Managing risk and waste mining in long-term production scheduling of open-pit mines

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Abstract

Open pit mine design and production scheduling deals with the quest for the most profitable mining sequence over the life of a mine. The dynamics of mining ore and waste and the spatial grade uncertainty make predictions of the optimal mining sequence a challenging task. A new optimization approach to production scheduling based on the effective management of waste mining and orebody grade uncertainty is presented. The approach considers an economic model, mining specifics including production equipment and the integration of multiple equally possible representations of an orebody. The utilization of grade uncertainty and optimal mining rates leads to production schedules that meet targets whilst being risk resilient and generating substantial improvements in project net present value. A case study from a large gold mine demonstrates the approach.

Introduction

Valuation and related decision-making in surface mining projects require the assessment and management of orebody risk in the generation of a pit design and a long-term production schedule. As the most profitable mining sequence over the life of a mine determines both the economic outcome of a project and the technical plan to be followed from mine development to mine closure, the effect of orebody risk on performance is critical (Ravenscroft, 1992; Dowd, 1994; Rendu, 2002). Geological risk is a major contributor in not meeting expectations in the early stages of a project (Vallee, 2000), when repayment of development capital is vital, as well as to production shortfalls in later years of operation (Rossi and Parker, 1994).

The adverse effects of orebody uncertainty on the traditional optimization of pit designs and corresponding key project performance indicators are documented in various studies (e.g., Dowd, 1997; Dimitrakopoulos et al., 2002; Farrelly, 2002). These past efforts deal with the use of stochastic simulation methods in assessing project risk for a given mine design and mining sequence. They do not, however, address the generation of optimal conditions under uncertainty, long-term production schedules or operational issues and interactions of ore and waste within the orebody space over the life of the mine. New integrated approaches can be developed to effectively deal with orebody uncertainty in production scheduling while maximizing cash flows, and may be based on two elements. The first element is the ability to represent orebody uncertainty through the stochastic simulation of multiple, equally probable deposit models. Although the technologies are available (e.g., Dimitrakopoulos, 2002), the use of multiple orebody models for production scheduling, instead of a single model, is not a trivial exercise. Generally, traditional optimization formulations are not compatible with stochastic modeling approaches. The second element in dealing with risk is a modified optimization framework that, while compatible with orebody uncertainty, integrates a variety of mining issues, particularly management of waste, equipment utilization, mill demand, and technological, financial and environmental constraints.

This paper presents a novel optimization approach that is shown to effectively integrate grade uncertainty into the optimization of long-term production scheduling in open pit mines. The approach is founded on the following two key elements:

- a framework for long-term production scheduling based on the concept of a "stable solution domain" and
- a new scheduling algorithm based on simulated annealing.

The approach generates "100% confidence" in the contained ore reserves, given the understanding of the orebody and minimizes deviations from production targets to acceptable ranges.

Related to the approach presented herein are concepts in Tan and Ramani (1992) and in Rzhenevisky (1968), where open pit production scheduling is seen as the determination of a sequence of depletion schedules in which at least two types of products, ore and waste, are removed to meet the mine's demand. The optimal schedule maximizes the net present value (NPV) of the project subject to constraints, including:

- feasible combinations of ore and waste production (stripping ratio) and
- ore production rates that meet mill feed requirements.

At the same time, an optimal schedule defers waste mining as long as possible and, in doing so, considers the mining equipment and capacity available. This approach is limited in

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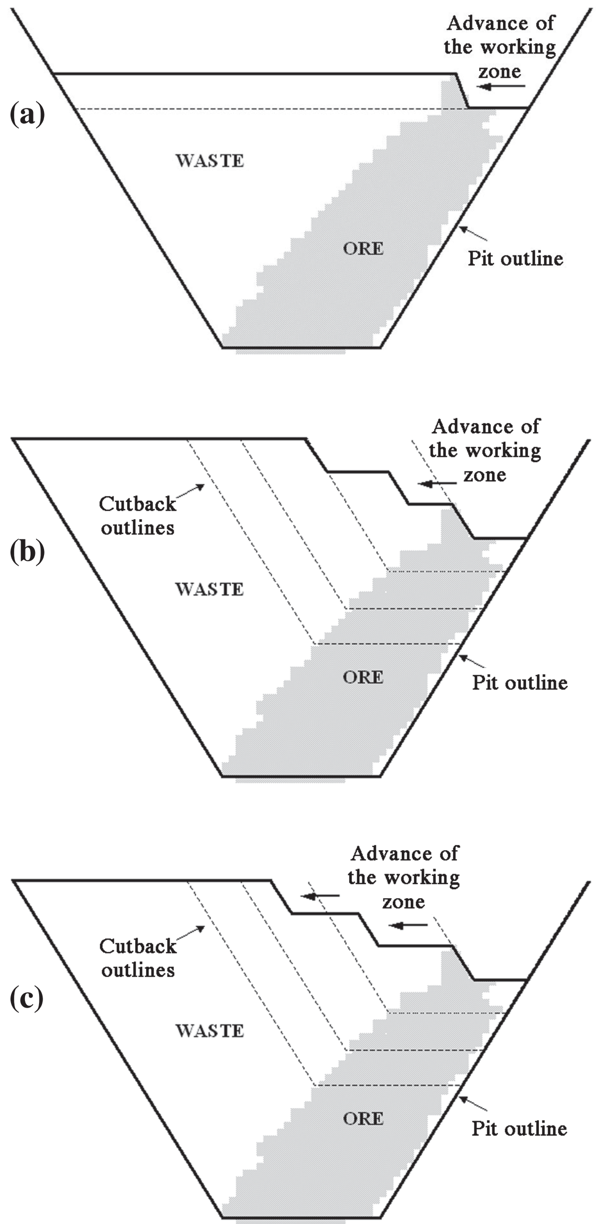

