Risk Analysis of a Large Copper Mining Complex under Joint Geological and Equipment Uncertainty

Luiz Resende Silva* and Roussos Dimitrakopoulos†

COSMO – Stochastic Mine Planning Laboratory

Department of Mining and Materials Engineering, McGill University, FDA Building, 3450 University Street, Montreal, Quebec, H3A 0E8, Canada.

Table of Contents

*luiz.resendesilva@mail.mcgill.ca

†roussos.dimitrakopoulos@mcgill.ca

Abstract

Conventionally optimized production schedules of mining complexes do not account for the different sources of uncertainty. The current work performs a risk analysis over such a production schedule incorporating the joint uncertainty in supply and equipment performance. This quantification of risk due to geological uncertainty and variability is assessed in the study through the use of geological simulations, where a series of orebody models are stochastically simulated conditionally to the available copper grade. Historical mining and processing production data provide the input for generating Monte Carlo simulations for equipment productions. The current risk analysis is performed for a 10-year life of mine deterministically optimized production schedule of a large copper mining complex. Such a mining complex comprises two deposits, two stockpiles, five crushers, three mills, two leach pads, a waste dump and several different mining equipment types and models. The schedule's response under the different joint uncertainty scenarios is measured, and the impact on metal production and cumulative discounted cash flows are compared to initial forecasts, assessing the risk in meeting these initial predictions. Results show the financial impact of not accounting for geological or equipment uncertainty and substantial differences between the planned forecasts and the schedule's responses.

Keywords: *Mining complex; Stochastic simulations; Risk analysis.*

1 Introduction

Mine operations usually comprise multiple components such as mineral deposits, stockpiles, mills, and leach pads. These elements together represent a mineral value chain, also known in the literature as a mining complex [8; 14]. The material extracted from the mines flows through different components and is transformed into sellable products at the end of the chain. This flow involves complex non-linear transformations, making it difficult to use conventional optimizers. Traditional optimizers approach this mining complex optimization by solving each part (e.g. extraction sequence of a mine) individually or sequentially (e.g. first the extraction sequence and later the destination policies). This approach does not benefit from the interaction and cooperation of different components, leading to sub-optimal solutions for the value chain as a whole [13]. Another pitfall of conventional optimization techniques lies in using a single estimated orebody model as input to the optimization process. Estimation methods cannot reproduce the in-situ variability of the deposit's grades and produce smooth representations of the orebody. The result misinterprets the proportion of tonnages and grades, leading to unrealistic expectations for the mine's production schedule and consequent net present value (NPV) [3]. Uncertainty in material supply coming from the mines has been recognized as the primary cause of technical risk in mining operations [23], leading to unexpected deviations in production targets [4; 5; 6; 16].

This spatial uncertainty and variability of spatially correlated attributes of interest in geoengineering, such as metal grades, can be quantified by employing geostatistical simulations for orebody models founded on the concept of random fields. Equally probable realizations of the desired attributes are generated conditional to the available data [9; 10; 19]. Based on the set of stochastic simulations generated, the Risk Analysis framework, well documented in the literature [3; 4; 5; 6; 16], proceeds by measuring the response of the deterministic schedule under the different possible scenarios for the orebody model and later comparing those with the initial forecasts.

Based on the framework of simultaneous stochastic optimization of mining complexes [7; 8], recent work has shown the benefits of including different sources of uncertainty in the optimization process, such as commodity prices [21]. The inclusion of equipment production uncertainty for stochastic optimization of short-term production scheduling and equipment allocation displayed the importance of integrating this information and how it can impact the results achieved [1; 15]. In the current work, the risk analysis framework is extended to incorporate the equipment production uncertainty and, along with geological uncertainty, assess the conventional LOM schedules responses and quantify the risk of meeting the initially planned forecasts.

The following sections present the method utilized to perform the risk analysis in the presence of joint geological and equipment uncertainty. An overview of the copper mining complex used in the study is shown, followed by results and a discussion of the risk analysis implemented. Conclusions are presented in the last section.

2 Proposed Approach

Next, the proposed approach is presented, with a brief discussion on generating the required simulations. Further explanations and peculiarities for the implementation are discussed in section 3 when outlining the application to the copper mining complex studied.

2.1 Generating simulations

The approach is founded on quantifying risk using a set of equally probable orebody model scenarios. These simulations are generated through Monte Carlo sampling from a conditional distribution function constructed from the available data, meaning the resulting realizations are based on and reproduce the available data, their distribution statistics and data variability [9; 10]. The sequential simulation approach is an alternative to generate these realizations and assess these desired attributes at each unsampled location of a three-dimensional orebody model. A known and widely used method for the simulation of spatially distributed attributes is the Sequential Gaussian Simulation (SGS) approach, based on second-order statistics and Gaussian assumptions [2; 9]. The simulation of the nodes discretizing the orebody model is performed by sampling a value from a Gaussian distribution, where the conditional mean and variance are obtained through kriging equations. These nodes are later averaged and up-scaled to represent the desired mining blocks used as input in the optimization.

