Incorporating Geometallurgical Attributes and Uncertainties into Mine Planning of an Open Pit Mine

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ABSTRACT

Strategic mine planning aims to capture the maximum economic value of the given mineral resources. Although it is true that much of that value is determined by the grades of economic minerals there are geometallurgical attributes, such as metallurgical recovery and ore hardness, which can directly influence the decisions about which sectors of the mine should be extracted or processed. In spite of the above, strategic mine planning usually tends to assume average fixed values for those geometallurgical variables, disregarding their spatial variability. Indeed, most 3D geometallurgical models are incorporated only within the medium- and short-term planning.

In the present study, simulated geometallurgical models created for a porphyry copper deposit are integrated in the long-term mine planning process to assess the impact on the ultimate pit limits and the life-of-mine production scheduling. These geometallurgical models, which take into account the spatial variability and uncertainty of copper grade, molybdenum grade, copper recovery and mill throughput, are used to construct different economic block models for the optimizations. In addition, throughput model is used to apply a processing capacity constraint, based on available milling hours, in the mine scheduling optimization.

With this new information incorporated within the planning, the optimization not only takes into account the ore grades but it also considers the effect of the recoverable fine copper together with the amount of mineral that can effectively be processed by the grinding circuit given the ore hardness. The results show that geometallurgical data with their associated uncertainties can change the decisions about pit limits and mining sequence and, consequently, impact on the financial outcomes.

INTRODUCTION

Strategic mine planning is a critical stage of a mining project that aims to capture the maximum economic potential of the given mineral resources. The decisions taken at this stage largely determine the expected cash flows of the project. For an open-pit mine, there are two important problems that the strategic planning process must address: the ultimate pit limit problem (it defines the mineable reserves) and the life-of-mine (LOM) production schedule problem (it defines when the reserves should be extracted in order to maximize the net present value). These problems depend considerably on the spatial variability of the deposit.

At long-term assessment, it is common practice to use resource block models that are limited to in-situ tonnes and grades, while metallurgical parameters are estimated by assuming fixed values. Taking the spatial variability of metallurgical attributes into consideration may have a very significant economic consequence, since they act as modifying factors for the realized value. A geometallurgical approach to mine planning is based on identifying these critical attributes and integrating them into 3D block models in order to ensure that their variabilities are fully taken into account (Dunham & Vann, 2007). Many studies have shown that incorporating geometallurgical data can improve mine planning optimization process. For instance, medium- and short-term plans have been improved by increasing the metal produced per unit of time (Contreras, Ortiz & Bisso, 2010; Rubio, 2006); while for the long-term, limits and sequence of extraction have been improved by integrating proxies of ore hardness and metallurgical recovery (Caceres et al., 2004; Bye, 2011).

The uncertainties, that are associated with grades and geometallurgical attributes, are other important aspect that mine planning must take into account. Geostatistical simulation techniques allow to quantify these uncertainties by stochastically generating a set of equally probable realisations of the deposit. There are different approaches to apply these simulated realisations to mine planning. For example, Dimitrakopoulos et al. (2002) uses grade simulations to evaluate the variability of a conventionally constructed plan, while approaches as Dowd (1994) or Dimitrakopoulos (2007) aim to construct many plans from each simulation to assess the risk. All approaches show that geologic uncertainty have important effects on ultimate pits and production schedules.

In the present study a geometallurgical approach to mine planning is tested in an open-pit Cu-Mo deposit. The aim of study is to assess the impact of incorporating long-term simulated geometallurgical models on the open-pit optimization process. As a result of this work it is possible to determine the potential impact that recovery and throughput forecasting, as well as a byproduct (as the Mo in a Cu deposit), have on the final pit and the LOM production schedule. In addition, by a risk analysis it explores how the spatial variability of these attributes might influence the mine planning outcomes and decisions.

