Mine Schedule Optimization and Mine Operational Realities: Bridging the Gap

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ABSTRACT: Advancement in solution algorithms and computing power continues to drive the adoption of optimization techniques within the underground mining sector. However, limitations in the available data and the choices made during the model setup can create a gap between optimal solutions and operational reality. This paper presents a mining practitioner's guide on effectively utilizing multi-time period knapsack constraints (MPKC) in scheduling underground mine production, which can close part of that gap. Models with MPKC implemented at different time fidelities, i.e., weekly, monthly and annual, are compared by evaluating solution quality and solver performance. We provide recommendations that can assist in developing both optimal and operationally representative schedules.

Keywords: Underground Mining, Production Scheduling, Optimization

1 INTRODUCTION

Well, let us see if this works as well as advertised. Optimization models are approximate representations of real-world systems. Practitioners often must make simplifying assumptions to ensure feasibility or relax constraints to improve tractability. Any such model's purpose is to provide useful information and improve decision-making abilities. With any model formulation, it is important that the assumptions made do not detract from the model's applicability to the operation. Advances in computation power and solution algorithms have enabled researchers to create and solve model formulations more complex and operationally representative than previously possible. In this paper, we explore some of the recent advances in constructing models with a particular focus on underground mine production schedules.

Williams et al. (1973) were the first to make use of operations research principles to develop an underground production schedule that maximized ore production at a copper operation. The original intent of the project was to formulate a linear program to produce "good" schedules; however, the group was unable to define the qualities that comprised a "good" schedule. Revising their approach, they instead set out to produce a tool to that would help planners evaluate several schedules and then choose the "best" option; while not necessarily achieving optimality, they expected to realize a significant improvement over manual scheduling. As computational power increased with time, researchers began developing integer programs, incorporating binary variables and allowing for 'yes-no' decisions (Trout, 1995; Winkler, 1996). Trout utilized an integer programming model to schedule the operational sequence, i.e., extraction and backfilling, of 55 stopes at the Mt. Isa copper mine in Australia. With over 3500 variables and 6900 constraints, it was substantially larger than previous attempts. After 200 hours of computation time, the program had not converged on an optimal solution; however, the solution did result in a 24% increase in NPV over the current mine schedule after only 1.6 hours of computation.

Surface mine optimization has been researched and applied to the industry since the 1960s, (Lerchs and Grossmann, 1964; Johnson, 1968). Today, there are numerous commercially available tools utilizing optimization techniques to improve surface operations, e.g., Geovia Whittle Dassault Systèmes (2018), Pit Optimizer Maptek Pty Ltd (2016), MineSight Economic Planner Hexagon AB (2019), to name a few. Over the last two decades, researchers and industry have worked to develop similar tools for underground mine planning. Today, underground mine planners utilize SOT+ (MIRARCO Mining Innovations, 2018), often in conjunction with a 3-dimensional mine design package. SOT+ uses heuristics to develop feasible schedules, iteratively improving over the previously best known solution, that may or may not provide an optimal solution.

Recent research has focused on using deterministic (Brickey, 2015; O'Sullivan, 2014; Little et al., 2008; Topal, 2008; Newman et al., 2003) and stochastic optimization (Carpentier et al., 2016) to produce robust and optimal underground mine schedules. This paper focuses on modeling techniques, existing and new, that can improve the solution quality of deterministic optimization applications to underground production scheduling. A substantive review of underground mine optimization applications can be found in Alford et al. (2007) and Newman et al. (2010).

2 UNDERGROUND MINE PRODUCTION SCHEDULING

Production scheduling is an integral part of the mine planning process. Scheduling underground operations differs from open pit scheduling and is generally considered more challenging and complex (O'Sullivan et al., 2015) to accomplish. Optimizing underground schedules, consequently, also differs significantly from open pit scheduling. Underground excavations are represented as activities, with varying shapes and sizes. Activities can be broadly delineated into (*i*) production, i.e., stopes, top-cuts, under-cuts, (*ii*) development, i.e., ramps, shafts, raises, and (*iii*) auxiliary, i.e., sumps, electric stations.