In the proposed approach, the equipment production uncertainty is integrated into the assessment also by employing Monte Carlo simulations. These equipment simulations are generated based on historical data [15] measuring the daily information such as production, availability and utilization from different mining and processing equipment types used in everyday activities. The cumulative distribution functions (CDFs) can be directly constructed from this historical data and the simulated daily productions for the different equipment types generated by direct sampling these CDFs [18].

These can be later up-scaled to yearly productions by merely accumulating the daily values based on the mining complex's scheduled number of working days. Care should be exercised when simulating such information since the output of a given piece of equipment can display strong correlations with another, as such, being necessary joint modelling. When this case is presented, decorrelation methods such as principal component analysis (PCA) can be employed to decorrelate the variables, which can be later simulated independently. In the current work, the production of the different equipment types was simulated independently based mainly on the lack of information about direct inter-correlation between equipment types, e.g. which type of shovel loads which specific kind of truck with a given frequency.

2.2 Integrating equipment uncertainty into the risk analysis

The risk analysis framework for geological uncertainty proceeds as shown in Ravenscroft [16] and [4], where the conventionally optimized schedule constructed with a single estimated orebody model undergoes assessment using a set of conditionally generated stochastic orebody simulations. The analysis proceeds following the main steps presented next:

1. The blocks composing the conventional mine production schedules are identified, where their respective information regarding the period of extraction and assigned destination are retrieved;

2. Each different orebody scenario is used in substitution to the estimated model, where the attributes in these simulated scenarios are used in the calculations for metal tonnages, average recovered grades and NPV, while all other mining, processing and economic parameters remain the same;

3. The responses of the conventional schedule under the set of simulations create a range of possible outcomes, which allows quantifying the risk in meeting the estimated forecasts in a probabilistic manner.

The proposed approach extends the above methodology by integrating other sources of uncertainty in the analysis, specifically the uncertainty related to the mining and processing equipment. This can be done by extending the reach of parameters tested in step 2. The equipment simulations discussed in section 2.1 are systematically used to replace the parameters, such as mining and processing rates, which are now variable and dependent on these realizations. This change implies the possible modification of the extraction sequence, i.e. if the simulated mining rate is smaller than the previous estimated one, the total planned tonnage for a given period will not be met, and many previously scheduled blocks are left not mined. Similar implications can be seen for the total tonnage planned to be processed in a given destination and period. The joint risk analysis proceeds following the implementation shown in the steps below, addressing the effects of the uncertainty in production, as mentioned earlier.

1. Retrieve the conventional schedule;
2. Identify the scheduled blocks and their assigned destination, which are considered fixed;
3. Based on each realization ω_e in the total number $\mathcal{S}_E$ of simulations for mining and processing equipment:
   (a) Calculate the available mining rate for each period;
   (b) Assign the simulated yearly capacity for any processing destination directly simulated or affected by components whose production or capacities were simulated;
   (c) Follow the planned extraction sequence such that:
      i. Blocks are extracted in their planned period while mining capacity is still available. Otherwise, blocks are left to the following period. The extraction proceeds to ensure that physical constraints are respected in the case of unmined blocks.
      ii. Extracted blocks are sent to their fixed destination, where the recovery, costs and profit are calculated. This is allowed while the related destination has processing capacity available for that period. Otherwise, if the destination has no processing capacity left and there is still mining capacity available, given that the destination has a stockpile associated with it, the block is extracted and sent to the stockpile. If the destination has no associated stockpile, the blocks' extraction is delayed to the next period.
4. For each equipment scenario $\omega_e \in \mathcal{S}_E$ from above, the material attributes in each realization ω_g from the total number $\mathcal{S}_G$ of orebody simulations are used to calculate metal tonnages, average grades and recovery profits, coupled with the total extracted and processed tonnages from step 3.

The above steps generate as results the risk profiles with the range of possible outcomes for the different scenarios, where the profiles are created with a cloud of $\mathcal{S}_E \times \mathcal{S}_G$ scenarios. The approach was implemented using Python 3.7 language [20], taking advantage of its many modules for data handling and parallelization of process.

3 Joint risk analysis of a large copper mining complex

This section applies the proposed approach to a large copper mining complex. First, the mining complex is outlined, where general information about its mineral value chain and conventional schedule is given. Economic parameters (e.g. prices and costs), material quality and production targets used in the study are scaled for reasons of confidentiality. Generic names are also used.

