Risk Analysis on Mining Planning and Reserves Assessment at a Brazilian Copper Mine

C. Diedrich, J. F. C. L. Costa and W. F. de Paula

Abstract Mining industry continuously investigates proper reconciliation procedures and techniques for mapping possible risks in ore recovery and mining planning. A case study at a Brazilian copper mine investigates the adequacy of using simulated grades for defining risky areas affecting mining planning and the defined mineral reserves. Conditional simulations were used to derive multiple copper grade models within a typical ore-body of the deposit and these models were compared against the real production (reconciliation). The comparison allowed a better understanding on grade variability and helped in defining a more consistent mining plan. The range of values derived from the simulations mapped areas of significant uncertainty affecting the pushback plan. Risk analyses were conducted using the planned mining sequence with the simulated models of copper grade, assessing the operational impacts on key economical factors (NPV, discounted cash flow). A Risk Scale (ESR) was defined by using the conditional simulated models and the ordinary kriged values (commonly used for budget and mill feed reference) in order to minimize grade variations ensuring less risk on completion of the metal production goals on mining planning. This risk-based mining sequencing approach was used on the annual mining plan and compared to the traditional approach and the real executed values. The results highlighted possible risks associated with the operational mining sequencing and demonstrated the benefits of using risk analysis as a tool to preview and review the mining planning, thus helping to take better strategic decisions by the copper mine management related to the technical and economic indicators.
Keywords: Conditional Simulation; Reconciliation; Mining Sequencing; Mineral Reserves

---

Cássio Diedrich - e-mail: `cassio.diedrich@vale.com`
Principal Geostatistician at South Atlantic Base Metals Copper Department, Carajás, PA, Brasil
João Felipe Coimbra Leite Costa - e-mail: `jfelipe@ufrgs.br`
Associate Professor at Federal University of Rio Grande do Sul, Porto Alegre, RS, Brasil.
Wellington Fabiano de Paula - e-mail: `wfpaula@bol.com.br`
Senior Mining Engineer at South Atlantic Base Metals Copper Department, Carajás, PA, Brasil.

1 Introduction

Identifying, assessing and managing risk may allow a better definition of financial resources on strategic investments ensuring that the activity or project is implemented in a logical manner during the mining of the mineral reserves, thus identifying opportunities to enhance business value through decision-making about the highlighted risks. Conditional simulation techniques allow the creation of equally probable scenarios (realizations) of the spatial distribution of the variable under study, which are useful for the grade variability mapping, reproducing some of the features of the experimental distribution (samples) and spatial connectivity. This technique can be applied on sensitivity analysis (risk analysis) supporting the resource evaluation, mine planning and mining production sequencing and redefining the expectations of the project and operational mining process [1]. With the simulated models it is possible to evaluate the main methods for risk analysis on the strategic mine planning and also for the operational pushback designs. In this case study an alternative approach (ESR-Risk Scale) is applied to incorporate risk in the mining sequencing process (risk-based) of medium and long term process considering the simulated models. The development of a production sequence (traditional and risk-based) is a very complex procedure due to the large number of variables and constraints involved. The processes involved in mining operations are determined primarily by the definition of a final pit through a pit optimization algorithm, with a logical extraction of each block from the block model. Next, it is determined a sequence of blocks defining the operational pushbacks, and calculating key economical indicators such as cash flow and net present value (NPV). Another important action in the estimation process is the reconciliation as it serves for calibrating and understanding the selectivity of the deposit and strategic planning associated with the mineral resources and reserves. The practical validity of any reserve or resource estimate ultimately consists of comparing the estimates against the actual production. Conditional simulation models can be used and compared to the real mining production values in order to validate and understand the real grade variability of the mineral contents, as well as a validation of the simulated models. This study aims at evaluating the possible benefits of incorporating grades uncertainty in medium and long term mining planning. The procedure would allow to verify the inherent risk and possible target deviations from the mining plan. The methodologies (traditional and risk-based production sequencing) applied through were validated against the real mining results (the reconciliation process).

2 Methodology

The steps of the current study comprise:

- conditional simulations to quantify the copper grade variability;

- reconciliation process to validate the copper grade variability provided by the conditional simulated models, which will serve as basis for risk analysis and for the risk-based mining sequencing methodology;
- definition of an objective function and use of annealing simulation to provide a single optimized risk model (ESR - Risk Scale);
- evaluation of the applicability of the proposed operational iterative risk-based mining sequencing approach using the ESR, in order to minimize the risk associated to the production goals (kriged grades) and deviation from the predicted mine plan, in comparison with the traditional approach;
- reconciliation from both the traditional and risk-based methodologies considering the operational and economic key performance indicators.

3 Mining Planning, Grade Uncertainty and Reconciliation Overview

Production scheduling provides a production sequence along a time period involving the removal of at least two types of materials: ore and waste. According to [2], the programming of an optimized production mining sequence depends on the geological characteristics of the deposit, mining conditions, processing technologies, and economic parameters associated both on space and time. The possible combinations of ore and waste rock removal (stripping ratio) and the ore production rate that meets the requirements of milling process are the two major technical limitations involved in the determination of the mining sequencing. The mathematical calculation for final pit definition is the first step in the production sequencing planning. Financial income is calculated from ore tonnages, grades, recoveries and product price. The mining advance is a step in the expansion of the mine to be developed under certain restrictions (slope angle, berm width, feed rate of the plant, area of operation, etc.) in order to ensure that the mining sequence is carried out properly. The definition of economic value of a block corresponds to assigning a value of economic return. Each step along the production chain has its own cost and its capacity limits.