The traditional production scheduling process endeavors to determine a feasible sequence of these activities such that operational objectives are met (Newman et al., 2010). When optimizing the schedule, the operational goal(s), e.g. maximizing net present value or minimizing costs, is represented by the objective function, while sequencing and resource limitations constrain the model. Operational objectives are often based on corporate goals. Sequencing constraints (or activity precedence) are derived from geotechnical limitations, and physical or operational sequencing. Lastly, resource constraints enforce operational limitations such as equipment capacity, milling capacity and even ventilation requirements.

Production schedules can be categorized on the basis of time horizon as either strategic (long-term) or tactical (short-term). As the names suggest, a strategic schedule is used to provide a big-picture view of the operation, while the tactical schedule aims to inform activity sequencing at a weekly, daily or shift fidelity.

2.1 *The UG-RCPSP model*

The underground production schedule optimization model is used to determine the start dates for a set of activities in order to maximize the operation's value (Net Present Value), while adhering to precedence and resource constraints (King et al., 2017). The Underground Resource Constrained Production Scheduling Problem (UG-RCPSP) model builds on the work of Brickey (2015), a particular case of the resource constrained project scheduling problem (RCPSP). The RCPSP is a known NP-hard problem (Artigues et al., 2013) that consists of scheduling activities over time, subject to precedence constraints. The following formulation is an example of the Underground Resource Constrained Production Scheduling Problem that we consider.

Indices and sets:

$a \in \mathcal{A}$	set of all activities
$\check{a} \in \check{\mathcal{A}}_a$	set of predecessors for activity a
$\bar{a} \in \bar{\mathcal{A}}_a$	set of predecessor activities $\bar{a}$ that must be completed one period in advance of activity a
$r \in \mathcal{R}$	set of resources, such as production and development capacity, whose limits are enforced on a daily basis
$r \in \hat{\mathcal{R}} \subset \mathcal{R}$	set of resources, such as production and development capacity, whose limits are enforced on a monthly basis
$t \in \mathcal{T}$	set of daily time periods
$m \in \mathcal{M}$	set of monthly time periods
$t \in \hat{\mathcal{T}}_m$	set of days contained in month m

Parameters:

c_a	monetary value associated with completing activity a [$]
q_{ra}	quantity resource r consumed on a daily timescale when completing activity a [tonnes, meters]
$\hat{q}_{ra}$	quantity resource r consumed on a monthly timescale when completing activity a [tonnes, meters]
$\bar{r}_{rt}$	maximum amount of resource r available on day t [tonnes, meters]
$\hat{r}_{rm}$	maximum amount of resource r available in month m [tonnes, meters]
d_a	duration of activity a [days]
$\hat{d}_a$	duration of activity a [months]
$d_{\bar{a}}$	duration, and any associated delay duration, of activity a [days]
δ_t	discount factor for period t [fraction]

Decision variables:

X_{at}	1 if activity a is completed by the end of time t; 0 otherwise

$$(\mathbf{Z}) \quad \max \quad \sum_{a \in \mathcal{A}} \sum_{t \in \mathcal{T}} \delta_t c_a (X_{at} - X_{a,t-1}) \tag{1a}$$

$$\text{s.t.} \quad X_{a,t-1} \le X_{at} \quad \forall\, a \in \mathcal{A}, t \in \mathcal{T} \tag{1b}$$

$$X_{at} \le X_{\bar{a},t-d_{\bar{a}}} \quad \forall\, a \in \mathcal{A}, \bar{a} \in \bar{\mathcal{A}}_a, t \in \mathcal{T} \tag{1c}$$

$$\sum_{a \in \mathcal{A}} \frac{q_{ra}}{d_a} (X_{at} - X_{a,t-d_a}) \le \bar{r}_{rt} \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T} \tag{1d}$$

$$\sum_{t \in \hat{\mathcal{T}}_m} \sum_{a \in \mathcal{A}} \frac{\hat{q}_{ra}}{\hat{d}_a} (X_{at} - X_{a,t-\hat{d}_a}) \le \hat{r}_{rm} \quad \forall\, r \in \hat{\mathcal{R}}, m \in \mathcal{M} \tag{1e}$$

$$X_{at} \text{ binary } \; \forall a \in \mathcal{A}, t \in \mathcal{T} \tag{1f}$$

The objective function (1a) maximizes discounted cash flow. Constraints (1b) and (1c) provide the sequence of activities, i.e., precedence, and enforce when an activity can begin based on predecessor requirements, respectively. Constraint (1d) represents a daily capacity for all resources, whereas constraint (1e) represents a multi-time period resource constraint. The latter constraint is discussed in detail in Section 2.1.1. Finally, constraint (1f) ensures that the decision variable is binary. This formulation was used to optimize the tactical production schedule at Barrick's Turquoise Ridge operation (Brickey et al., 2019).