CASE STUDY

The case study is a porphyry deposit which has been mined by open-pit method, to produce copper and molybdenum concentrates from sulfide ores. The sulfide ore is sent to the processing plant which comprises a primary crusher, a grinding plant (SAG mill/ball mills/pebble crusher) and a concentration plant which consists of collective and selective flotation for separating copper and molybdenum concentrates as final products. The maximum ore processing capacity is projected at 19.4 Mt per year over the LOM, with a mining rate of 43 Mt per year for the first 18 years and, from then, it is expected to be increased up to 54 Mt per year. Considering these capacities, the life of the mine is extendable beyond 60 years. The available information to mine planning consists of long-term block models of grades and processing performance attributes. The following attributes have been characterized and regionalized:

- Grades: Cu (%) and Mo (g/t or ppm)
- Copper metallurgical recovery (%)
- Throughput rate (TPH), this attribute predicts the tonnes per hour that can be processed in the milling circuit and it based on grindability test data (SPI, BWI and CI) and the current operational configuration.

These attributes have been conditionally co-simulated, using geostatistical techniques, to generate fifty stochastic realizations. The simulated realizations also consider the correlation between attributes. Figure 1 shows a plan view of the models with the associated histogram for conditional simulation number 1. Expected value models, called E-type, which consider the average of all realizations at each block, are also calculated to be used in the optimizations.

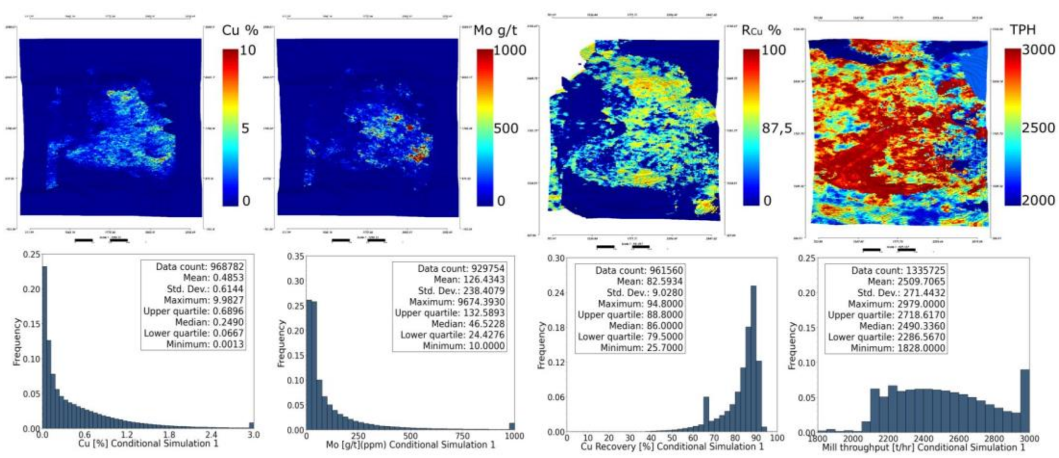

Figure 1 Plan view, geometallurgical models (top) with the associated histogram (bottom) for conditional simulation 1. From left to right: Cu grade (%), Mo grade (g/t), copper recovery (%), mill throughput (t/h)

METHODOLOGY

Stage 1: Final pit

In order to analyze the impact of geometallurgical models on final pit optimization, five different income schemes are used to construct the economic model for the optimizations. The Table 2 summarizes the cases (income schemes) that are evaluated, it indicates how an attribute is considered in the assessment. The value to be maximized in each scheme also differs.

Table 1 Summary of cases to be assessed in the final pit stage

Income scheme	Cu grade	Mo grade	Cu recovery	TPH
1	Used	Not considered	Fixed at 84%	Not considered
2	Used	Used	Fixed at 84%	Not considered
3	Used	Used	Used	Not considered
4	Used	Used	Used	Used
5	Used	Used	Used	Used

- **Income scheme 1-2-3:** the usual total undiscounted value of the pit is maximized.
- **Income scheme 4:** The value of each block is calculated considering a modification in the fine copper calculated, that is obtained by multiplying the fine-copper-per-hour by a representative processing time (3.18 hours). Maximizing this modified value ensures that priority is given to the most convenient block to process (i.e. with lower processing time).
- **Income scheme 5:** the incomes and costs per hour, on an hourly basis, are calculated for each block. Then, the total sum of profits per hour is maximized.

