tables 2 and 3). Table 4 describes all the parameters used in the model, e.g., activity duration, resource consumption, resource capacities, and multi-time period targets. All decision variables, objective function, and constraints in the model are defined as follows:

Decision Variables:

$$y_{at} = \begin{cases} 1, & \text{if activity } a \text{ starts in time period } t \\ 0, & \text{otherwise} \end{cases}$$

$$x^+_{gml} = \begin{cases} 1, & \text{if } l \in \mathcal{L}^+ \text{ is achieved for goal } g \text{ in multi-time period } m \\ 0, & \text{otherwise} \end{cases}$$

$$x^-_{gml} = \begin{cases} 1, & \text{if } l \in \mathcal{L}^- \text{ is not achieved for goal } g \text{ in multi-time period } m \\ 0, & \text{otherwise} \end{cases}$$

Table 3 Subsets and indexed sets

Symbol	Description
$\mathcal{A}^h \subseteq \mathcal{A}$	Set of activities available to be scheduled within current scheduling horizon
$\mathcal{A}^c \subseteq \mathcal{A}$	Set of activities previously scheduled and carrying over to current scheduling horizon
$\mathcal{A}_r \subseteq \mathcal{A}$	Set of activities consuming resource $r \in \mathcal{R}$
$\mathcal{A}_e \subseteq \mathcal{A}$	Set of activities utilizing equipment $e \in \mathcal{E}$
$\mathcal{P}_a \subset \mathcal{A}$	Set of predecessors for activity $a \in \mathcal{A}$
$\mathcal{T}_m \subseteq \mathcal{T}$	Set of shifts $t \in \mathcal{T}$ contained in multi-time period $m \in \mathcal{M}$

Objective Function:

$$\mathcal{STUG}: \text{ Minimize } w_{\mathcal{A}} \cdot \frac{1}{|\mathcal{A}^h|} \cdot \sum_{a \in \mathcal{A}^h} \sum_{t \in \mathcal{T}} y_{at} \cdot \overline{pen}_{at} + w_{\mathcal{G}} \cdot \frac{1}{|\mathcal{G}| \cdot |\mathcal{M}|} \cdot \sum_{g \in \mathcal{G}} \sum_{m \in \mathcal{M}} \left(\sum_{l \in \mathcal{L}^+} w_{\overline{g}} \cdot x^+_{gml} \cdot pen^+_{gml} + \sum_{l \in \mathcal{L}^-} w_{\overline{g}} \cdot x^-_{gml} \cdot pen^-_{gml} \right) \tag{3}$$

Subject to:

$$\frac{1}{b_{gm}} \cdot \sum_{t' \in \mathcal{T}_m} \sum_{a \in \mathcal{A}} q_{ag} \cdot (\sum_{t=max\{t'-d_a+1, es_a\}}^{t'} y_{at}) + x^-_{gml} \geq f^-_l \qquad \forall\, g \in \mathcal{G};\; m \in \mathcal{M};\; l \in \mathcal{L}^- \tag{4}$$

$$\frac{1}{b_{gm}} \cdot \sum_{t' \in \mathcal{T}_m} \sum_{a \in \mathcal{A}} q_{ag} \cdot (\sum_{t=max\{t'-d_a+1, es_a\}}^{t'} y_{at}) - x^+_{gml} \leq f^+_l \qquad \forall\, g \in \mathcal{G};\; m \in \mathcal{M};\; l \in \mathcal{L}^+ \tag{5}$$

$$\sum_{a \in \mathcal{A}_r} q_{ar} \cdot \left(\sum_{t'=max\{t-d_a+1, es_a\}}^{t} y_{at'} \right) \leq \overline{c}_{rt} \qquad \forall\, r \in \mathcal{R}; t \in \mathcal{T} \tag{6}$$

$$\sum_{a \in \mathcal{A}_e} \left(\sum_{t'=max\{t-d_a+1, es_a\}}^{t} y_{at'} \right) \leq \overline{c}_{et} \qquad \forall\, e \in \mathcal{E}; t \in \mathcal{T} \tag{7}$$

$$\sum_{t'' \leq t} y_{at''} \leq \sum_{t'=es_{a'}}^{t-d_{aa'}} y_{a't'} \qquad \forall\, a \in \mathcal{A}, a' \in \mathcal{P}_a, t \in \mathcal{T} : t \geq es_a \tag{8}$$

$$\sum_{t \in \mathcal{T}} y_{at} \leq 1 \qquad \forall\, a \in \mathcal{A} \tag{9}$$

$$y_{a1} = 1 \qquad \forall\, a \in \mathcal{A}^c \tag{10}$$

$$y_{at} \in \{0, 1\} \qquad \forall\, a \in \mathcal{A}; t \in \mathcal{T} \tag{11}$$

$$x^-_{gml},\; x^+_{gml} \in \{0, 1\} \qquad \forall\, g \in \mathcal{G};\; m \in \mathcal{M};\; l \in \mathcal{L}^-,\; \mathcal{L}^+ \tag{12}$$