3.1 Objective Function (ESR - Risk Scale) and Mining Planning

The risk based approach for medium and long-term mining production sequencing and for managing grade uncertainty [3] is given by a risk scale formula (ESR, Eq. 1). The risk scale formulation allows considering multiple variables or mining subjects on the equation being possible to accept a non-linear relationship. The ESR formulation defines the average relative deviations from production targets (kriged grade) for the different simulated models s, referred to the block i, weighted by the conditional coefficient of variation λ_i. The use of the conditional coefficient variation results in a better definition of the local risk for the selected attribute balancing the equation, since it takes into account the variability and precision of the local average value used for calculating the relative difference against the kriged values (budget and productions goals reference).

$$ESR = O = \frac{1}{|S|} \sum_{i=1}^{I} \sum_{s=1}^{S} \frac{|\theta_i^* - \theta_i(s)|}{\theta_i(s)} \lambda_i \tag{1}$$

where:

- $s \in \{1, \ldots, S\}$ and represents the index of the simulation models;
- $i \in \{1, \ldots, I\}$ and represents the index of the blocks;
- θ_i^* represents the material goal (kriged value) for the block i;
- $\theta_i(s)$ represents the simulated value s for the block i;
- λ_i is the conditional coefficient of variation for the block i considering all the s simulated models.

If the average relative deviation and the conditional coefficient of variation referred to the simulations tend to zero, then the accuracy and confidence for the assumed risk class value for the estimated block in the definition of mining plan will be high, ensuring less risk.

3.1.1 Annealing Simulation and Risk-Based Mining Planning

The annealing simulation is a generic name for a number of optimization algorithms based on the principle of stochastic relaxation [4] [5] [6] [11].The basic idea is to continually perturb an initial image until some pre-specified characteristics be defined by an objective function. The simulation begins with the determination of an initial image. Each perturbation is accepted or not depending on the initial image and the objective function. In this process it is analyzed the probability of the block to belong to a given ESR risk scale class defined. The blocks are considered candidates in exchanging ESR classes according to their probability of belonging to a particular risk class. This initial image is then perturbed by a random block selection among the possible ESR classes to which a given block can belong (see next section for details). All favorable perturbations (in which the objective function is minimized) are accepted and all unfavorable perturbations are accepted with a probability derived from an exponential probability distribution (item 3.1.2). The optimization process is terminated when the perturbations do not result in a decrease of the objective function or when a specified minimum value of the objective function is achieved. The result of the averaged annealing optimizations for each simulated model is a single ESR risk scale model, which represents a chance of misuse or lower risk associated to the pre-established deterministic values (kriged). These ESR blocks are commonly used iteratively (or by linear programming) during the annual mining sequencing in an attempt to minimize the risk on achieving the goals defined by kriged grades, which is the budget and target reference for the mining company on the achievement of goals:

$$MinO = \frac{1}{|S|}\sum_{d=1}^{D}\sum_{i=1}^{I}\sum_{s=1}^{S}\frac{\left|\theta^{*}_{d,i}-\theta_{d,i}(s)\right|}{\theta_{d,i}(s)}\lambda_i \tag{2}$$

where:

- $d \in \{1,\ldots,D\}$ and denotes the index for the target, class or process of material;
- $\theta^{*}_{d,i}$ represents the target (kriged values) of material defined for the class d referred to the block i;
- $\theta_{d,i}(s)$ represents the current value of the simulated value s for the defined material d, referred to the block i.

3.1.2 Perturbation Mechanism

During the annealing simulation it is necessary the exchange of blocks in attempt to minimize the ESR objective function. The perturbation mechanism consists of a random exchange of blocks with respect to its current candidate ESR class values (i.e. block with moderate risk) by a given block with lower risk class (i.e. block with low risk). The candidate blocks are determined by using values from the simulations regarding the neighboring blocks to calculate the probability of the block belonging to a lower risk class. Candidates for an exchange are the blocks in classes obtained through the calculation of probability stemmed by a training image [7], which has a high probability of assuming a lower risk class, minimizing the defined objective function (ESR). The figure below (Fig. 1) presents 26 blocks connected to a centered block (yellow block) as a part of a mineral resources block model. The block highlighted in yellow has an ESR value (risk) equal to the blocks of green color and higher than the blue blocks. This block is a candidate to take a lower ESR class, since it interfaces with several blocks of lower ESR, indicating that there is high probability of occurrence of this class of lower risk.

For the case study described in section (item 5), there was no access restriction applied to any candidate block (slope angle, mining operating area and roads) since the aim is only to reclassify the risk associated with the blocks changing the given ESR value considering the inherent probability to assume a lower risk class. During the mining sequence it was proposed taking into account all the constraints inherent to the mining process. The annealing process is an iterative process, following a random path to visit each node of the grid. If a risk class value d_{actual}, randomly determined and different from a previous class $d_{previous}$ defined by $O_{previous}$ and O_{actual} as the corresponding energies (objective function), then the probability distribution for the acceptance of a perturbation is applied through the Metropolis criterion [8], given by Boltzmann distribution where:

- if $O_{actual} \leq O_{previous}$ then $d_{previous}$ is replaced by d_{actual};
- if $O_{actual} > O_{previous}$ then $d_{previous}$ is replaced by d_{actual} with probability p and $d_{previous}$ is maintained with probability 1-p.