3.1 Overview of the copper mining complex

3.1.1 Mining complex and material flow

The copper mining complex consists of two mines (Mine A and Mine B) having 185,810 and 67,784 blocks, respectively, with a selective mining unit (SMU) size of 25×25×15 m3. The stratigraphic sequence of material is waste rock, followed by copper oxide, mixed and copper sulphide. The mining complex produces copper concentrate and copper cathode as primary products and gold, silver and molybdenum concentrate as secondary products. The material extracted from both mines is classified into 4 main material types (waste, oxide, high-grade sulphide and low-grade sulphide) based on geological and grade properties (copper soluble CuS, copper total CuT, and copper soluble to copper total ratio). The extracted material can be sent directly to one out of 9 different destinations (5 crushers, 2 stockpiles, 1 bio leach pad for low-grade sulphide and 1 waste dump). Material sent to one of the five crushers is further directed to one of the three processing mills (for high-grade sulphide) and an acid leach pad (for oxide) that supplies material to the port and a copper cathode plant, respectively, following the flow of material shown in figure 1.

The primary product generated at the port is copper concentrate. Although different secondary products such as gold, silver, and molybdenum concentrates are also produced at the port, in the present study, only the impact of the primary product underwent analysis since the orebody simulations contained only CuT and CuS grades as the simulated attributes. Figure 2 shows the cross-sections of two randomly selected simulations for the two deposits for copper total (CuT) grade

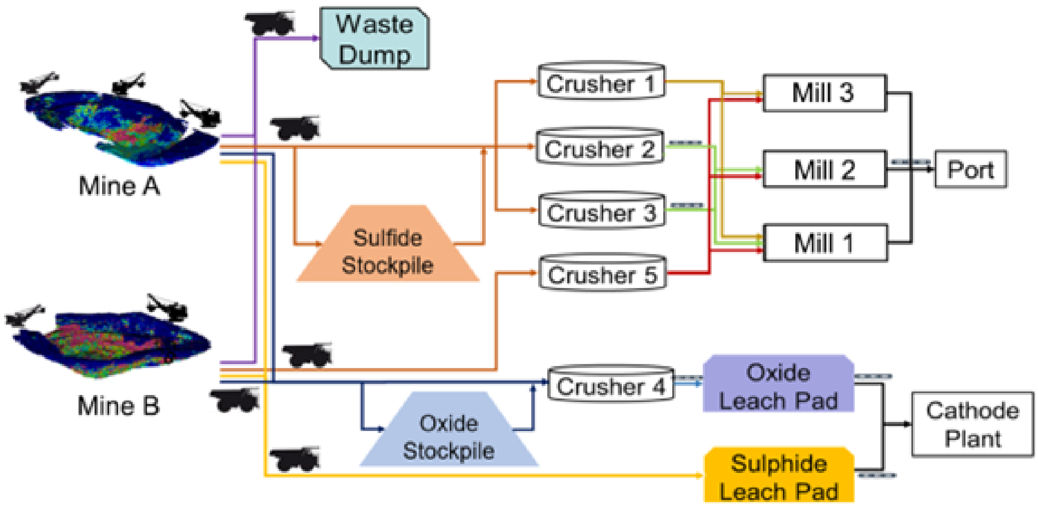

Figure 1: The flow of material at the copper mining complex.

compared to the estimated deposits. The variability in this attribute is easily seen in the simulations compared to the smooth representation of the estimated models. The mining complex provided the simulations used in the present work.

3.1.2 Conventional LOM schedule

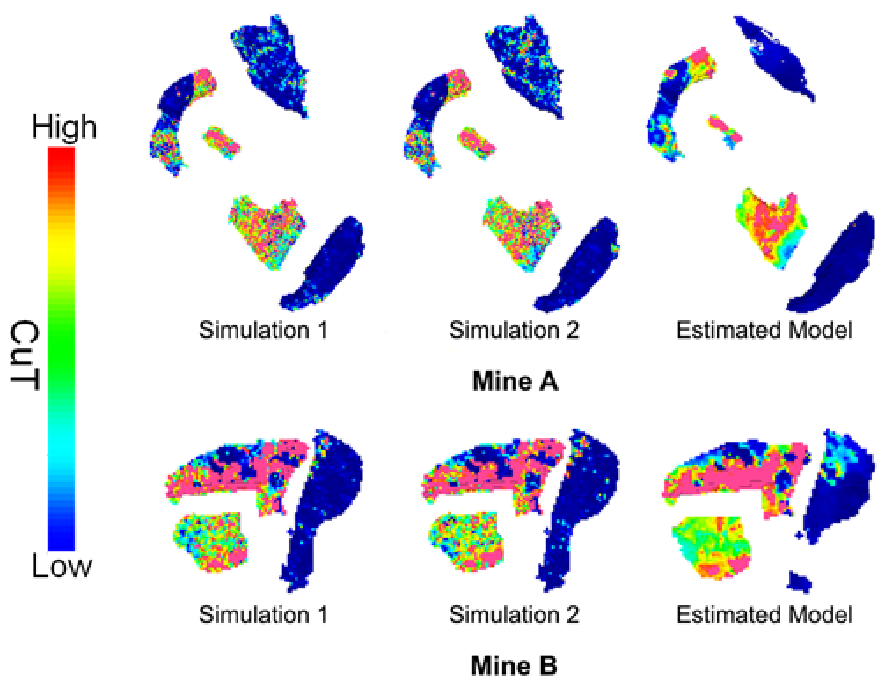

Figure 2: Examples of simulations of the copper total (CuT) grades for the two deposits compared to the estimated model.