The objective function (3) consists of two components. The first component minimizes activity start time deviations from the medium-term plan. The second component minimizes deviations from the forecast target values of operational goals, i.e., ore tonnage (t) and lateral development (m). The objective function achieves this by introducing penalties for the respective deviations. By minimizing these penalties, we obtain schedules that achieve forecast targets and that follow the medium-term plan. Using Eqs. 1 and 2, the first component applies the respective normalized penalty for an activity a that gets scheduled in time period t. The total penalty resulting from activity deviations is then divided by the number of activities available for scheduling within the current horizon. This yields the average penalty for the deviation of activities from their forecast start dates.

The second component of the objective function applies a penalty for each multi-time period m, depending on whether a given goal g is under-achieved or over-achieved during that period. The severity of the penalty is a function of the severity of the under-achievement or over-achievement of the goal. When the goal is not met, the binary variable x^-_{gml} turns on via constraint 4 in order to implement the appropriate penalty. The binary variable x^+_{gml} turns on via constraint 5 for over-achievement. The total goal penalty is then divided by the product of the number of multi-time periods and the number of goals. This yields the average penalty for all goal devia-

Table 4 Model parameters

Parameter	Description
d_a	Duration of activity a (number of time periods)
$d_{aa'}$	Sum of $d_{a'}$ and minimum delay between activities a and a' (number of time periods)
es_a	Earliest start (time period) for activity a
$\overline{c}_{rt}$	Maximum operational capacity available for resource r in time period t (tonnes or meters)
$\overline{c}_{et}$	Maximum number of concurrent activities utilizing equipment e in time period t
b_{gm}	Operational target for goal g in multi-time period m, i.e., medium-term forecast (tonnes or meters)
q_{ar}	Consumption of resource r by activity a (tonnes or meters per time period)
q_{ag}	Contribution of resource towards goal g by activity a (tonnes or meters per time period)
$\overline{pen}_{at}$	Normalized earliness/tardiness penalty for activity a for starting in time period t (unitless; ranges from 0.00 to 1.00)
f_l^+	Goal over-achievement value $l \in \mathcal{L}^+$ (unitless; ranges from 1.00 to 1.10)
f_l^-	Goal under-achievement value $l \in \mathcal{L}^-$ (unitless; ranges from 0.80 to 1.00)
pen_{gml}^+	Penalty assigned if $l \in \mathcal{L}^+$ is achieved for goal g in multi-time period m, i.e., over-achievement penalty (unitless)
pen_{gml}^-	Penalty assigned if $l \in \mathcal{L}^-$ is not achieved for goal g in multi-time period m, i.e., under-achievement penalty (unitless)
$w_{\mathcal{A}}$	Scaling factor (relative importance) of minimizing activity deviation (unitless)
$w_{\mathcal{G}}$	Scaling factor (relative importance) of minimizing goals deviation (unitless)
$w_{\overline{g}}$	Priority scaling factor for goal g (unitless)

tions. Parameters $w_{\mathcal{A}}$ and $w_{\mathcal{G}}$ are weighting factors by which mine planning engineers can assign respective priorities to the two components of the objective function. A higher value for either parameter more heavily weights the impact of the corresponding penalty, and this forces the solver to prioritize accordingly.

Constraints 4 and 5 ensure the achievement of target values for all goals in each multi-time period. This is achieved by preventing under-achievement or over-achievement for the respective goal achievement values being considered. Constraints 6 impose shift-based resource capacity, i.e., ore tonnage (t) and lateral development (m), constraints on the activities. Constraints 7 limit the number of concurrent activities that utilize equipment type e in a given time period t. Constraints 8 enforce the physical precedence between activities and allows for lags between an activity and its predecessor. Constraints 9 ensure each activity is scheduled at most once, while constraints 10 enforce the start of carryover activities in the first time period of the scheduling horizon. Constraints 11 and 12 ensure that the decision variables y_{at}, x_{gml}^-, and x_{gml}^+ are binary.