For each income scheme and conditional simulation, an optimal pit is calculated by applying Lerchs-Grossman (LG) algorithm. It should be noted that the final pit with extraction rates and temporal discounting is obtained in the next stage with a direct block scheduling strategy.

Stage 2: LOM production schedules

The second stage consist in scheduling 25 final pits (randomly selected from the pits obtained above). The schedules are obtained by an optimization algorithm based on direct block scheduling, therefore, nested pits are not used to guide the sequence. Three different strategies are compared:

- **Scheduling scheme 1:** the economic model is constructed as income scheme 1 (see Table 1)
- **Scheduling scheme 2:** the economic model is constructed as income scheme 3 (see Table 1)
- **Scheduling scheme 3:** the economic model is constructed as in the previous case, but the processing capacity constraint changes. While in the previous cases, the maximum processing capacities are considered in term of tonnages (as it is traditionally done); in this case the total available times at the milling plant, at a given period, is considered. For this purpose, the milling hours for each block are calculated based on TPH model.

MineLink library (Delphos M. P. Laboratory, 2016) was used, through Python 2.7, in order to implement the LG algorithm and develop a heuristic to solve the block sequencing problem. MineLink is a library of data structures for the mine planning, mining scheduling and algorithms to solve them. It was developed at Delphos Mine Planning Laboratory at Universidad de Chile.

RESULTS AND DISCUSSION

The results of the pit optimization are presented below. For each income scheme, a risk analysis for undiscounted value, and other key indicators, is carried out using each optimal pit obtained from the 50 simulated models. The deterministic values reported by E-type models are also shown (see Figure 2 and Table 2). It is seen that, when molybdenum credits are added to the assessment, the undiscounted value of the pits significantly increases in around 10 % and the other indicators also increase. On the other hand, at first sight, the scheme 2 (whit fixed recovery) shows the best outcome, however, when these same pits are reevaluated with the recovery model, the expected value falls to MUS$ 10,192 which is below the expected value of the scheme 3. Therefore, assuming a fixed recovery can be misleading as, for instance, in this case where the values have been overestimated. In the case when TPH model is incorporated into the assessment, key indicators decrease both in value and tonnages.

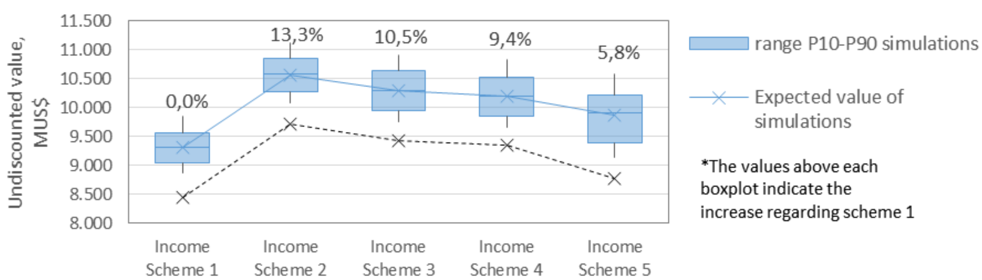

Figure 2 Comparison of risk profiles for undiscounted values of final pits obtained from the different income schemes. The economic values for the schemes 4-5 were revaluated with the economic model of scheme 3

Another aspect that the results show, it is a consistent discrepancy between the predictions realized by means of simulated models and E-type models. The optimizations through E-type models lead to pits with significantly lower undiscounted values and tonnages. The main cause of this behaviors is due to the smoothing of the Cu grade distribution. As shown in Figure 3-left, given the selected cut-off grade (around 0.58 %Cu), the predicted quantity of fine copper will be underestimated for E-type models, given that the predicted average grade is less than the expected for simulated models (note that this occurs for any cutoff) while the predicted tonnages are relatively similar for both types of models. On the other hand, when the reserves defined by one particular optimal pit are evaluated (see Figure 3-right), the E-type model will overestimate the amount of ore tonnage for the cut-off grade into consideration. This fact has a significant impact when tonnages defined by estimated models, such an E-type model, are scheduled under processing capacity limits.