The long-term mine production plan currently used at the mining complex is optimized using a two-step optimization approach, where: (I) the extraction sequence of multiple mines is optimized independently of each other using Whittle version 4.5.4 [22], a widely used software for strategic mine planning, and; (II) the destination of the extracted material follows the cut-off grade policy presently used at the mining complex, based on Lane's approach [12; 17], with the utilization of different processing streams defined using a separate optimization model. Also, this two-step optimization process is performed using estimated mineral deposits, shown in figure 2, as is the standard practice in the mining industry. This long-term mining plan of the copper mining complex generated with this two-step approach results in the conventional mine production plan [11].

Since the planned schedule is based on linear programming optimization, it results in a plan with a partial block extraction sequence instead of a mixed-integer programming optimization. Partial block extraction leads to unrealistic assumptions about in-block homogeneity and selectivity, i.e. the program assumes that a block's attributes are evenly spread within its volume and that its different parcels can be mined in different periods and sent to various processing destinations [3]. In the current work, the extraction sequence followed in the scenarios for the risk quantification uses a schedule with integer extraction. This integer schedule directly results from fixing a single period of extraction and destination to each block based on the information from the largest parcel in a block. Post-processing was done to ensure that the integer schedule constructed respected all physical constraints. The differences between the fractional and the integer schedule (e.g. planned mined tonnages and planned tonnages at the destinations per period) are neglectable.

Economic parameters and production targets used to generate the conventional plan are the same as the ones used for the analysis but scaled for confidentiality reasons.

3.1.3 Simulations for equipment production

As described in section 2.1, the simulations for the equipment production were generated using historical data from the mining complex to construct the CDFs for the different equipment. The data was collected between 2014 and 2016. The mining complex operates using 4 different models of trucks and 6 different models of shovels in the mining fleet, with varying numbers of each piece of equipment in each of the mines. Since the available data set did not present any specific information regarding the equipment's allocation or how these different trucks and shovels interacted between themselves, the data was split considering equipment types (trucks or shovels) and models (e.g. truck A, truck B, shovel A, shovel B) to generate the CDFs and later the simulated production.

The available data was collected and reported daily; therefore, the simulations were also generated on the same daily scale. For the simulation process, since 10 years of daily production needed to be constructed to avoid extreme repetition of data, the simulations were generated as follows:

1. For each equipment type and model, 1 year (365 days) of simulated production was generated sequentially for 10 years;
2. Each year of simulated production was conditioned to a smaller subset of the initial data, composed of 365 data points randomly selected to create the distribution.

Before creating the CDFs, the data underwent a cleaning preprocess, where the information for availability and utilization was used to flag potentially corrupted data. First, any data point with zero availability or utilization and with non-zero production was discarded, as it is impossible to have production for a piece of unavailable equipment. Furthermore, data points with availability higher than 25% and zero production were also discarded, i.e. a piece of equipment available for more than 6 hours in a day without production was not considered. In this particular case, it was assumed that the reason for the equipment not producing did not have a relation with its actual possibility to produce and keeping these values would increase zero production frequency. The data points erased in the second step had an impact of less than 4% for shovels and 0.9% for trucks, not altering their overall distribution in any form. For the crushers, data cleaning was not required.

During the collection of the historical data used to simulate the productions, the mining complex operations were downsized due to technical reasons, impacting the equipment performance and providing data related to sub-use. Based on current average productivity information, the distributions for the different equipment were shifted to meet the mining complex current production records to address this issue. Figure 3 shows randomly selected examples of the data distribution after cleaning and shifting the means from which the CDFs were generated. They offer a reproduction of the data's distribution in the simulations generated.