3 Case Study

The case study mine forms part of an underground mining operation that is located in South America. The operation contains six major mineralized zones, with an annual production of approximately 334,000 ounces of gold [32]. The operation is a multi-mine complex with three high-grade underground operating mines. As part of an expansion project, two additional underground deposits are being developed into mines, one of which is the focus of this study. The operation adopts a combination of transverse and long-hole stoping mining methods with a variation of the Avoca method when the vein width is less than 6 m. Mining proceeds in an overhand (bottom-up) approach, and mined out stopes are backfilled using waste rock fill, cemented rock fill, or a combination of both.

A medium-term plan is already in place for the case study mine (Mine Y) at a daily fidelity over a period of 5 years. Access to this mine is through a decline that connects from the surface to a ramp system (Fig. 3). The decline, along with two raises serve as air intakes while another raise and two drifts that link an adjacent mine, provide air exhaust for ventilation. The total planned airflow through this mine is approximately 200 m^3/s. Based on the medium-term plan, management of the mine would like to produce flexible short-term schedules that can accommodate unforeseen operational disruptions. The scheduling framework should be capable of accommodating disruptions that affect production rate and capacity momentarily, and be able to correct the ensuing deviations from the medium-term plan. To this end, we apply our formulation to data from Mine Y to assess impact of different operational scenarios on the schedule. The dataset is in the form of Deswik CAD and scheduler file formats. From this,

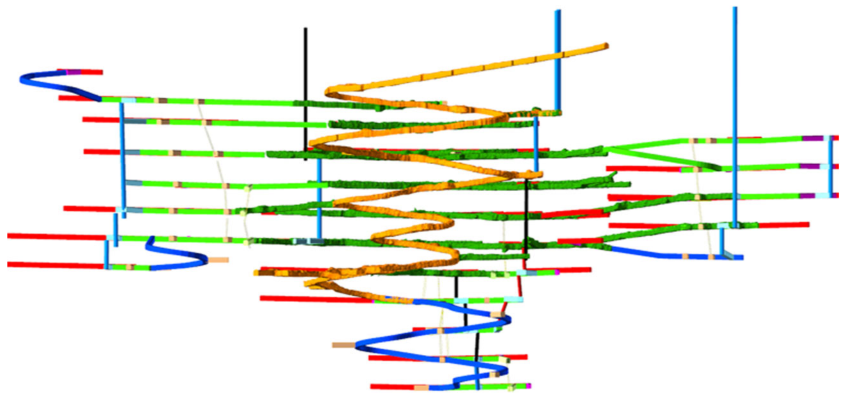

Fig. 3 Design and layout of declines, drifts, and raises at mine Y (Source: Mine Y, 2019)

we obtain the three-dimensional design of the mine (Fig. 3), activity definitions, resource assignment and activity precedence structure .

Table 5 shows the shift-based resource and equipment capacities used in this case study. The shift-based resource capacities, i.e., the first six resource constraints, are obtained from the daily maximum values using Eq. 13. The division by 2 in the equation is based on the assumption that the resource capacities are evenly divided between the two shifts in a day. The multiplication of the daily maximum value by a factor of 1.10 is based on the assumption that the available resources have a capacity that is 10% more than the daily maximum value. The equipment capacities, i.e., concurrent activity constraints, remain the same for both daily and shift fidelities. Table 6 shows the monthly, i.e., multi-time period, goals considered in this study. The table shows the respective target values for the amount of ore extracted and the amount of lateral development completed for each month. These values are obtained from the medium-term plan. Activities considered for scheduling include development drilling, production drilling, stoping and backfill activities. Section 3.1 describes the scenarios we consider in this case study. All scenarios are coded with the Python programming language and solved with the Gurobi solver, version 9.0.1 [19]. We run the scenarios on a HP EliteDesk 800 G2 TWR computer with 8 cores at a processing speed of 3.4 GHz each, and 16 GB of RAM. We impose on the solver a time limit of 15 min, and a target integrality gap of 0.1%. The integrality gap refers to the optimality gap between the objective function value of the relaxed linear-programming solution and that of the integer solution.

$$\text{Shift resource capacity} = 1.10 * \frac{\text{Daily maximum}}{2} \qquad (13)$$

3.1 Scenario Considerations

The scenarios we consider are sets of 30-day and 60-day short-term schedules created at 12-hour shift fidelity, with a 30-day look-ahead period in each case. The look-ahead period limits how far ahead one can look in the production forecast and include activities in the model. For instance, with a scheduling horizon of 30 days, the activities we consider for scheduling are those within a 60-day window, i.e., activity horizon, in the forecast, but scheduling is limited to the first 30 days. To do this, we first filter the set of activities to include those whose forecast start dates are within 60 days from the short-term schedule start date. We further filter these activities to include those whose early start dates fall within