Using novel algorithms (Bienstock and Zuckerberg, 2009; Muñoz, 2012), in conjunction with heuristics (Chicoisne et al., 2012), it has been shown that it is possible to solve very large integer problems relatively quickly. Researchers at Adolfo Ibañez University and University of Chile, Santiago, have developed a tool, *OMP Solver* that leverages these new algorithms to solve both surface and underground scheduling problems. The following sections present various features that can be used with *OMP Solver* to create models with greater tractability and more operationally representative schedules.

2.1.1 *Multi-Time Period Knapsack Constraints*

Mining operations often use average production rates to create strategic and tactical schedules. These averages might reflect the daily, weekly or even monthly production rates for a given mining method or activity, often corresponding to the fidelity of the desired schedule. Considering the highly variable activity durations seen at several underground mining operations because of the non-homogeneous nature of the mine design, the average production rate method may leave available production unscheduled. For example, the assigned production rate for five stopes is 500 tons per day; however, the average mine production rate over the year is 1200 tons per day. When using an integer program, this means that production capacity will be under-utilized by 200 tons per day. Many practitioners have incorporated continuous variables (Nehring and Topal, 2007; Little et al., 2008), in conjunction with integer variables, to account for this occurrence; yet, there are still challenges associated with solving such large-scale mixed integer problems.

To retain an integer formulation, an alternative was developed that allowed the same flexibility seen in mixed integer programs while allowing the use of newer solution methods. We present Multi-time Period Knapsack Constraints (MPKC) that allow practitioners to create schedules with variable production rates, by achieving or limiting resource capacities measured over multiple time periods. For example, a mine's extraction rate can vary from day-to-day, but the ore production target is set at the annual level. Figure 1 shows how an operation might have a maximum daily production capacity and also a weekly capacity that does not equate to the same production quantity. In this case, the operation's goal will be to produce a schedule that achieves the weekly target. Incorporating MPKC reduces the negative impacts of varying durations and production rates associated with underground activities, while still retaining integrality.

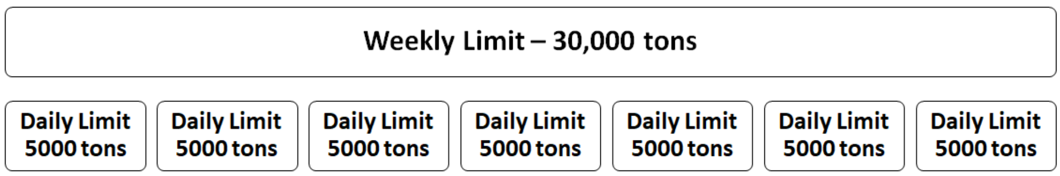

Figure 1. Visualizing a multi-time period knapsack constraint

The implementation of MPKC must be carefully considered to achieve the desired benefit. One challenge in effectively utilizing this tool is in correctly matching the evaluated time horizon to the desired schedule fidelity. To illustrate the effects of MPKC, we evaluated two scenarios with different fidelities of MPKC, annually and monthly. We used the model described in Section 2.1 for these scenarios, each solved for a 10-year time horizon at the daily fidelity. The MPKC was implemented on the ore production capacity while also slightly relaxing the daily ore production capacity, i.e., allowing for more capacity than the average daily rate. Annual production targets ramp up through the initial years, leveling off in year 2023. In the case of the monthly-fidelity MPKC model, the annual production targets were broken down into equal monthly values.

Figures 2 and 3 show monthly production profiles, subdivided across years (dot-dashed line) and quarters (dashed line). For the annual-fidelity, Figure 2, the solver schedules a majority of the production in the first 9 months of each calendar year. This behavior is attributable to the time value of money. Hence, the solver, wanting to maximize operational value, will schedule as much production early in the year as possible, instead of distributing it more evenly throughout the year. We refer to this as "front-loading". Operationally, this "front-loading" is neither feasible, nor desirable. By modifying the MPKC to represent monthly production targets, we see that front-loading is virtually eliminated and the production profile is significantly more consistent. Front-loading may still be occurring within the month which may require using MPKC with shorter time horizons; however, considering the long-term nature of the schedule, this is acceptable accuracy.