Figure 1 — Schematic representation of three mining schedule configurations: (a) worst-case mining schedule; (b) best-case mining schedule; and (c) intermediate mining schedule.

that no physical mining schedule is produced and issues of uncertainty are not addressed, as they are in the approach presented herein. Godoy (2003) provides a detailed review of past work and new applications in the context of the nested Lerchs-Grossman algorithm and nested pits that can be mined independently (Whittle and Rozman, 1991; Hustrulid and Kuchta, 1995).

It should be noted that an optimal long-term mine production schedule can be found within a "domain of feasible solutions," that is, within combinations of ore and waste that can be produced from a specific orebody. The nested pit optimization framework, mentioned above, establishes this domain based on two extreme cases of mining waste deferment. The worst mining case (Fig. 1 (a)), where a bench is mined out before starting the next, is producing the maximum quantity of waste from the pit needed to recover a certain amount of ore (highest stripping ratio). This schedule shows a poor NPV as the expense for mining waste at the periphery of the pit is incurred early, and thus discounted little, whereas the income from mining ore at the bottom of the pit is delayed for later periods and, thus, is heavily discounted. The opposite happens in the best mining case (Fig. 1 (b)), corresponding to the sequential mining of the independent nested pits, where mining occurs in each successive bench of the smallest pit and then each successive bench of the next pit and so on. This schedule has the lowest stripping ratio and highest NPV, whilst providing the necessary working room and safety conditions for mining operations. The intermediate mining schedule in Fig. 1 (c) shows mining of the first bench leading to the commencement of mining in the next cutback.

In searching for an optimal ore-production and waste-removal schedule, a feasible solution domain can be represented in a cumulative graph, bounded by the curves of the best and worst mining cases. The solution domain accounts for all physically possible combinations of stripping ratios. Figure 2 shows the solution domain of the gold deposit discussed in a subsequent section. Any non-decreasing curve within the solution domain characterizes a production schedule having different combinations of stripping ratios over the life of the mine and reflects possible spatial arrangements for working zones. There are many feasible schedules of waste removal given a single ore-demand scenario from the mill. An optimal schedule in terms of NPV will tend to follow the curve representing the minimal quantity of waste (Tan and Ramani, 1992; Godoy, 2003), that is, where mining waste is deferred as long as possible.

In the following sections, a risk-based approach to life-of-mine production scheduling is presented. It includes:

- the determination of optimum mining rates for the life of mine, whilst considering ore production, stripping ratios, investment in equipment purchase and operational costs; and
- the generation of a detailed mining sequence from the previously determined mining rates, focusing on spatial evolution of mining sequences and equipment utilization.

The approach is then demonstrated through an application at the Fimiston Gold Mine (Superpit), Western Australia. The results of the new approach are compared with traditional production scheduling. Finally, the benefits of the approach are presented in the conclusions.

A new risk-based approach to production scheduling

The risk-based approach presented in this section differs conceptually from traditional approaches in many aspects. For a start, all traditional approaches use a single estimated orebody model to produce a mining schedule. Such an estimated orebody model is based on imperfect geological knowledge, so estimation errors are propagated to the various mining processes involved in the optimization, and related geological uncertainty is not included or assessed. The approach presented here quantifies geological uncertainty using a series of stochastically simulated, equally probable models of the orebody. Subsequently, a multistage optimization process utilizes these models to produce a risk-resilient, long-term mining schedule. The multistage process starts by generating a series of mining schedules, each corresponding to one of the simulated spatial distributions of orebody grades representing the possible orebody. These mining sequences are optimized within their common feasible solution domain, termed "stable solution domain" (SSD), and post-processed to provide a single mining sequence. This optimization process has the following four stages, as shown in Fig. 3:

- *Stage 1:* Derive a solution domain of ore production and waste removal "stable" to all simulated models of the distribution of the grades of the deposit.
- *Stage 2:* Determine the optimal production schedule of waste removal and formation of mining capacity within the stable solution domain from Stage 1. This generates optimal mining rates for the life of mine, given the equipment considered.
- *Stage 3:* For each one of the available simulated orebody models, generate a physical mining sequence constrained to the mining rates from, and equipment selection in, Stage 2.
- *Stage 4:* Combine the mining sequences generated in Stage 3 to produce a single mining sequence that minimizes the chances of deviating from production targets.