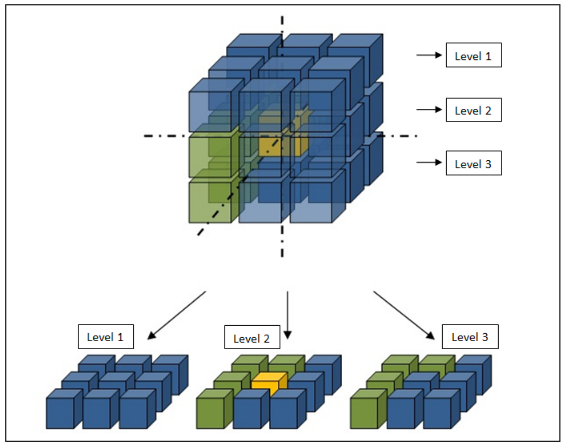


Fig. 1 Representation of 26 blocks connected to any block (block candidate for ESR class exchange, yellow), low risk class blocks (ESR, in blue) and moderate risk class blocks (ESR, green and yellow).

where p incorporates the difference of energy and the "temperature" (T) of the system (monotonous function which decreases with the duration of the process) by the following equation:

$$p = exp\left(\frac{-(O_{actual} - O_{previous})}{kT}\right) \tag{3}$$

where k is called Boltzmann constant.

3.2 *Conditional Simulation and Grade Uncertainty*

The stochastic simulation methods were originally developed to correct the smoothing effect and other artifacts displayed in the maps produced via kriging estimation [9]. Unlike kriging methods, the stochastic conditional simulation techniques allow the uncertainty to be evaluated. Conversely to the interpolation, the implementation of stochastic simulation methods does not result in a single estimate of the map of the variable of interest. These techniques allow the creation of several equally likely scenarios (realizations) of the spatial distribution of the variable under study replicating some of the features of the experimental distribution (samples statistics and spatial continuity). Thus, by combining all simulated models, it is possible to measure the uncertainty associated with any local or global statistic, in a more realistic way, considering the variability inherent to the data. Simulation preserves more characteristics of the input data than other estimation techniques; it also has the benefit of providing the risk dimension to resource/reserve evaluation studies that kriging cannot readily provide [12].

3.3 Mining Reconciliation

During mining reconciliation the estimated tonnages, grades and metal content are compared against actual mined values. The aims are to measure the performance of the operation, supporting the calculation of the mineral asset, validating the Mineral Resource and Reserve estimates and providing key performance indicators for short and long-term control [10]. Currently, regular and efficient reconciliation should also highlight improvement opportunities and allow for proactive short term forecasting by providing reliable calibrations to critical estimates. For the auditing process conducted for lending banks, security exchanges or corporations, the confidence of the resource model is considered one of the high-impact risk elements in the mining prediction. For operational mining development, however, the reconciliation of the resource model to actual production is an added requirement, where all the predicted budget and expected goals of the project by a mining company is related to this resource model. Therefore, the expected tonnage, grade and metal must be correctly predicted to ensure less risk, fulfillment of production targets and deliver shipments to customers at contracted quality.

4 Case Study

The study was undertaken at the Sossego Mine Complex, which is located in the Carajás region in Brazil. Presently, the Sossego Mining Complex has two main deposits: Sequeirinho and Sossego Hill. These deposits outcrop as a series of copper oxide-bearing hills along a strike length of at least 3 km. The study will only be referred for the Sequeirinho Deposit. The Sossego Mining Complex is a copper mine with a small amount of gold associated. Chalcopyrite is the main copper mineral. The complex comprises two open pits (Sossego and Sequeirinho) and a mineral processing plant (primary crushing, milling, flotation process and filtration). The production at Sequeirinho Pit (Fig. 2) uses front loaders (19m3 of bucket capacity), electrical shovel excavators (54m3 bucket capacity), off road trucks (240t and 150t of load capacity) and auxiliary equipments for infrastructure operation and for mining process. The mine operates 16m height benches, which is at the same size of the selective mining unit (SMU) defined as 10mN x 10mE 16mRL blocks.

4.1 Geology and Mineralisation

The Carajás volcanic sedimentary sequence, located in the Carajás mining district, is composed mainly of bimodal volcanics and chemical sediments, including the banded iron formations (BIF) that host the Carajás iron deposits, pyroclastic and clastic sediments. The basin is filled with a meta-sedimentary and meta-volcanic sequence, granites and schist. The units are intruded by Archean intrusive. These

Fig. 2 Aerial view of the Sequeirinho Open Pit Mine.

units have a strong correlation with copper–gold mineralization in Carajás. The Sequeirinho Deposit is situated in the southern portion of the Carajás sigmoid along a regional shear structure striking west northwest – east southeast, and dipping steeply to the south. The mineralization is structurally controlled, cutting the felsic volcanic, granite and gabro host rock units. The latter are hydrothermally altered to actinolite-magnetite rich rock. The contacts between high-grade mineralization and barren material are abrupt. For Sequeirinho, two zones were interpreted: disseminated zone, usually grading between 0.2 and 1% Cu, corresponding to the structurally controlled alteration halo, and sulfide breccias zone, generally grading in excess of 1.0% Cu, associated with actinolite alteration and other host rocks.

4.2 Short Term Block Model Estimation

The short term block model is estimated by using ordinary kriging in the same block support as the long term model (10mN x 10mE x 16mRL) after adding to the dataset the copper grade values provided by samples from the blast holes (16m along the bench height). This model is compared with the long term model and the operational production (reconciliation).