Table 5 Resource availabilites

No.	Resource	Daily maximum	Capacity per shift
1	Ore extraction (t)	1600	880
2	Primary development (m)	12.5	7
3	Lateral development (m)	23.2	13
4	Ramp development (m)	6	3.5
5	*Other development (m)	12.1	7
6	Backfill (m^3)	1400	770
7	Number of concurrent development advance activities	4	4
8	Number of concurrent ore extraction activities	3	3
9	Number of concurrent production drilling activities	3	3

*Refers to all other development in waste

Table 6 Monthly goals and target values (forecast)

Month	Goals	
	Ore tonnage (t)	Lateral development (m)
1	34,670	383
2	33,356	323

the available scheduling horizon, i.e., the first 30 days. This ensures that the model contains only activities which could actually be scheduled within the scheduling horizon under consideration. This is for the purpose of improving model tractability and allowing for flexibility in the scheduling process to enhance accommodation of operational disruptions.

The problem instances we consider are shown in Table 7. The first instance is a 30-day horizon, i.e., 60 shifts, and has 13,920 decision variables of type y_{at}. The second instance is a 60-day horizon comprising 120 shifts with 42,000 decision variables of type y_{at}. The first scenario is a base case which solves for these instances under expected operating conditions. We further simulate operational disruptions for these instances by reducing ore extraction capacity and development advance rate for specific shifts. We summarize all scenarios as follows:

1. Base case
2. Reduced ore extraction capacity
3. Reduced development advance rate

4 Results and Discussion

Using the problem instances outlined in Table 7, we solve for all scenarios at a 12-hour shift fidelity. We utilize a grace period of two shifts and an allowable goal deviation margin of ±2%. That is, schedules which produce goals within this margin are acceptable to the mine planner. We present summarized results for the base case in Table 8 using the resource constraints and target values in Tables 5 and 6, respectively. The results show that each instance of the base case satisfactorily achieves the targets for the respective goals. This is because all goal deviations are within ±2% of their respective target values (Table 6). Likewise, there are no significant deviations in activity start times as all activities are scheduled within the grace period of 2 shifts. To further illustrate how closely the base case schedule follows the medium-term plan (forecast), we present cumulative plots for both goals over a period of 60 days (Figs. 4 and 5). From the figures, we realize that the base case closely follows the medium-term plan with minimal deviation from both ore tonnage and lateral development targets. Thus, under normal operating conditions, this formulation is able to schedule at a finer fidelity while not significantly deviating from the medium-term plan.

Table 7 Problem instances

Problem instance	1	2
Schedule horizon (shifts)	60	120
Number of activities	232	350
Decision variables (y_{at})	13,920	42,000
Resource constraints	540	1,080
Precedence constraints (base case)	8,360	26,734

Time limit: 900 s (15 min). Target integrality gap: 0.1%

We further demonstrate how this formulation can be used for rescheduling in the event that operational disruptions occur. We then assess the impact of the disruptions on the ensuing schedules, and make informed decisions where necessary. We begin by simulating different scenarios of mill breakdown, leading to reduced ore extraction capacity for different shifts within the first week of the scheduling horizon. Here, the assumption is that there is not enough space to stockpile ore at full production capacity when the mill breaks down. The mine has a limited stockpile space for ore rehandling, which is located on the surface and accessed via a ramp and decline system. Consequently, we assume a 75% reduction in ore extraction, resulting in a new capacity of 220 tonnes per shift as against the regular capacity of 880 tonnes per shift (Table 5). This would be hauled to the stockpile over the period that the mill is down. We create new schedules for three cases of breakdown lasting 2, 3 and 4 days respectively. In each case, the breakdown occurs 2 days into the start of the scheduling horizon. So, the first case, termed the best case scenario (because it has the least repair duration), disrupts operations for shifts 5 to 8. The second case, termed the mild case scenario, disrupts operations for shifts 5 to 10, while the third case, termed the worst case scenario, disrupts operations for shifts 5 to 12.