Table 2 Key indicators for final pits obtained by different income schemes

Income scheme Case	Tonnage, Mt			Ore Tonnage, Mt			Cu Fine content, Mt			Mo Fine content, kt		
	E-type	Simulations		E-type	Simulations		E-type	Simulations		E-type	Simulations	
	value	Avg	CV	value	Avg	CV	value	Avg	CV	value	Avg	CV
1	2,800.2	3,073.0	3.4%	1,323.7	1,314.7	2.4%	16.9	17.7	2.2%	384.4	376.8	3.0%
2	2,980.8	3,257.5	3.9%	1,435.4	1,425.2	2.7%	17.7	18.6	2.4%	423.9	428.6	3.4%
3	2,966.7	3,295.1	4.6%	1,412.5	1,416.8	3.1%	17.5	18.5	2.8%	422.5	431.0	3.8%
4	2,924.7	3,105.2	2.3%	1,411.2	1,373.5	1.9%	17.5	18.0	1.7%	417.5	415.7	3.1%
5	1,967.5	2,455.3	6.9%	1,200.5	1,266.8	3.6%	14.5	16.2	3.8%	368.3	387.8	3.8%

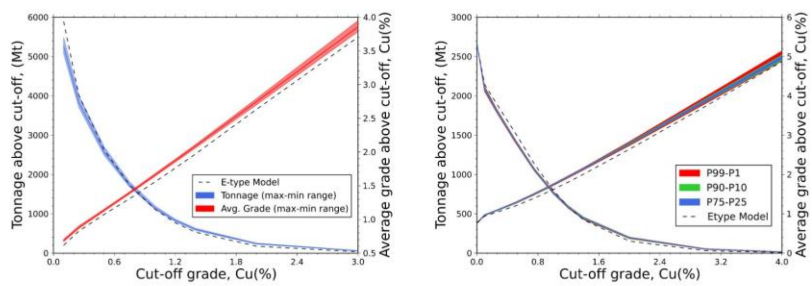

Figure 3 Grade-tonnage curve for estimated and simulated models, for total resources (left) and for economic reserves within a single optimal pit (defined for the conditional simulation 1 and income scheme 1) (right)

The results of the production scheduling are summarized in Figure 4, which presents the risk profiles for the net present value (NPV). When comparing the base scheme with the geometallurgical schemes an increased expected NPV is achieved, 3.2 % when Mo and recovery model are used and 8.3 % when a processing constraint based on available milling hours is added.

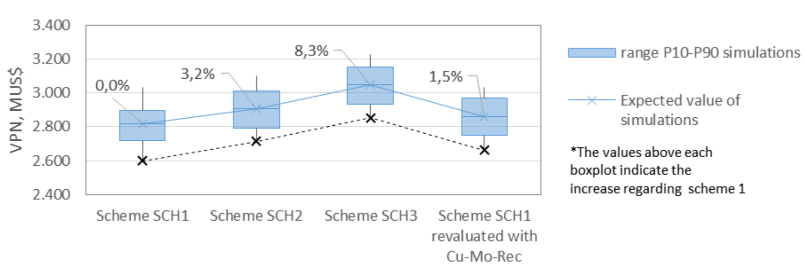

Figure 4 Comparison of risk profiles for the NPV of optimal schedules obtained from the different schemes

Figure 5-a-b-c compares the performance of schedules obtained from a specific conditional simulation with different schemes, which explains the previous results. It can be seen that the scheme 3 regarding the other schemes achieves: slightly better cash flows at the beginning of extraction, a greater quantity of ore to process for a large part of the LOM, and also allows that the processing times available are fully saturated over time.