3.2 Risk analysis results

The results presented next quantify the risk of the schedule in meeting its production forecasts in the presence of uncertainty of the material supply and the capacities of the equipment used. The output values for a given project indicator (e.g. total tonnage extract, metal produced, cash flows) are represented by risk profiles, which are expressed as probability values, shown as the P10, P50,

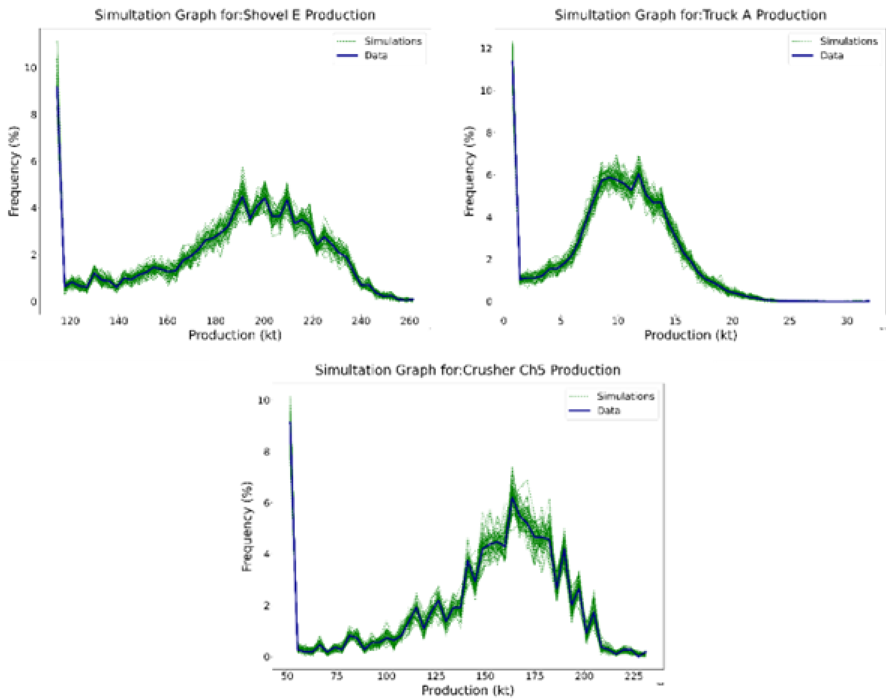

Figure 3: Examples of distributions for different equipment types. Simulations for production (green) reproduce data statistics (blue).

and P90 percentiles. P10 represents a 90% chance of having at least that value, which means that the values for 90% of the scenarios are higher than the P10. P50 represents the value at which 50% of scenarios fall above and 50% fall below, and P90 represents a 90% chance of having a value below it.

First, figure 4 shows the mining capacities for the two mines for each year of the LOM period studied, where the simulated capacities are dependent on the realizations for the trucks and shovel productions. The planned mining capacity was calculated, assuming that each piece of equipment's average production would be maintained throughout the year. It also shows that considering this average yearly mining capacity consistently overestimates the available capacity. This impacts the extraction sequences, resulting in insufficient extraction capacity to meet the planned tonnages feeding the different processing destinations, which can be seen in figure 5, where the cumulative difference in ore tonnages reaching the three mills and two leach pads can be up to 3.7% less for the mills and 6.3% less for the leach pads at the end of the 10 years (comparing with the P50). This difference is also caused by the uncertainty in the production by the crushers, which can be seen in the increase of material sent to the stockpiles (figure 6 left). This is a direct consequence of the mills

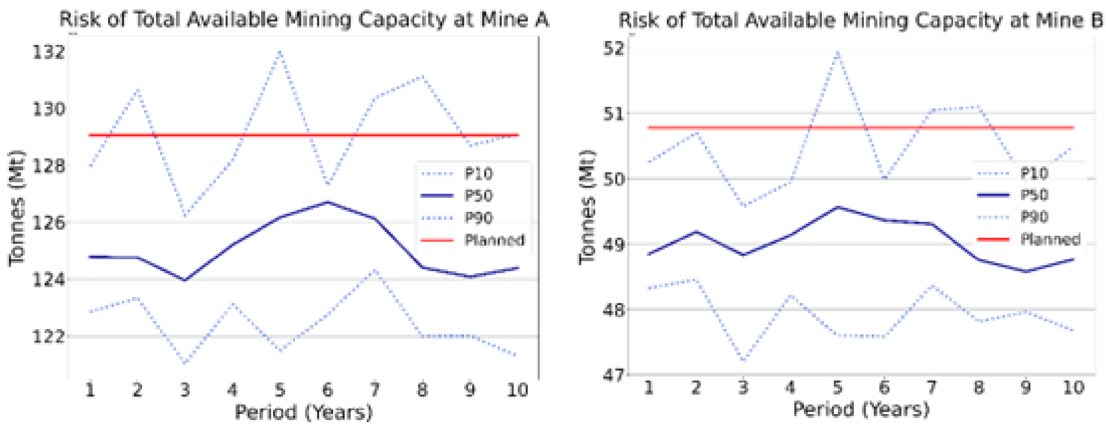

Figure 4: Risk profiles for the total available mining capacities for Mine A (left) and Mine B (right).

and crushers reaching their maximum simulated processing capacity. No noticeable risk spread is seen for the cumulative total tonnage of material sent to the waste dump (figure 6 right), given the spatial location of the blocks scheduled to this destination, which require being extracted (respecting precedence and slope constraints) to allow accessibility to the ore material.