Table 9 is a summary of the results for the mill breakdown cases, with emphasis on the ore tonnage since it is the goal that is directly impacted by the reduced ore extraction capacity. Despite the disruptions, all scenarios solve within the acceptable integrality gap of 0.1% and time limit of 900 s, signifying a good quality solution. We observe that the amounts of ore tonnage produced by the best case and mild case schedules are all within the acceptable goal deviation margin of ±2%. So, despite the reduced ore extraction capacity in the first week for these cases, the new schedules are able to make up for the deficit, even within the first month. This is further illustrated in Fig. 6, where the best and mild cases get on

Table 8 Results for base case scenario

Problem instance		1	2
Solution time (s)		1.5	12.6
Integrality gap (%)		0.0	0.0
Activities considered		133	250
Activities scheduled	Within grace period	133	250
	Outside grace period	0	0
Goals deviation from target (%)	Ore tonnage	−1.78	−1.83
	Lateral development	−1.63	−1.70

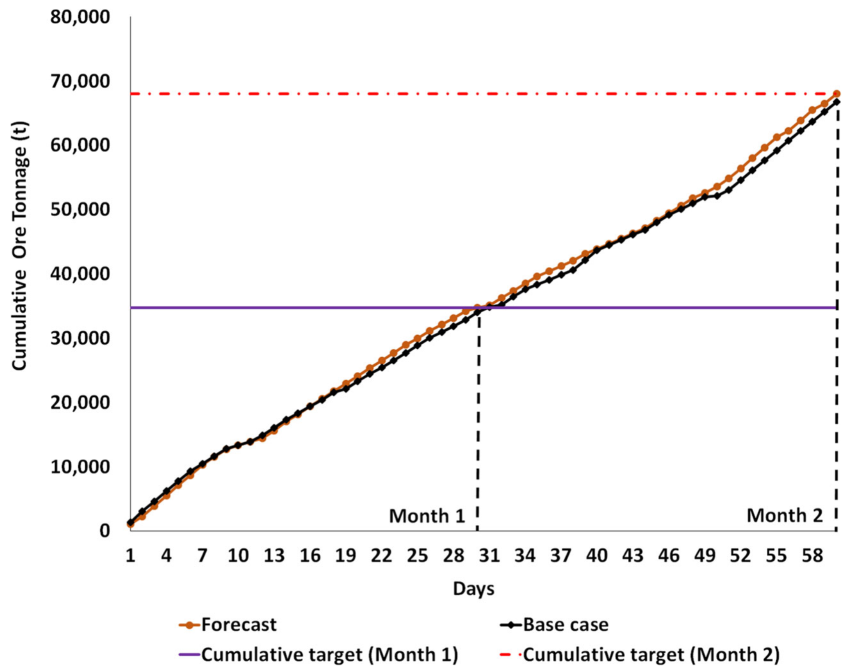

Fig. 4 Cumulative ore tonnage for base case scenario. The base case closely follows the medium-term plan with minimal deviation from ore tonnage target

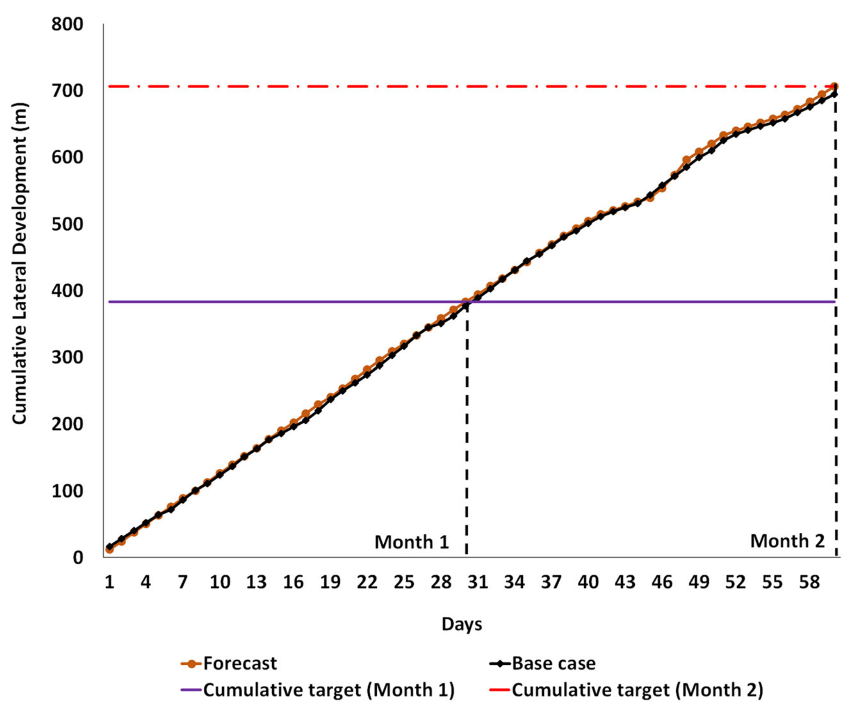

Fig. 5 Cumulative lateral development for base case scenario. The base case closely follows the medium-term plan with minimal deviation from lateral development target