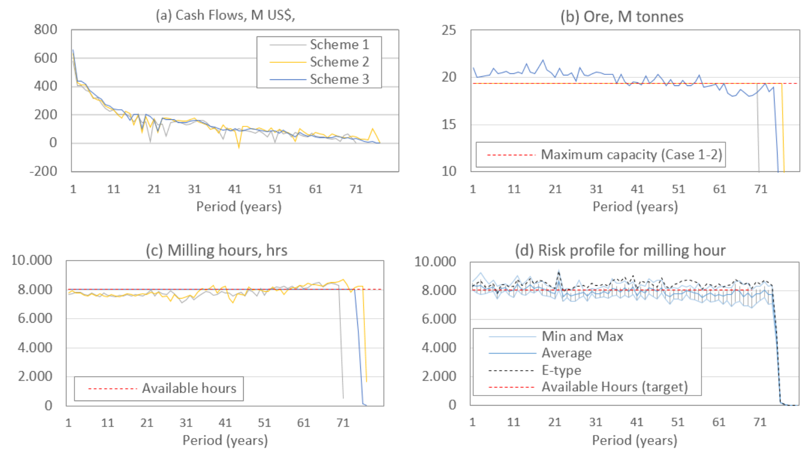

Figure 5 Comparison of (a) Cash Flows, (b) Ore and (c) Milling hours based on LOM schedules obtained from the realization Nº37 with different schemes; (d) Risk profile for used milling hours in the schedule SCH3-R37

The previous analysis, however, is from a deterministic point of view that does not consider the other probable scenarios of the actual deposit. When a specific schedule is evaluated using the 50 simulated realizations, it is possible to assess the effect of the uncertainty. This is shown in Figure 5-d where a risk analysis was carried out for the milling hours used per year in the schedule SCH3-R37, it can be seen that the variability is considerable which means a high risk of not meeting or exceeding the milling throughput targets. The probability of achieving a feasible schedule is only 2 %, while there is a 24 % probability when it is considered a tolerance of ±5 % for available hours planned and a compliance in at least 80 % of the periods. This high risk is a consequence due to the use of a deterministic optimization process which utilizes individually each realization, so that, the obtained schedule does not guarantee feasible solutions in presence of uncertainty. In practice, the robustness of processing/mining capacities along with NPV performance of each schedule may be examined to select the most favorable balance. To give an illustration of schedules, Figure 6 visually shows the differences between the obtained sequences from the evaluated scheduling schemes.

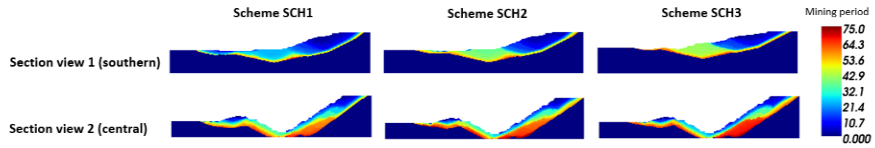

Figure 6 Two different East-West section views of the block sequences obtained by the E-type models from the different scheduling schemes

CONCLUSIONS

The present study analyses some practical uses of long-term geometallurgical models to adding value in the strategic planning of an open pit Cu-Mo mine. The results of the study show that the integration of the spatial variability, of both grades and geometallurgical data, changes the mine planning decisions as well as project valuation. The results suggest that extra credits from molybdenum, metallurgical recovery and ore hardness/grindability (considered through a throughput model) can increase the NPV of the project in up to 8-9 %. This improvement has been achieved principally by means of an hourly processing constraint which allows the scheduling giving priority to softer materials (lower processing times) with high recoverable metal. In this way the most convenient blocks are first extracted in order to maximize both the throughput over the life-of-mine, and the NPV as result. However, in presence of uncertainties it is revealed that the probability of achieving a schedule is really low in terms of available processing times. In view of the above, this approach with geometallurgical data may be used to select a low risk schedule and to remedy the high risk identified periods. By contrast, a conventional approach without this valuable information may lead to production schedules with low reliability to be realized. Even more if it is considered the use of smoothed models, such as E-type and kriging models, which tend to wrongly estimate ore tonnages and NPV. Future study should address the incorporation of these attributes into new strategies for ore definition, mine design and risk-based optimization.

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