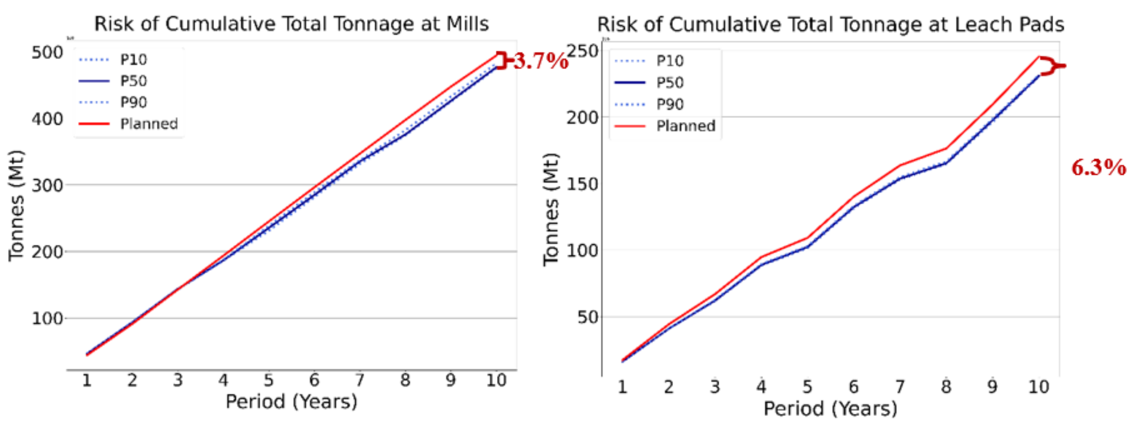

Figure 5: Risk profiles for the cumulative total tonnage of high-grade sulphide ore at the three mills (left) and cumulative total tonnage of low-grade sulphide and oxide ore at the two leach pads (right)

Figure 7 shows the impact of the above, coupled with the uncertainty in the material supplied. The total recoverable copper at the mills is expected to be lower than the predictions in the conventional long-term plan by approximately 7.3%. The results below show that the material feeding the mills contains more low-grade sulphide. In comparison, the sulphide leach pad also receives more sulphide with lower overall grades than the initial plan, which can be seen in the 9.2% less

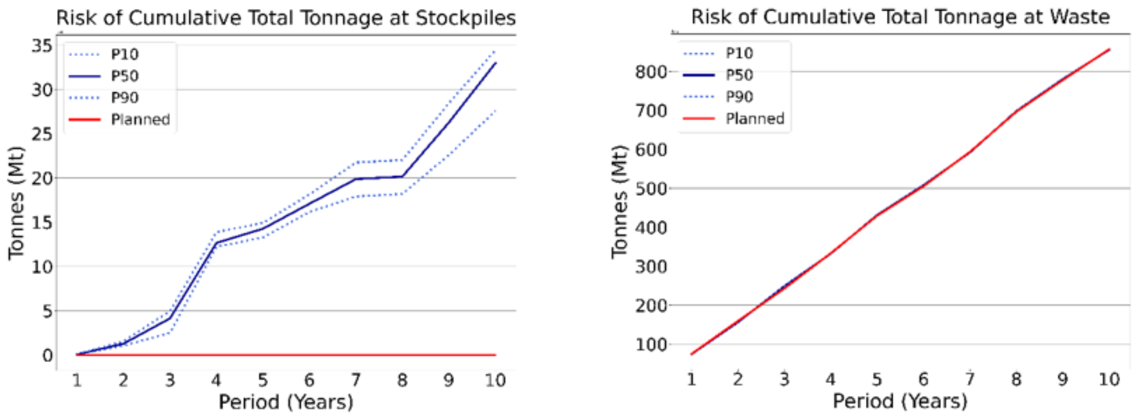

Figure 6: Risk profiles for the cumulative total tonnages at the stockpiles (left) and the waste dump (right).

recoverable copper at the leach pads. The differences between the recoverable copper seen in the initially planned forecasts and the ones shown in the risk profiles come from the inability of the estimated models to reproduce the actual variability of the mineral deposits and the overestimation of ore tonnages mined and processed. This can be further noticed in figure 8, where it is possible to see that, differently from the initial forecasts, there is misclassification of material (e.g. low-grade sulphide or oxide at the mills).