These four stages are discussed in detail below.

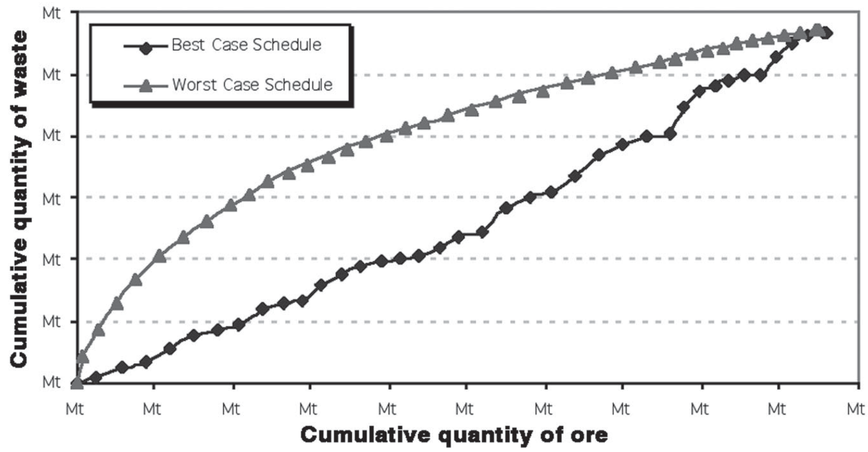

Figure 2 — Solution domain of ore production and waste removal.

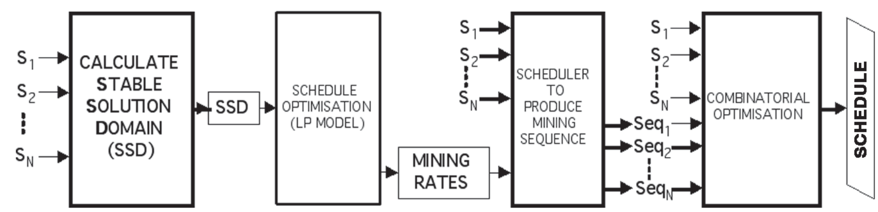

Figure 3 — Schematic representation of the process developed for optimizing long-term production scheduling. (S stands for simulated orebody model and Seq. for mining sequence.)

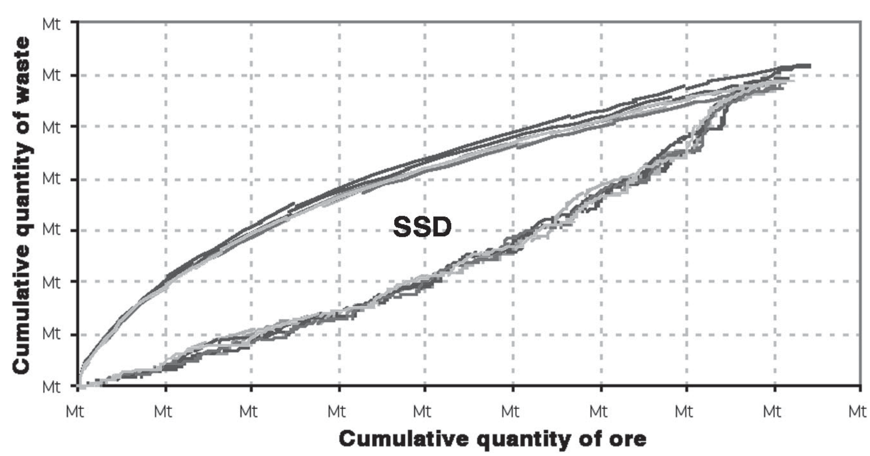

Figure 4 — A stable solution domain (SSD) derived from six simulated orebody models.

Stage 1: Derivation of the stable solution domain (SSD). The derivation of the stable solution domain starts from a design with ultimate pit limits, a sequence of cutbacks and a set of stochastically simulated orebody models. The SSD is generated from the cumulative graphs of ore production and waste removal from each one of the simulated orebody models and the ultimate pit limits and cutbacks available. Figure 4 presents cumulative graphs and solution domains for a series of simulated orebody models and grade distributions in an open pit gold mine, discussed in a subsequent section. The common part of all the cumulative ore and waste graphs forms the SSD. This new domain represents a solution domain that, according to the orebody grade uncertainty quantification from the set of the available stochastic simulations, provides 100% confidence in the contained reserves. Note that this procedure is general and independent of the objectives driving the optimization of production scheduling.