2.1.2 *Enforcing start and completion dates*

The desired outcome of an optimized underground production schedule is a collection of activity start dates that maximize value while adhering to precedence and resource constraints. In some

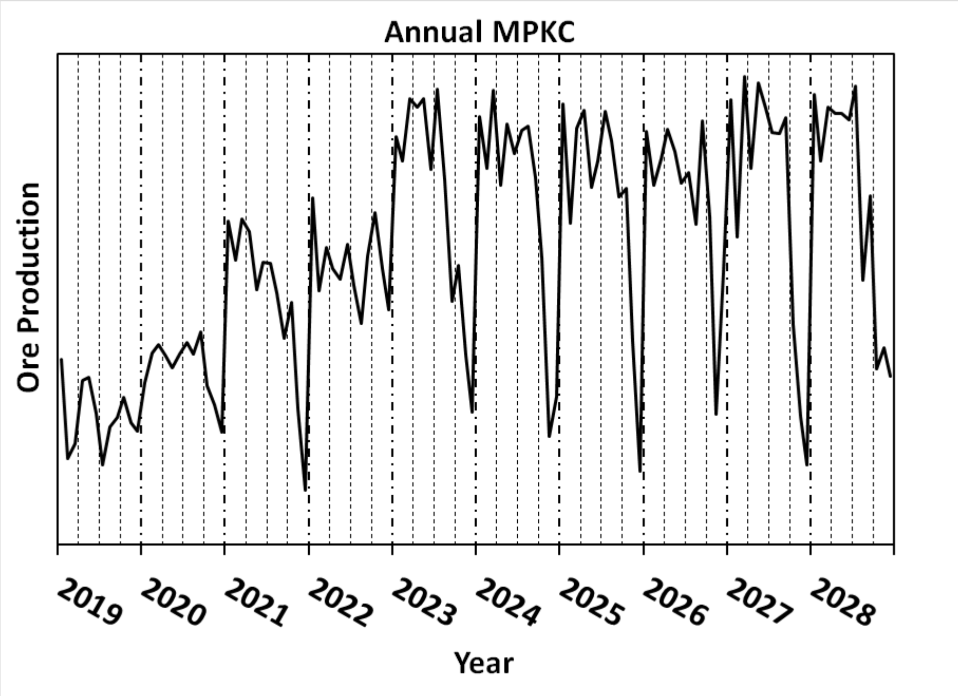

Figure 2. Monthly ore production scheduled over 10 years using annual multi-time period knapsack constraints