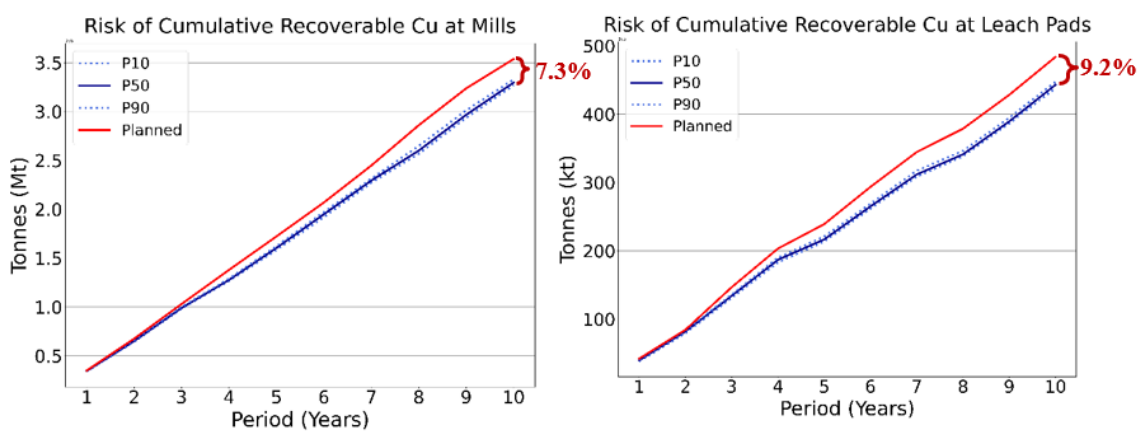

Figure 7: Risk profiles for the cumulative recoverable copper at the mills (left) and leach pads (right).

The inability to model the variability of the deposit's properties also results in underestimating the total tonnages of metal sent to the waste, shown in figure 9, where close to 34% more copper is sent to the waste. The decrease in recoverable copper observed in the risk analysis caused by the

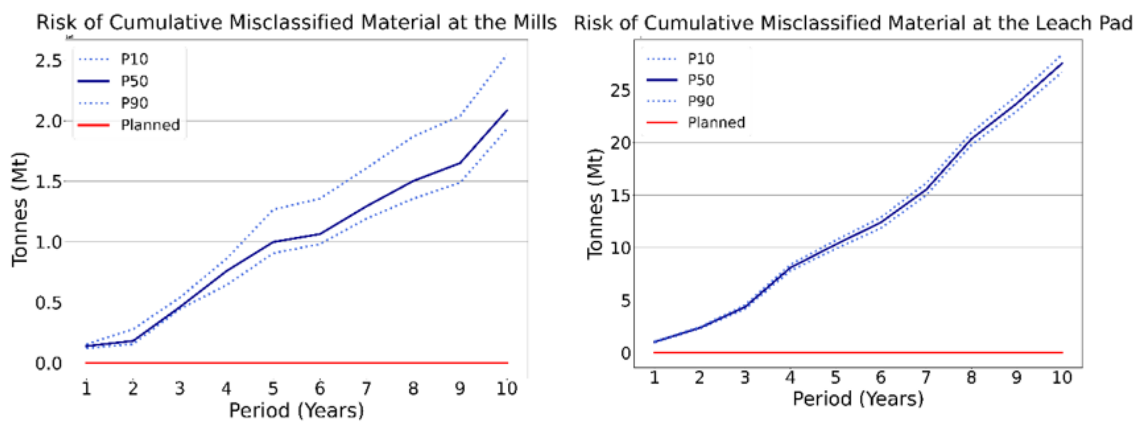

Figure 8: Risk profiles for the cumulative tonnage of misclassified material at the mills (left) and leach pads (right).

joint uncertainty in material supply and production capacities directly impacts the discounted cash flows (DCF) forecasted. At the end of the LOM, the cumulative DCF generated in the analysis is almost 11% lower than the one predicted by the conventional plan, as shown in figure 10. Such difference carries an enormous impact, which can be translated, for a large mining complex, into tens of millions less revenue than expected.