Stage 2: Schedule optimization. Given the SSD from the previous stage, a linear programming (LP) optimization formulation results in a schedule for ore production and waste removal, and the formation of optimal mining capacities within the SSD. The LP formulation discussed next, is based on the following objective function

$$\begin{aligned}\mathrm{MAX}\sum_{i=1}^{n} d_i(1-R)\Big[\big(S_i - C_i^{ma}\big)\gamma_i - \big(C_{p_i}^{m} + C_{p_i}^{p} + C_{t_i}\big)\big(\alpha_{p_i}\big)^{-1}\Big]M_{p_i} \\ -\sum_{i=1}^{n} d_i C_{s_i}^{m}\big(\alpha_{s_i}\big)^{-1} M_{s_i} - \sum_{i=1}^{n} d_i C_{w_i} W_i \\ -\sum_{k=1}^{K}\sum_{z=1}^{Z}\sum_{i=1}^{n} d_i h_{kzi} NC_{kzi} - \sum_{k=1}^{K}\sum_{z=1}^{Z}\sum_{i=1}^{n} d_i u_{kzi} DC_{kzi}\end{aligned} \qquad (1)$$

where $i=1, ..., n$ denotes time periods considered.

Table 1 — LP model variables in objective function Eq. (1).

Constant	Definition
M_{p_i}	Primary and secondary ore metal
M_{s_i}	Secondary ore metal
W_i	Waste quantity to be removed
NC_{kzi}	Added capacity for k-th type, z-th model of production equipment
DC_{kzi}	Decreased capacity for k-th type, z-th model of production equipment

Table 2 — LP model constants in objective function Eq. (1).

Constant	Definition
n	Number of time periods to be considered
Z	Number of types of mining equipments
K	Number of total types of equipment
J	Number of models of production equipment
di	Discount factor $d_i = (1+r)^{-i}$, where r is the interest rate
Si	Selling price of metal
$C^m_{p_i}$, $C^m_{s_i}$	Unit mining costs of primary and secondary ore
$C^p_{p_i}$, $C^p_{s_i}$	Unit processing costs; primary and secondary ore
C_{w_i}	Unit mining cost of waste removal
C^{ma}_i	Marketing cost per unit payable metal
R	Royalty as percent of the net revenue
α_{p_i}, α_{s_i}	Primary and secondary ore metal grade
γ_i	Total recovery of the payable metal
C_{t_i}	Time costs for operating support services
C^{max}_{kj}	Capacity limit of k-th type and j-th model of production equipment
h_{kzi}	Unit purchase cost of k-th type, z-th model of mine equipment
u_{kzi}	Unit ownership cost of k-th type, z-th model of mine equipment

Definitions of constants and variables in the objective function and constraints are given in Tables 1 and 2.

The objective function Eq. (1) corresponds to the schedule's economic outcome on the basis of discounted cash flow analysis, before taxation and without treatment of related depreciation and depletion allowances. The objective function represents a mining operation where the secondary ore is only stockpiled. The main variables of the optimization model are the time-related primary ore metal, secondary ore metal and waste. While the variables corresponding to the waste quantities allow for the ore-waste relation to be optimized over time, the metal variables allow for the metal quantities to be optimized. The metal optimization accounts for the ore quality at different parts of the orebody. The remaining variables of the optimization model are the added capacity and decreased capacity of each type and model of the mine equipment, which deals with the stabilization of the mining rate over time as a function of capacity.

Mining rates are also stabilized through the economic parameters of unit purchase and ownership costs of each type and model of equipment. The unit purchase cost is determined by the value of the equipment divided by its production capacity. The unit ownership cost is determined by the ownership cost of the equipment divided by the production capacity. Thus, the penalty for decreased capacity is defined as being equivalent to the ownership cost, which reflects a penalty for having idle equipment. In this context, the stabilization of the mining rate over time is determined as a search for the balance between the purchase and ownership costs of the production capacity and represents a direct incorporation of the capital investments in the optimization. As noted above, although developed in a different context, the LP formulation relates conceptually to that in Tan and Ramani (1992). It is also analyzed in detail in Godoy (2003).

Figure 5 displays the SSD and a typical solution produced by the LP model. This optimum solution corresponds to a production schedule that maximizes the NPV within the SSD. This is unique in the sense that the geological uncertainty has been effectively integrated into the optimization process.

Stage 3: Mining sequencing. The LP in Stage 2 generates a set of optimal mining rates. The third stage uses these mining rates to produce a series of physical production schedules that describe the detailed spatial evolution of the working zones in the pit over the life of the mine. The sequencing needs to obey slope constraints, needs to consider equipment utilization and needs to meet mill requirements while matching the mining rates previously derived. Any scheduling algorithm that accommodates these criteria may be used.

This stage generates multiple mining sequences, one for each simulated grade model representing the orebody. The alternative mining sequences present two characteristics that allow the derivation of a single mining sequence. These characteristics are that all schedules are technically feasible solutions that maximize the project's NPV within a common solution domain; and that all schedules are based on distinct but equally probable models of the spatial distribution of grades within the deposit.