4.3 Generation of Conditional Simulations

The Turning Bands method was selected for running conditional simulation. The study was conducted separately at several geological domains (areas of mineralization) in order to generate realizations reproducing the distributions (histograms) and spatial continuity (variogram) of the samples along each stationary domain. Thirty realizations at the point support were performed conditioned to the data regularized at 2m composites on a fine grid model of 2.5mN x 2.5mE x 4mRL. The simulations were validated by comparing the reproduction of the input first and second order statistics. After that, the point simulations were reblocked (Fig. 3)to 10mN x 10mE x 16mRL blocks.

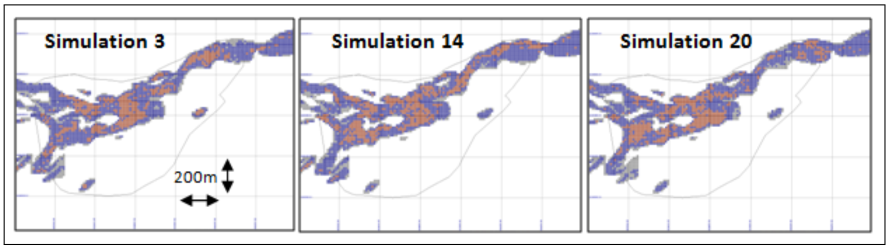


Fig. 3 Individual stochastic simulations, Cu% grades (gray, waste; blue, low grade; red, high grade).

4.4 Reconciliation x Simulations

According to the item 3.3, the reconciliation procedure computes the deviation from planned to actual mining grades and tonnages. From that, a set of factors (mining call factors) is applied on future estimates. The practical validity of any mineral resources and reserves consists of comparing estimates with the actual data obtained during the production. At Sossego Mining Complex, the reconciliation procedure is accomplished using three main factors to measure performance indicators:

- F1 = STM / LTM (between topographic surfaces and only within the mineralized long term ore boundary) - used for reconciliation and verification of the efficiency of the estimation method used and predicted by the long term model;
- F2 = PREM / STM - useful to check the short term model forecasting and what was actually produced during operation. The control of hauled material is made by a dispatching system that allows to record and encode different types of ores and waste and their destination. The high accuracy of the GPS system is used at excavators and loaders, and the low precision is used for the transport fleet;
- F3 = PLANT / TSC PREM - used for verification of what was expected (STM) in the mining operation (PREM) and what was actually processed in the processing plant (crushing, grinding and flotation). The mass of the processed ore on the plant is controlled by a dynamic balance on the conveyor belt at selected points and by a static balance to control the produced concentrate at the time of the transportation. The dynamic balance has an approximately error of + / - 1% and the balance has an approximately error of + / - 0.1%.

In order to do that, it is necessary to have the results and the comparison of information from long term model (LTM, copper grade estimation using data from diamond drill holes), short term model (STM, copper grade estimation using data from blast hole samples), production (PREM, obtained by the loading and hauling controls at the mine) of the total ore sent to the primary crusher (TSC PREM, measured by a high precision conveyor balance at the crusher) and the ore processed at the plant (PLANT, measured by differential weighting system for high precision at the conveyor belt feeding the SAG mill). The next figure (Fig. 4) presents the reconciliation process and the main routes at the Sossego Mining Complex.

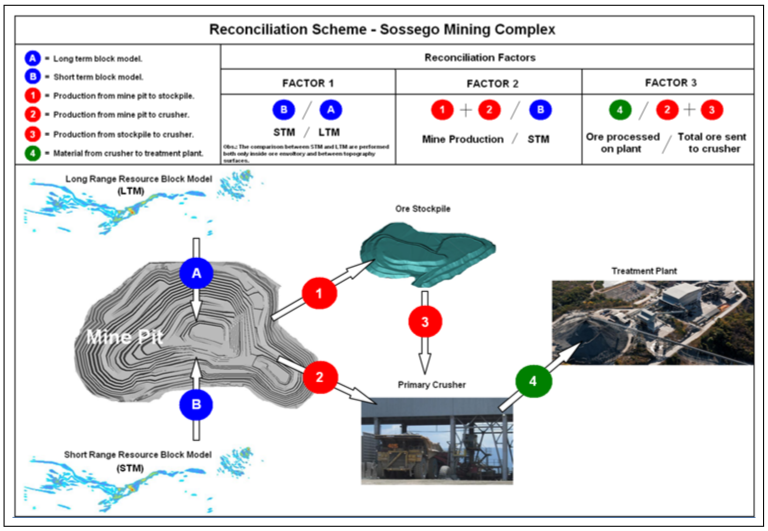


Fig. 4 Reconciliation scheme, Sossego Mining Complex.

The results (Fig. 5) of the factor F2 (PREM / STM), which has an error of approximately 2% relative to the total mass (t) produced, -1% for the copper grade and -3% to the amount of metal (t) in relation to the estimation, demonstrate the high confidence for the estimation technique applied to the short term model (STM) and the operational process control of materials involved on mining process. The value of the factor F3 (Plant / TSC PREM), which has an error of approximately 3% relative to the total mass (t) processed in the plant, 0% for the copper grade and -3% of metal (t), demonstrates the high confidence on the quantity and quality of the ore produced and sent to the plant. The process indicates that there is a systematic global error for the produced metal in each stage (Factors 2 and 3) from approximately 3% year average value. These errors are mainly associated to the mass differences among the processes, resulting in a global systematic error of -5% for the entire process. The grade differences on both steps (Factors 2 and 3) of reconciliation, for the predicted short term model and the executed values at the processing plant, present a relative global error of 0% (F3) and -1% (F2). Thus, the short term block model values are consistent to be used as the real values and to validate the conditional simulated models.