Table 9 Results for reduced ore extraction capacity scenarios

Case		Best case		Mild case		Worst case	
Problem instance		1	2	1	2	1	2
Solution time (s)		12.4	223.6	16.7	227.3	22.1	294.8
Integrality gap (%)		0.02	0.00	0.0	0.00	0.07	0.09
Activities scheduled	**Within grace period**	103	192	91	168	85	171
	Outside grace period	33	57	51	82	52	76
Ore tonnage deviation from target (%)		−1.71	−1.79	−1.85	−1.77	−5.00	−3.39

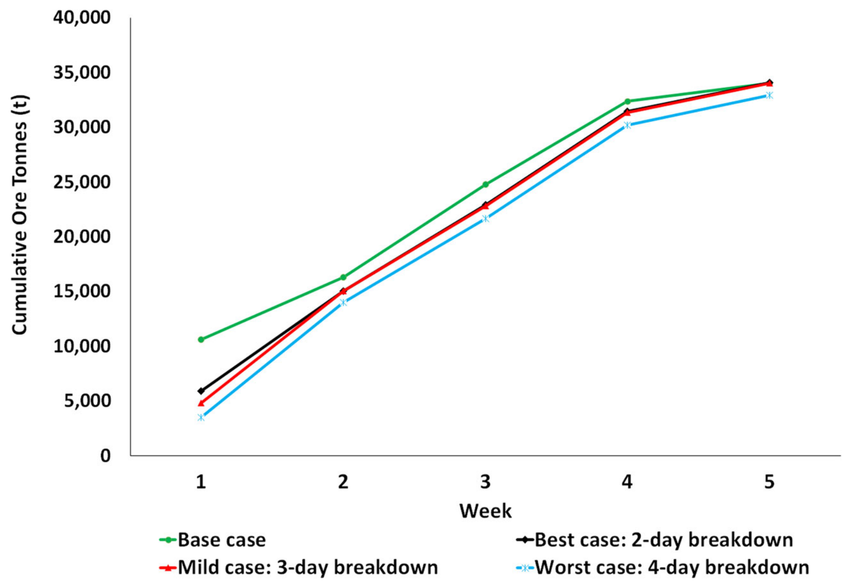

Fig. 6 Impact of reduced ore extraction capacity on schedule. The best and mild cases are able to make up for the initial tonnage deficit, and get on track, i.e., follow the base case, by the fifth week

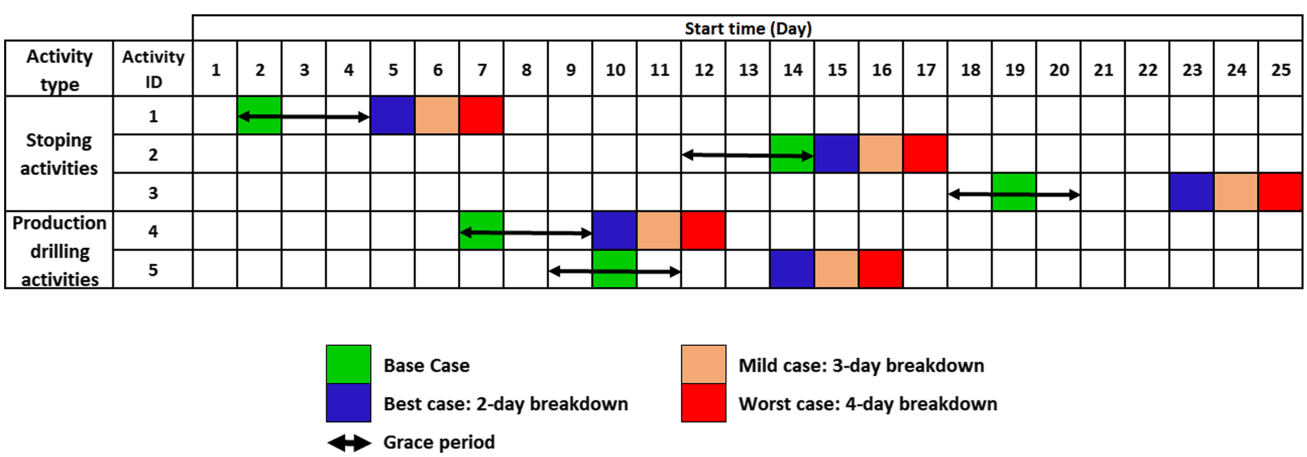

Fig. 7 Start times for stoping and production drilling activities for 30-day schedules. Relative to the base case, all other scenarios have their activity start times pushed forward to accommodate the reduced ore extraction capacity in the first week. The best case shows lesser activity movement compared to the mild and worst cases