Stage 4: Combinatorial optimization. The fourth stage considers the production schedules generated in Stage 3 and derives a single mining sequence. A combinatorial optimization algorithm based on simulated annealing has been developed and is outlined here. The basic idea in simulated annealing is to continuously perturb a suboptimal configuration until it matches some prespecified characteristics coded into an objective function (Kirkpatrick et al., 1983). Each perturbation is accepted or not depending on whether it carries the objective function value towards a predefined minimum. To avoid local minima, some unfavorable perturbations maybe accepted based on a probability distribution (Metropolis et al., 1953).

The annealing formulation first selects an initial mining sequence, where blocks with maximum probability (e.g., 95%) of belonging to a given mining period are frozen to that period and not considered further in the combinatorial optimization process. Block probabilities are calculated from the results of Stage 3. The initial sequence is perturbed by random swapping of (nonfrozen) blocks between the candidate mining periods. Favorable perturbations lower the objective function and are accepted; unfavorable perturbations are accepted using an exponential probability distribution. Annealing stops when perturbations no longer lower the objective function or when a specified minimum objective function value is reached.

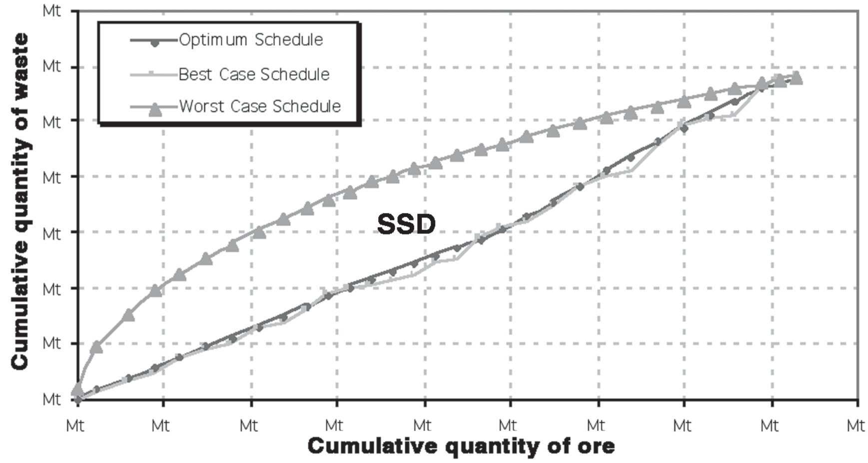

Figure 5 — Optimal solution (green curve) obtained inside the SSD, derived from a series of simulated resource models.

The objective function is a measure of the difference between the desired characteristics and those of a candidate mining sequence. Consider, for example, the objective of meeting a series of optimal mining rates derived in Stage 2, i.e., the prescription of ore production and waste removal for the life of the mine. If a mining sequence achieves that objective for all the equally probable simulated orebody models, there is a 100% chance that the production targets will be met, given the knowledge of the orebody as represented in the simulations. An objective function is built to measure the average deviation from the production targets for a given mining sequence over a series of simulated orebody grade models. The objective function is defined as the sum of components representing mining periods

$$O = \sum_{n=1}^{N} O_n \tag{2}$$

where

O_n, n=1,…,N are component objective functions and
N is the total number of production schedule periods.

For each n component (period), the objective function measures the average deviation of ore and waste production $\theta_n^*(s)$ and $\omega_n^*(s)$ of the perturbed mining sequence from the target productions $\theta_n(s)$ and $\omega_n(s)$ over the S simulated grade models, with s=1, …, S

$$O_n = \frac{1}{S}\sum_{s=1}^{S}\left|\theta_n^*(s) - \theta_n(s)\right| + \frac{1}{S}\sum_{s=1}^{S}\left|\omega_n^*(s) - \omega_n(s)\right| \tag{3}$$

The decision to accept or reject a perturbation is based on the change to the objective function,

$$\Delta O = \sum_{n=1}^{N} \Delta O_n \tag{4}$$

The resulting sequence meets the production target for each period with minimum chance of deviation. That is, this mining sequence will achieve the production targets, within the prescribed mining rates, given any of the simulated orebodies. None of the individual mining sequences from Step 3 will meet these requirements. Note that the objective function can be modified to include other production targets, such as head grade, metal quantities and blending requirements. An important aspect of the procedure is the mechanism of swapping blocks. To ensure the final solution avoids physically inaccessible blocks in any period, the perturbation mechanism must be set to recognize the spatial evolution of the mining sequence. To achieve this, the perturbation mechanism is defined so as to restrict the candidate periods, of any given block, to only those having physical access to the block without violating slope constraints (Godoy, 2003).