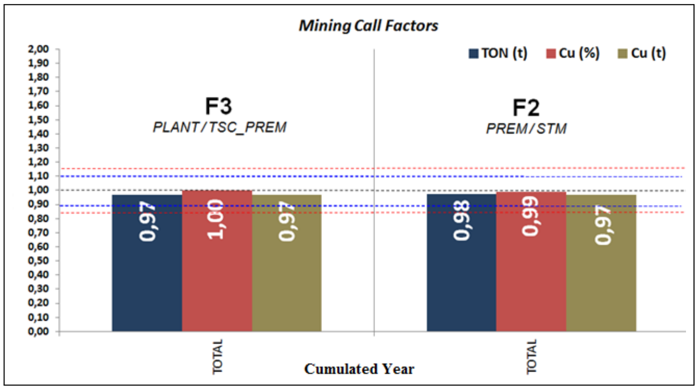


Fig. 5 Factors F2 and F3 (tonnage, grade and metal content) of the annual reconciliation control.

The validation of using conditional simulation for estimation and risk analysis process in mineral resources and reserves, as a tool to map the intrinsic variability of the copper grades, is presented below (Fig. 6). The F1 values of the relative comparison between the short and long term models (STM / LTM), only within the long term ore boundary, present significant variability during the checked months (provided by seven simulations used to characterize the space of uncertainty of the grades, ranked by the grade average of the blocks, i.e. minimum, maximum, P5th, P25th, P50th, P75th and P95th, selected on the simulations distribution). One outcome from the simulation study applied to reconciliation was the ability to investigate the selectivity of the kriged resource estimate compared to the real and predicted variability over the deposit. These differences are important since they highlight where the kriged model (budget reference) applied on a mining scheduled plan may be expected to under or over perform relative to the actual selectivity of the modeled block size and company goals. In fact, all assumptions taken from the simulation models to verify the risk on reserves are comprehensive since they represent the possible real grade variability and the related financial uncertainty.

5 Risk Analysis on Mineral Reserves

This item presents an application of the approach described at 3.1. It is based on the risk scale (ESR) used for annual mining production sequencing (operational design) at Sequeirinho Pit. It is also developed an economic evaluation of the proposed methodology regarding the real financial gain and the improvements in grade control.

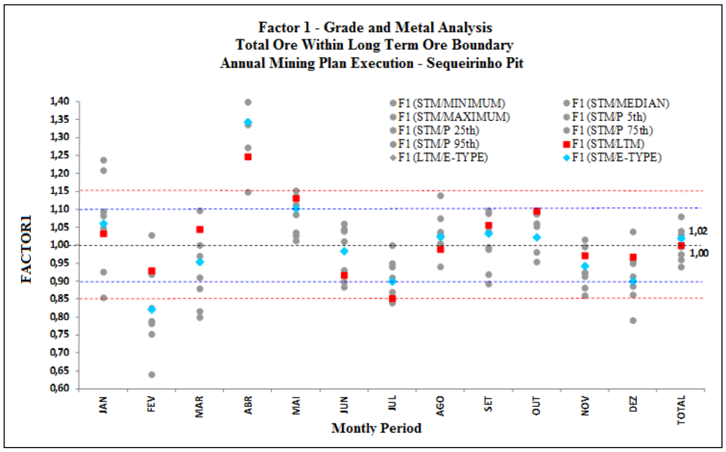


Fig. 6 Factor F1 and the real copper grade reconciliation against the simulated values in the annual mining plan executed at Sequeirinho Pit.

5.1 Operational Annual Risk-Based Mining Sequencing

For that, it is necessary an approach that quantifies the deviation of goals and minimizes the risk during the production sequencing (annual mine plan) considering it for the life of the mine plan (LOMP). The determination of tonnage production and operating indexes (availability, utilization and productivity) of each equipment selected by LOMP are the first steps to prepare the production schedule. Next, the mining sequence is calculated by using both the traditional and risk-based methodologies as follows:

- use the production rates defined by LOMP to generate a production schedule based on defined goals using the grade block model estimated by ordinary kriging, which is the main reference for calculating budget and to define the ore quality in the mining company, ignoring any possible risk (traditional mining sequence);
- use the production rates defined by LOMP to generate a production schedule based on defined goals using the grade block model estimated by ordinary kriging, but now taking into account the associated risk (optimized ESR), resulting in a risk-based mining sequence. The risk-based results are compared to the traditional one (original sequence).

5.2 Annealing Simulation

Before applying the risk-based mining sequencing considering the single averaged ESR model it is necessary to proceed the annealing simulation for each individual simulation model. During annealing simulation the ESR values (for each simulation) are transformed into risk categories (categorical numbers) associated with their ranges and categories of risk. This coding allows the algorithm to identify different categories of risk. The choice of values for defining the categories depends on qualified person analysis given the mineral deposit. The parameters (Table 1) used in the annealing simulation (applied on Isatis software) and for defining ESR categories (Table 2) are presented below:

Table 1 Annealing simulation parameters.

Description	Definition
Simulated Image	Annealing (min, max, P5th, etc.)
Training Image (proportional calculation model)	E-Type simulations
Initial Image	Simulation (min, max, P5th, etc.)
Seed Number	423141
Transition probabilities weight	1
Boltzmann Constant (k)	1e-006
Number of variograms (neighborhood)	26
Number of Simulations (min, max, P5th, P25th, P50th, P75th, P95th	7

Table 2 ESR risk class definition.