Table 10 Impact of worst and mild case scenarios on development advance rate and duration

Activity ID	Base case		Mild case		Worst case	
	Rate (m/d)	Duration (hrs)	Rate (m/d)	Duration (hrs)	Rate (m/d)	Duration (hrs)
1	5.4	15.6	4.1	20.7	2.7	31.1
2	5.4	15.6	4.1	20.7	2.7	31.1
3	5.4	15.6	4.1	20.7	2.7	31.1
4	5.4	15.6	4.1	20.7	2.7	31.1
5	5.4	15.6	4.1	20.7	2.7	31.1

Table 11 Results for reduced development advance rate scenarios

Case		Mild case		Worst case	
Problem instance		1	2	1	2
Solution time (s)		1.4	13.7	0.1	9.9
Integrality gap (%)		0.00	0.00	0.00	0.00
Activities scheduled	**Within grace period**	131	248	131	249
	Outside grace period	0	0	0	0
Lateral development deviation from target (%)		−1.63	−1.70	−1.78	−1.60

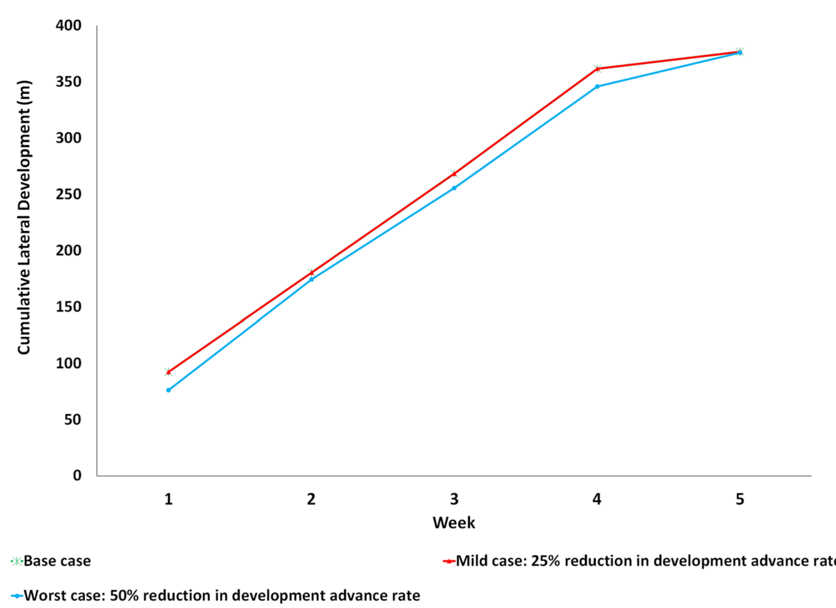

Fig. 8 Impact of reduced development advance rate on schedule. The base case and the mild case are superimposed on each other while the worst case makes up for the initial lateral development deficit and catches up by the fifth week

track, i.e., follow the base case, in the 5th week. Figure 6 is a cumulative ore tonnage plot built from the 30-day schedules for the respective cases. In making up for the deficit, the rescheduled instances for the best and mild cases involve significant movement of activities outside the grace period, when compared to the base case scenario (Tables 8 and 9). We show some activity movement for the reduced ore extraction capacity scenarios relative to the base case in Fig. 7. The figure shows the start times for stoping and production drilling activities in the respective 30-day schedules. We observe that relative to the base case, all other scenarios have their activity start times pushed forward to accommodate the reduced ore extraction capacity in the first week. Generally, the best case shows lesser activity movement compared to the mild and worst cases.

Regarding the worst case, we observe the model's attempt to get back on track as the ore tonnage deviation improves from −5.00% to −3.39% over the 1st and 2nd problem instances in Table 9. This is corroborated by the trend in Fig. 6; it attempts to approach the base case with time. We also observe significant movement of activities in the model's attempt to make up for the deficit incurred in week 1 (Fig. 9). Despite this, the deviation in ore tonnage at the end of the 60-day schedule is above the ±2% margin. In a circumstance of prolonged mill breakdown as this, the mine planner may accept the deficit for the current horizon, and adjust the target when solving for the next horizon, so as to make up for the current horizon's deficit. In doing this, the planner must ensure the adjustment is within the bounds of the resource capacity constraint for the goal under consideration.