Application in a large open pit gold mine

The practical aspects of the proposed method were tested in a case study using data from the Fimiston open pit (Superpit) in Western Australia. Fimiston is operated by Kalgoorlie Consolidated Gold Mines. The gold deposit is an intensely mineralized shear system developed largely within the so-called Golden Mile dolerite. The mineralization is localized in mainly steeply dipping, NNW to NW striking lodes, consisting of a high-grade lode shear zone and a lower-grade alteration halo. Gold lodes can be up to 1,800 m (5,900 ft) long, have vertical extents of 1,200 m (3,900 ft) and be up to 10 m (33 ft) wide. The Fimiston pit is a conventional open pit, truck-and-loader operation. It has a mining rate of approximately 85 Mt (94 million st) per year, making it the single largest open pit operation in Australia, on a tons per year basis. Of this, some 12 Mt (13 million st) of ore are produced and milled through the Fimiston mill. The mill currently consists of a grind-float circuit for processing refractory sulfide ore, electrowinning, smelting and then pouring of gold bullion.

The orebody block model used in this application included 648 individual mineralized lodes discretized into 321,937 ore blocks. Block grades were simulated 20 times using the direct block sequential simulation method (Godoy, 2003). For scheduling, all models were reblocked to 20 x 20 x 20-m blocks.

It is important to note that the determination of the ultimate pit limits and cutbacks is outside the scope of this application. The risk-based schedule developed was based on predefined ultimate pit limits and sequence of cutbacks, which were derived using the traditional block model of the deposit and

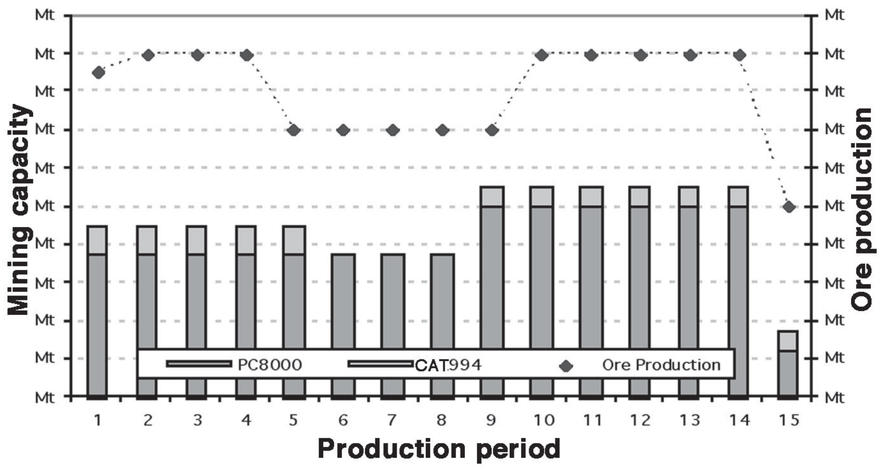

Figure 6 — Formation of mining capacity, as produced by the LP optimization constrained to the SSD, and ore production target over 15 production periods.

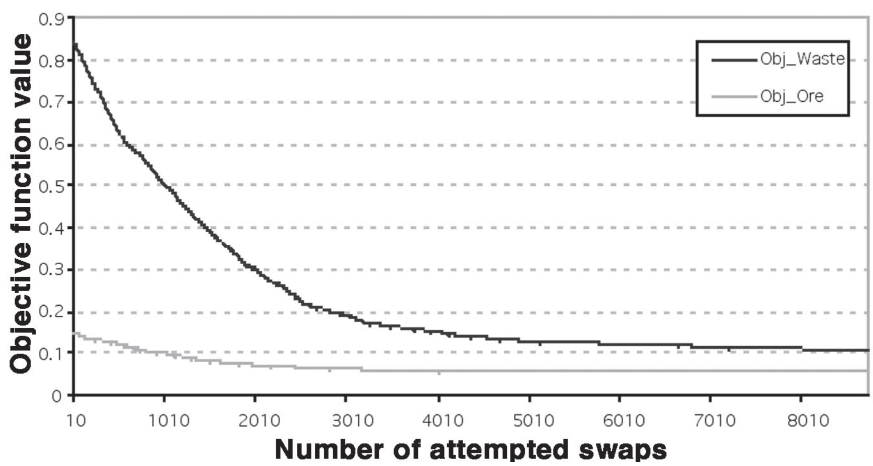

Figure 7 — Evolution of component objective functions: deviations in total ore (top line) and waste (bottom line) quantities vs. attempted number of swaps.

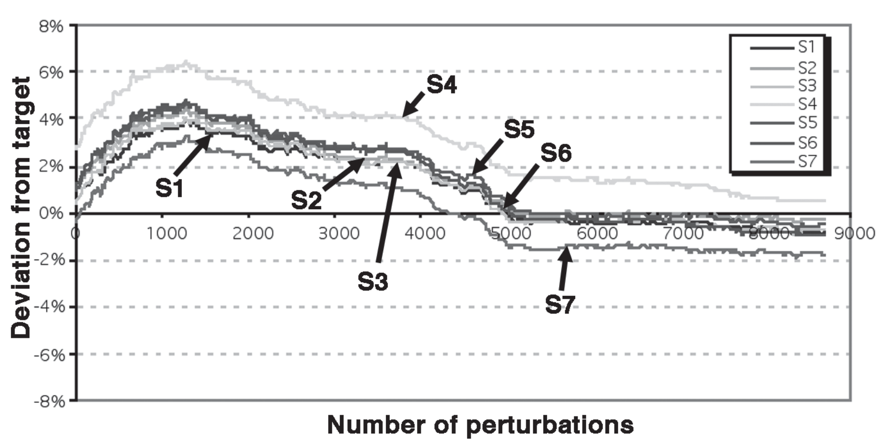

Figure 8 — Evolution of component objective functions: deviations of ore production in Period 4 for seven simulated models.

the nested pit implementation of the Lerchs-Grossman pit optimization algorithm (Lerchs and Grossman, 1965; Whittle, 1999).