Description	Definition (Objective Function, Eq.1)
Number of Risk Classes	4
Number of Intervals	4
Interval 1 - Low Risk Class	1
Interval 1 - Lower value	0.000
Interval 1 - Higher value	0.090
Interval 2 - Low-Moderate Risk Class	2
Interval 2 - Lower value	0.0901
Interval 2 - Higher value	0.1500
Interval 3 - Moderate-High Risk Class	3
Interval 3 - Lower value	0.1501
Interval 3 - Higher value	0.2700
Interval 4 - High Risk Class	4
Interval 4 - Value	>0.2700

Figure 7a (Fig. 7a) presents an initial image (before annealing simulation) related to one simulation model, showing the risk classes frequency (1, low risk; 2, low to moderate risk; 3, moderate to high risk; 4, high risk). Figure 7b (Fig. 7b) presents the simulated model resulting from the annealing algorithm for the initial image, showing the ESR changed risk classes after the annealing process, which presents

the possibility to reclassify the risk on the blocks given the probability to assume a lower risk class. Figure 8 (Fig. 8) shows the average (ESR, single model) of the optimized simulation models processed individually by annealing simulation. This ESR averaged single model will be used as the risk model for mining sequencing in an attempt to minimize the risk on the operational mining plan. The blocks in blue represent the ESR categories 1 (low risk) and 2 (low to moderate risk). The red blocks refer to the ESR categories 3 (moderate to high risk) and 4 (high risk).

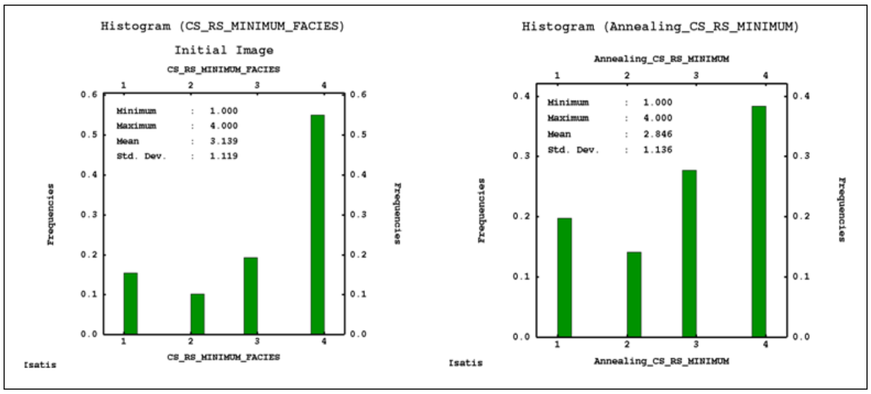


Fig. 7 (a) Initial image (1, low risk; 2, low to moderate risk; 3, moderate to high risk; 4, high risk); (b) the annealing simulation result with the ESR (1, low risk; 2, low to moderate risk; 3, moderate to high risk; 4, high risk) values for the simulated model.

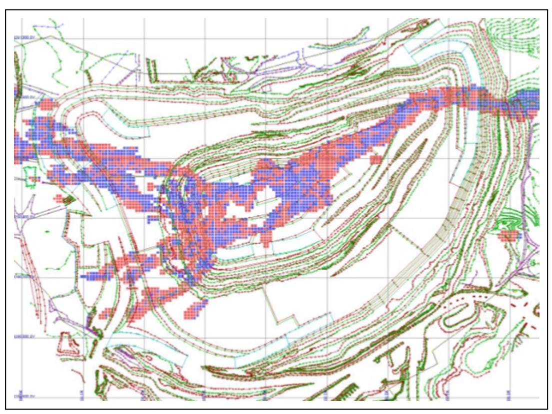


Fig. 8 Final single averaged ESR image of all simulated grade models obtained by annealing simulation (blue, risk categories 1 and 2; red, risk categories 3 and 4).

After setting the minimized ESR model, this model can be used on the mining sequencing considering the inherent risks (Eq. 2). It is expected an effective reduction in the objective function compared to the values obtained using the original output sequence, which is associated to the ore quality and the achievement of the targets. The annealing simulation was important to define the ESR models since it homogenized the possible risk areas, minimizing the objective function and the incoherent salt-pepper effects over the risk classes among the blocks, defining the most probable low risky areas through probability calculation.

5.3 Operational Mining Sequencing

At section 3.1, it was developed the annual risk-based mining sequencing for comparing against the traditional sequence. The production requirements and grade content to meet the overall production and ore sequencing in the mine as well as the amount of ore in stock for plant feed will be considered the same as the original mine plan (traditional sequence) developed (Fig. 9b). The geometry of the risk-based mining sequence (Fig. 9c) must necessarily meet all operating assumptions (operational stages, slope angles, operational area, berm width, vertical mining bench development, equipments productivity, equipments location, etc.). Figure 9a (Fig. 9a) show the mining sequencing along 12 months resulted from the two methodologies which is possible to verify how mining sequencing, considering all the operational constraints and production rates, can be alternatively changed during the annual mining plan providing less risk and simultaneously achieving the goals (see results on item 5.4). The colors for each pushback were coded as:

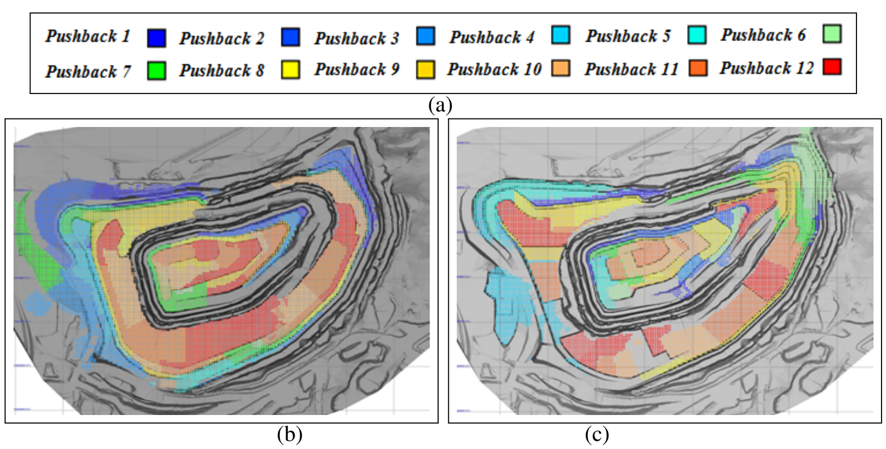


Fig. 9 (a) Pushback sequence and colors indicating the order of the mining sequence (b and c); (b) original mining sequence (traditional); (c) risk-based mining sequence.

5.4 Results

The results (Table 3) present the grade and tonnages obtained for both traditional (ORIG) and risk-based (RISK) sequencing. Note the reduction on grade variability and target deviation in the risk-based sequence for the cumulated year. The budgeted amount (LTM CU-OK) in the risk-based production plan was closer to reality performed (CU OK-STM) during mining than the traditional approach.

Table 3 Traditional (ORIG) and risk based (RISK) mining sequencing results.

Pushback (definition)	Waste (kt)	Ore (kt)	Cu(%) OK LTM	Cu(%) EType	Cu(%) Sim1	Cu(%) Sim2	Cu(%) Sim3	Cu(%) Sim4	Cu(%) Sim5	Cu(%) Sim6	Cu(%) OK STM
1 RISK	4,133	452	0.95	0.86	0.78	0.98	0.81	0.95	0.79	0.99	0.91
1 ORIG	3,643	545	1.03	0.87	0.83	1.02	0.75	0.90	0.80	1.08	0.87
2 RISK	2,232	997	1.11	1.08	1.07	1.01	1.01	1.10	1.15	1.20	1.10
2 ORIG	3,432	460	1.04	1.12	1.05	0.98	1.21	0.94	1.05	1.19	1.14
3 RISK	3,698	594	1.31	1.10	1.09	1.26	1.04	1.14	1.11	1.15	1.27
3 ORIG	3,413	646	1.34	1.14	1.05	1.23	1.03	1.31	1.27	1.19	1.24
4 RISK	4,725	214	0.84	0.75	0.59	0.78	0.63	0.76	0.79	0.74	0.76
4 ORIG	3,745	653	1.01	0.93	0.85	0.87	0.77	0.74	1.03	0.86	0.87
5 RISK	4,171	409	1.10	1.01	0.87	1.15	1.15	1.16	1.12	0.97	1.05
5 ORIG	4,285	472	0.88	0.78	0.74	0.87	0.64	0.64	0.71	0.70	0.84
6 RISK	3,743	704	1.01	1.00	0.92	1.11	0.89	1.17	1.23	0.96	1.04
6 ORIG	4,375	693	1.20	1.09	0.90	1.45	0.94	1.04	1.36	1.02	1.13
7 RISK	4,106	902	1.17	1.08	1.00	1.44	1.05	0.90	1.25	1.11	1.11
7 ORIG	4,231	891	1.16	1.00	0.88	1.29	0.89	1.11	1.07	1.08	1.11
8 RISK	4,814	877	0.85	0.83	0.89	0.78	0.80	0.77	0.86	0.94	0.93
8 ORIG	4,714	700	1.08	1.04	1.16	1.00	0.95	0.90	1.15	0.99	1.14
9 RISK	3,730	1,174	1.26	1.29	1.03	1.29	1.22	1.31	1.22	1.39	1.24
9 ORIG	4,090	798	1.19	1.09	0.95	1.25	1.12	1.30	1.05	1.03	1.21
10 RISK	4,249	854	1.06	1.07	1.06	1.09	1.14	1.06	1.21	1.07	0.97
10 ORIG	4,067	900	1.10	1.03	0.98	1.18	0.91	0.95	1.28	1.01	0.98
11 RISK	4,836	268	1.05	0.91	0.80	1.03	0.81	0.76	1.18	1.20	1.03
11 ORIG	4,408	535	0.95	1.00	1.00	1.15	0.89	1.00	1.16	0.98	0.98
12 RISK	4,437	742	1.07	1.04	0.96	1.17	1.02	1.09	0.98	1.06	1.00
12 ORIG	4,329	829	1.21	1.13	1.10	1.04	1.00	1.22	1.08	0.95	1.15
Cumulated year RISK	48,874	8,187	1.09	1.04	0.97	1.12	1.01	1.05	1.11	1.10	1.06
Cumulated year ORIG	48,732	8,122	1.11	1.03	0.96	1.13	0.93	1.03	1.10	1.01	1.06

Since the contents and destinations of the material in the production process can vary significantly for each pushback, it was performed the standardization of risk profile. This helps in highlighting the changes and differences between the two approaches, i.e., for each pushback p and for the simulations s, the expected risk is defined as:

$$ExpectedRisk_{p,s} = \frac{\theta_p^*}{\theta_p(s)} \tag{4}$$

where θ_p^* is the target set by the LTM for each pushback p and $\theta_p(s)$ is the value for the simulations s.