We also consider another form of operational disruption that impacts development advance rate. We consider a cluster of development drilling activities located in a poor ground zone, e.g., area where the rock mass is highly fractured or other characteristic has caused difficulty in conducting an activity. In such situations, the development advance rate is often reduced. We solve for two scenarios representing a 25% and 50% reduction in the development advance rate, respectively. The former scenario is termed the mild case, and the latter is termed the worst case. We show the impact of these scenarios on the development advance rate and duration in Table 10. The activities listed therein are all development drilling activities that are spatially close to each other, and occur within the first four days of the scheduling horizon. For the mild case, a 25% reduction in the rate leads to a 33.3% increase in duration. The worst case, which causes a 50% decrease in the rate, leads to a 100% increase in duration.

Results for the 30-day and 60-day schedules for these scenarios are in Table 11, with emphasis on lateral development since it is the goal that is directly impacted by development drilling activities. We observe that all scenarios satisfactorily achieve their respective lateral development goals, i.e., each goal achievement is within the ±2% allowable goal deviation margin. All scenarios are able to make up for the reduced development advance rate without moving activities outside the grace period. These results are similar to the base case scenario (Table 8), considering the number of activities scheduled and the goal deviations; the mild case shows the same deviation values. This goes to show that the model is robust to disruptions in development advance rate–even for the worst case, and only needs minor adjustment to get on track. We further corroborate this observation with a cumulative plot from the 30-day schedules for the first 5 weeks (Fig. 8). The figure shows that the base case and the mild case are superimposed on each other while the worst case makes up for the deficit and catches up in week 5. We investigate activity movement among the three scenarios using the 30-day schedules. We show, in Fig. 9, the start times for the development advance activities in poor ground. We observe that all five activities have the same start times in the base case and mild case. Relative to the base case, the worst case only offers slight adjustments for activities 2 to 5, and all adjustments are within the grace period of two shifts. The foregoing suggests that the short-term schedule is not as sensitive to these development advance disruptions as it is to the ore extraction capacity disruptions.

Fig. 9 Start times for development advance activities in poor ground. All activities have the same start times in the base case and mild case. Relative to the base case, the worst case only shows slight adjustments for activities 2 to 5, and all adjustments are within the grace period of two shifts

5 Conclusion and Future Work

We present the underground short-term production scheduling problem as a rescheduling of the medium-term plan at a finer fidelity. The goal is to develop a tool that can help the mine planner generate short-term schedules that achieve forecast targets without significantly deviating from the sequence of activities in the medium-term plan. With this goal in mind, we develop a formulation that is able to closely follow production forecast under normal operating conditions. The strength of this tool lies in its ability to make up for deficits resulting from operational disruptions. We demonstrate this by simulating disruptions involving reduction in ore extraction capacity and development advance rate. While it is known that any underground mine operation will experience unexpected challenges leading to deviations from the plan, this model provides a tool to adjust and recreate a production schedule in a very short time frame to accommodate the ensuing disruptions. Aside from its rescheduling capability, this tool can help mine planners conduct further analysis on the impact various disruptions have on the schedule. It can help identify those conditions or disruptions that are more detrimental to the achievement of forecast targets, or otherwise. This research contributes the following:

- Generalized formulation to schedule short-term underground mine production activities to optimality.
- Underground production scheduling tool that rapidly makes up for deficits from operational disruptions via optimal activity rescheduling.
- Analytic tool for assessing the sensitivity of operating conditions or disruptions to the achievement of forecast targets.
- Flexible formulation that allows for the prioritization of production goals based on operational conditions at the mine.

In the future, we seek to incorporate in the formulation respirable dust, diesel particulate matter, heat, and other ventilation-related constraints in order to create more realistic schedules that address current environmental challenges and to enhance miners' health and safety. The model is generalized in such a way that operations can tailor constraints to meet unique safety and health concerns. We also seek to capture elements of uncertainty such as activity duration and activity rate in our future work to provide better representation of real-world scenarios. With the advancement of internet-of-things (IoT) and operational technology (OT) systems, mine production scheduling can be revolutionized via real-time update and incorporation of relevant parameters to rapidly create schedules and make informed decisions quickly.

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Declarations

Conflict of Interest The authors declare no competing interests.

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