The application of the proposed method started with Stage 1 and the derivation of the SSD (Fig. 4). This was followed by the optimization of the production schedule in terms of ore production and waste removal (Fig. 5). The schedule of ore production was identified with the mill demand over 15 production periods and is shown by the dotted line in Fig. 6. It is important to note that the fluctuations in ore production do not indicate a variable mill production rate. The mill production rate is constant over the life of the mine. Periods characterized by a reduction in ore demand only indicate input of ore from other sources, such as underground operations.

The LP optimization model in Stage 2 produced the optimal formation of mining capacity as a combination of Komatsu PC8000 face shovels, CAT 994 loaders, CAT 793C trucks and nine pieces of support equipment, including dozers, graders and water carts. It was assumed that the purchase of the starting fleet was carried out at the first production period. Therefore, the respective capital costs were charged to the first year. The replacement costs were charged to the first year after the end of the equipment life. The ore production target and the optimal formation of mining capacity, as produced by the LP model, are presented in Fig. 6. The increased mining capacity in Periods 9 through 14 clearly shows the deferment of waste mining, which, as noted above, is a characteristic of the optimization model.

Stage 3 of the proposed approach is the mining sequencing, where the Stage 2 prescription of ore and waste production and equipment selection forming the mining capacity are used to generate the mining sequences. The Milawa algorithm (Whittle, 1999) was used in this case study to generate one sequence for each of the 20 simulated grade models of the Fimiston loads. In the final stage, the combinatorial optimization algorithm was used to combine the multiple mining sequences. One of the mining sequences was randomly selected as the starting mining sequence for annealing. Figure 7 shows the ore and waste component objective functions vs. the number of accepted perturbations. The optimization stopped after 202,669 perturbations, with 8,716 being accepted, when the maximum was reached and there was no change in the objective function.

Figures 8 and 9 illustrate the evolution of the component objective function for Periods 4 and 7, respectively. The figures show the percentage deviation from target ore tonnages plotted against the number of accepted perturbations for a set of simulated models. Figure 8 shows that the swapping of blocks between different periods causes an increase in the values of the component objective functions related to Period 4 for up to the first 1,400 perturbations. For the same perturbations, the component objective functions related to Period 7 (Fig. 9) show the opposite behavior. This is because the decision rule of whether to accept or reject the perturbations is based on a global average over all production periods. In fact, as shown by the global component objective function of ore production (bottom curve in Fig. 7), the region of up to 1,400 perturbations presents the steepest descent of the optimization process. What is achieved here is a swapping of volumes between different production periods, to distribute regions of high-grade uncertainty among production periods where their negative impact to ore production is minimized. Note that none of the individual mining sequences from the 20 simulated orebodies minimizes the effect of grade uncertainty, meets production requirements or maximizes NPV.

The effectiveness of the proposed method is demonstrated in Fig. 10, which shows the risk profile in ore production for the final mining sequence produced by the risk-based approach in this study. The bars indicate average expected percent deviation from the target ore production. The largest deviations are in Periods 2, 5 and 8 and are -3%, +3.5% and +2.7%, respectively. The magnitudes of these deviations are considered very small and are easily managed by rehandling ore from alternative sources for the periods presenting a shortfall. Risk profiles for any schedule are generated from the comparison of the schedule with each of the simulated orebodies.

Figure 11 compares the proposed approach to the conventional approach, using NPV. Grade risk analysis on the base-case life-of-mine schedule from the traditional scheduling approach, where grade uncertainty is not taken into account, shows that forecast NPV will not be reached. Similarly, Godoy (2003) shows deviations for various production periods in the order of 13%. Compared to the base-case schedule, the approach in this study shows an NPV increase of about 28%, illustrating the benefits of both managing waste mining and integrating orebody uncertainty in production scheduling.