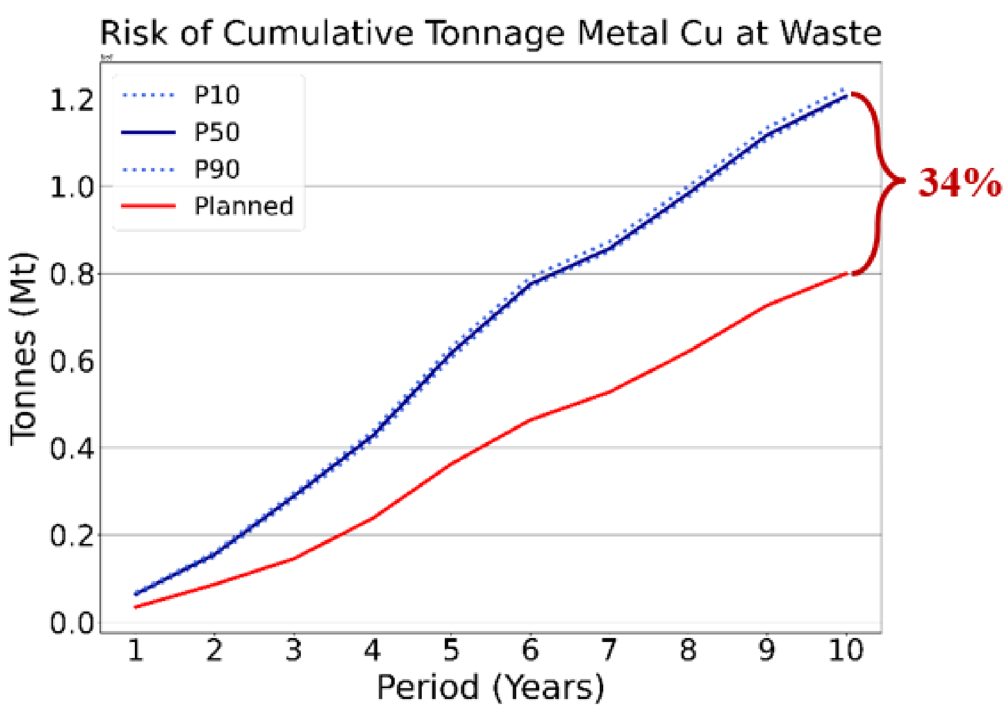

Figure 9: The risk profile for the total tonnage of copper at the waste dump.

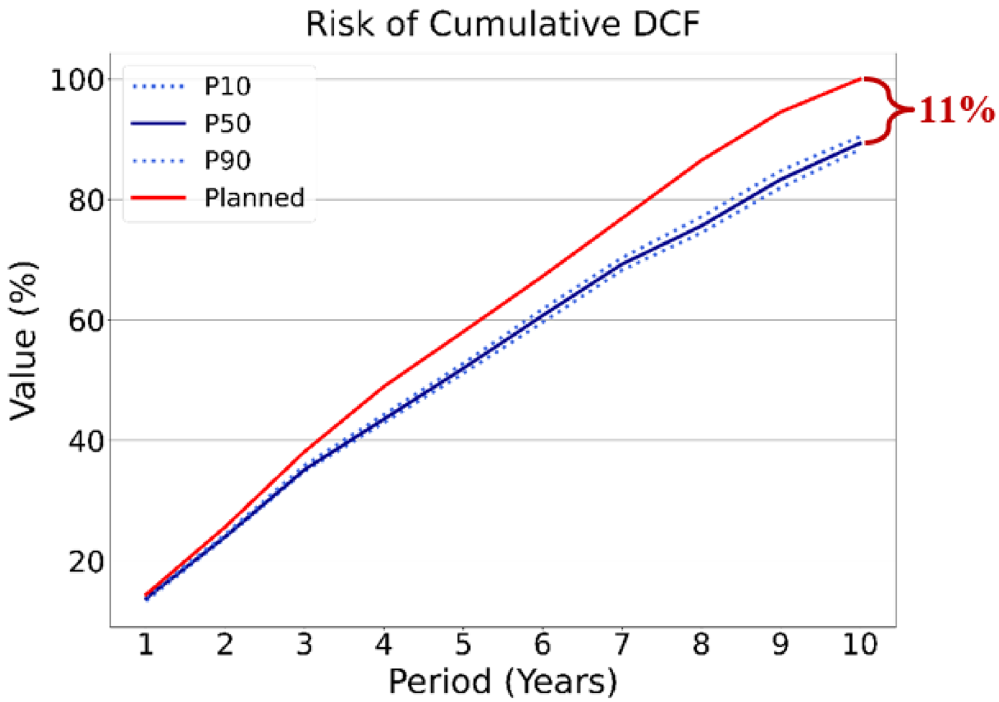

Figure 10: The risk profile for cumulative discounted cash flow.

4 Conclusion

This work presents the implementation of the risk analysis framework for the LOM schedule of a large copper mining complex. The analysis was expanded to integrate the uncertainty related to different sources, such as equipment production. Risk quantification was done using stochastic simulations, which enabled us to describe and assess the uncertainty and variability of data, especially for geological deposits, where limited information is obtained through drilling campaigns. Stochastic simulations are also used for modelling the uncertainty and variability of equipment production, where historical data was used to generate the realizations.

The risk analysis shows significant shortfalls of the conventional schedule in the presence of uncertainty inherent to a mining operation with several complex interconnected components. Results for the studied mining complex show that the uncertainty related to equipment production significantly impacts the recoverable tonnages due to the inability to meet the planned extraction and processing forecasts, evidencing even further the pitfalls of conventional deterministic mine planning. The consequences of ignoring this uncertainty can be seen in the substantial differences in the discounted cash flows. For the case study, results show close to 11% less revenue, which can be translated into tens (or even hundreds) of millions of dollars for large mining complexes.

Although the uncertainty cannot be eliminated, it can be incorporated during optimization using stochastic optimization formulations, which, as a result, generate more robust and better-informed solutions when compared to the deterministic counterparts.

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