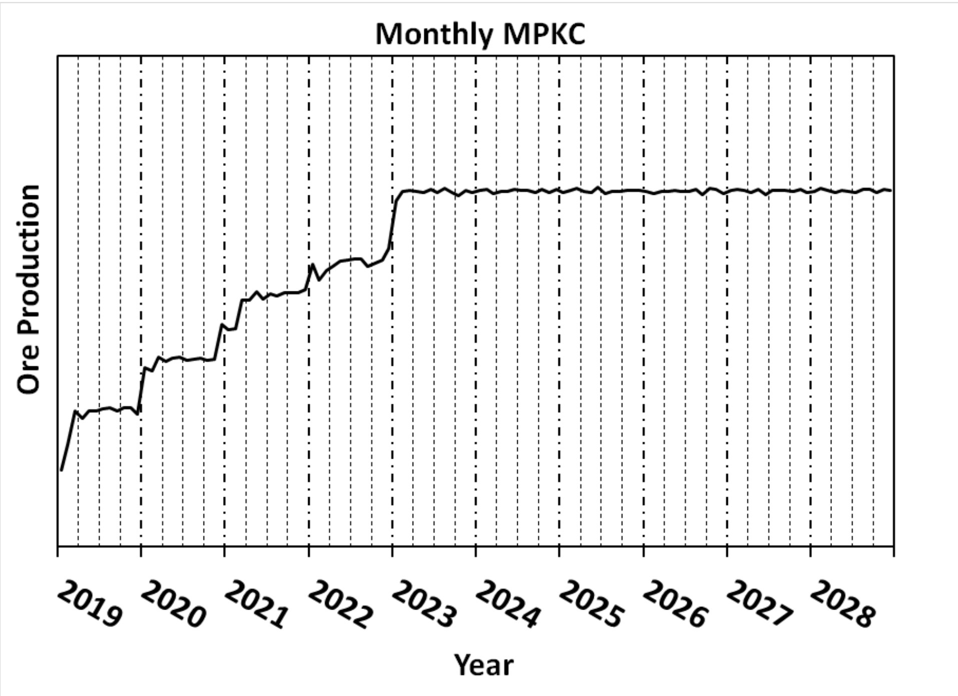

Figure 3. Monthly ore production scheduled over 10 years using monthly multi-time period knapsack constraints

instances, a mining operation may have fixed dates as to when an activity can begin or a deadline for the completion of an activity. Precedence among activities are used to control activity sequencing and often are associated with operational or geotechnical limitations. For the most part, it is enough to formulate the model with these precedence and resource constraint components to capture the essence of the operation. There may be instances when activity start and completion requirements are needed to satisfy a mine's strategic goals. For example, a new shaft and other associated capital development may need to be completed before the mine's planned expansion can proceed. Disregarding such deadlines creates a less accurate model and may result in improper resource allocation, i.e., equipment, and unrealistic production profiles.

To provide a fixed start date for an activity, we add a "dummy" activity, i.e., an artificial activity that consumes no resources, to create a time delay between the start of the schedule time horizon and the set start date activity. To set a completion deadline for an activity, we use MPKC to provide some flexibility as to when the activity can start, while ensuring that the activity is completed by the desired deadline. In many cases, the activity is not necessarily required to be completed on a given date, but that it be completed prior to the deadline. To accomplish this, the activity is evaluated as a unique resource. That resource is constrained by a MPKC where the associated time horizon ends at the required completion date. The use of MPKC allows the schedule flexibility to ensure that the activity is completed while also considering the global scheduling problem.

2.1.3 *Ventilation*

In an underground mining operation, the ventilation system helps to maintain a hospitable environment for workers (Hartman et al., 1997). It also accounts for a significant portion of a mine's total energy requirement. The systems are designed during the initial mine planning phase and can be difficult to modify once in operation. As regulatory levels for many contaminants have been substantially lowered over the past couple of decades (Bugarski et al., 2012), underground mines, with limited capacity to increase ventilation quantities, are seeing the effect manifest as a loss in production (Brickey, 2015). To this end, incorporating ventilation into the overall planning process can help utilize existing ventilation infrastructure more efficiently and provide better insight into future expansions (Brickey and Lopes, 2017).

Modeling ventilation is challenging, owing to its highly dynamic nature. To incorporate ventilation into the production scheduling process, we begin by treating ventilation as a consumable resource (Brickey, 2015). In this simplified method, each activity is assigned a fresh air requirement, based on empirical data or an engineer's estimate. Ventilation capacity is determined by the amount of air flow possible with existing ventilation infrastructure and other considerations. In this manner, ventilation becomes a resource capacity constraint, similar to tonnage (see 1d in Section 2.1). Another approach to controlling ventilation is to restrict the number of concurrent activities on each working level or within a ventilation district. For example, a mine may be divided into multiple ventilation districts and each can only receive a fixed maximum quantity of air. This fixed amount of air directly limits the number of activities that can be supported. These methods, while simplistic, can be effective at evaluating the impact of ventilation on production.

3 CONCLUSIONS

Improved computation power and solution algorithms have allowed practitioners to formulate and solve increasingly complex models for underground production scheduling. These advances present another opportunity for each practitioner: enhancing model representation to more closely reflect reality. In this paper, we outlined useful tools and guidelines that an underground mine scheduler can use to create more operationally representative schedules. MPKC can overcome the limitations of using averages for constraints and induce some operational flexibility into the schedule, while still retaining integrality and take advantage of the new solution algorithms. In addition, known activity start and completion information should also be incorporated into the model to more closely adhere to the strategic mine plan. Lastly, ventilation is a critical consideration for underground mines and an approximation should be included in scheduling models. These tools help improve model and schedule quality, lessening the gap between theory and implementation.

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