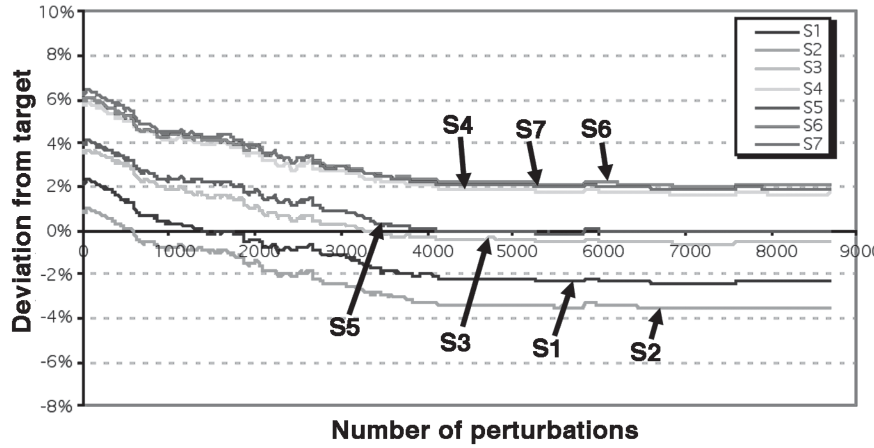

Figure 9 — Evolution of component objective functions: deviations of ore production in Period 7 for seven simulated models.

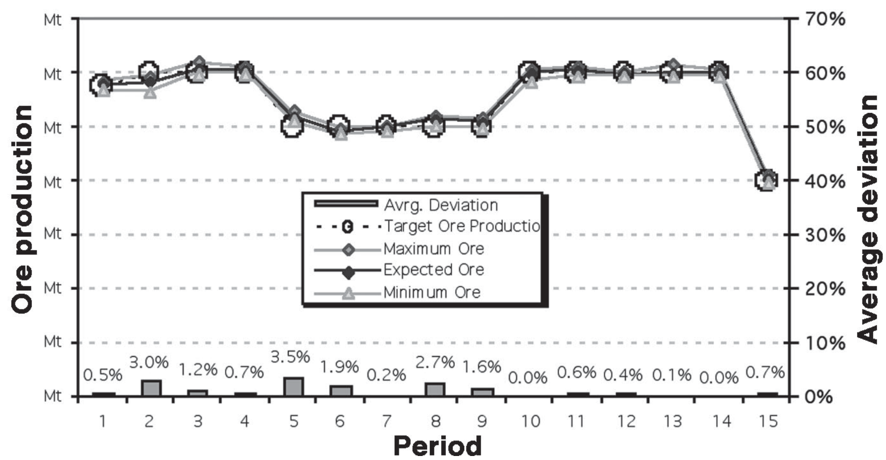

Figure 10 — Risk profile for ore production in the final schedule.

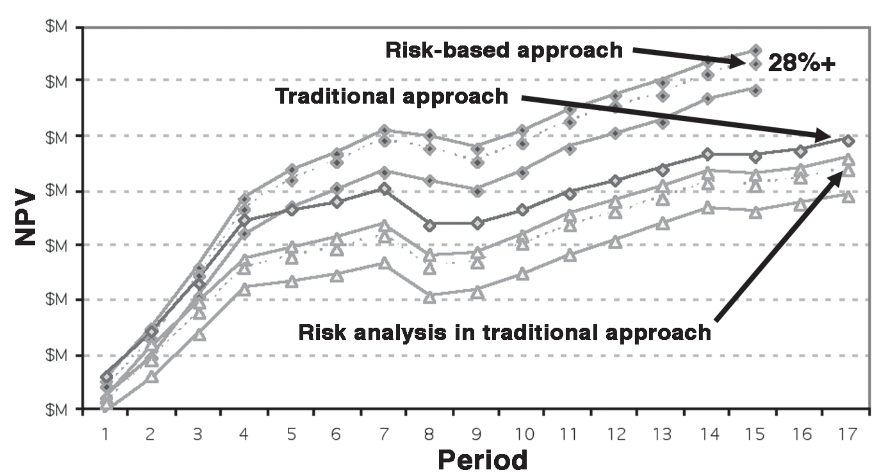

Figure 11 — Risk profile on cumulative NPV for the schedule produced by the risk-based approach (top lines), cumulative NPV as forecast by the base-case schedule (middle line) and risk profile on cumulative NPV on the schedule developed using the traditional approach (bottom lines).

Conclusions

A new risk-based, multistage optimization process for long-term production scheduling has been presented in this paper. The process integrates orebody uncertainty, waste management, economic and mining considerations to generate a prescription of optimal mining rates, aiming to maximize a project's NPV. The subsequent utilization of grade uncertainty and optimal mining rates leads, through combinatorial optimization, to life-of-mine production schedules that meet required targets, whilst being risk resilient and substantially improving project NPV.

A case study at the Fimiston open pit, Western Australia, shows how the approach capitalizes on mining waste deferment and quantified grade uncertainty to provide a risk-resilient, life-of-mine schedule and simultaneously increase asset value. Key elements of the approach are the assessment of the inherent source of orebody uncertainty and the ability to drive the mining sequence through zones where the risk of not achieving the target ore production is minimized.

Comparison of results with those of the traditional scheduling practices shows the potential to considerably improve the valuation and forecasts for life-of-mine schedules.

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