Overall (Fig. 10), the risk-based process provided smaller differences about the grades and other goals during the annual extraction. The range of cumulative difference for the traditional sequencing approach, considering the simulated models for variability analysis for this sequence ranges between [-7%, 20%] with expected average difference of 8% compared to the target set. The risk-based approach presents a variability ranging between [-3%, 12%] with an expected average difference of 4% compared to the defined goal. Note that it was possible to reduce the differences in the planned goals using ESR in the development of mine plan. Also it is presented (Fig. 11) the real executed differences by both mining sequences compared to the real extraction values (STM). Overall, for the annual mine plan, the difference between the predicted and real grades was 2% considering the risk-based sequence and 5% without considering the inherent risk. This result highlights the real effectiveness in terms of reconciliation of the applied approach. The financial impact is discussed next (section 5.5).

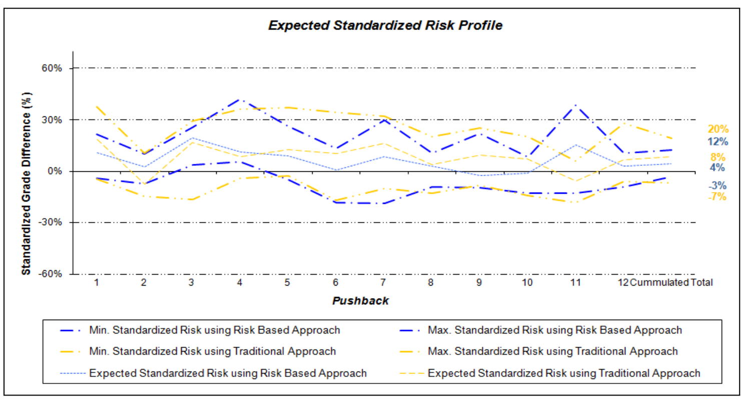


Fig. 10 Planned (LTM / Simulations) risk analysis profile (yellow, traditional sequence; blue, risk-based sequence).

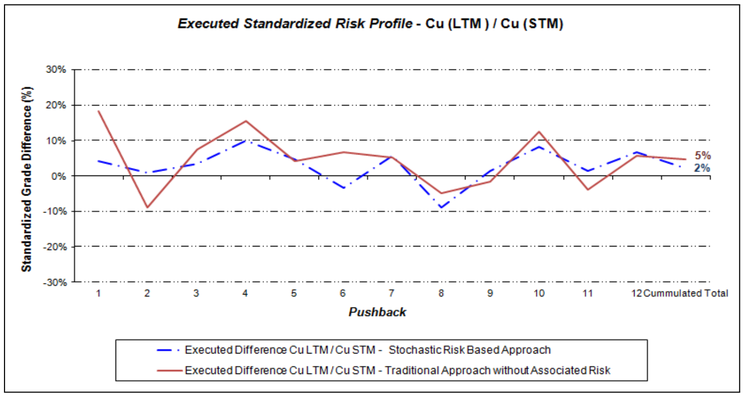


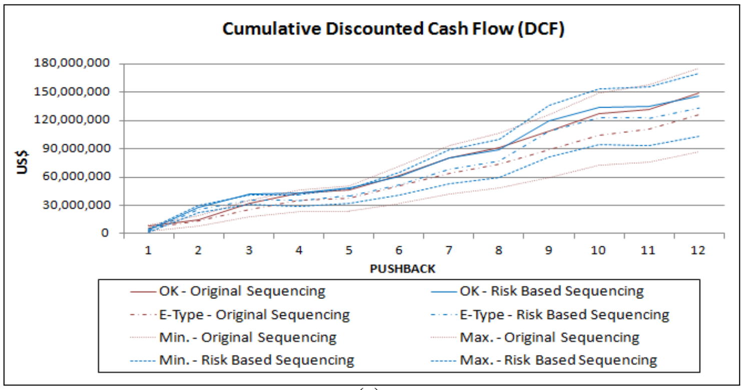
Fig. 11 Executed (LTM / STM) risk analysis profile (red, traditional sequence; blue, risk based sequence).

5.5 Economic Analysis

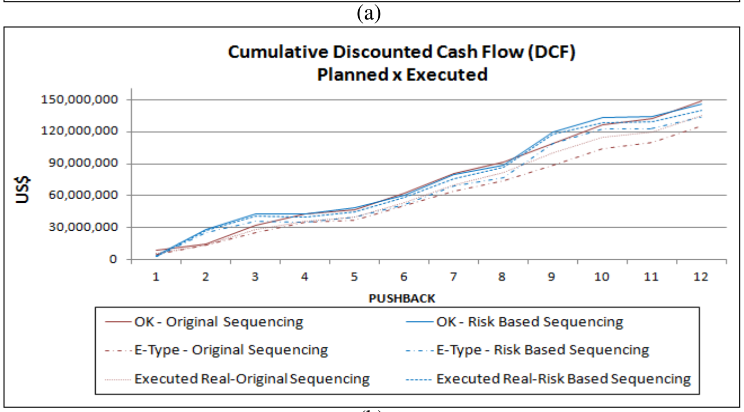
The total expected cash flows (Fig. 12ab) (Table 4) using the traditional approach is US$ $149.1 x 10^6$ and US$ $146.2 x 10^6$ for the risk-based. The simulated NPV variation for the traditional approach ranges between US$ $[86.6;175.6] x 10^6$ and US$ $[102.6; 170.1] x 10^6$ for the risk-based approach. The NPV expected uncertainty interval for the traditional approach is US$ $89 x 10^6$ against US$ $67.5 x 10^6$ of the risk-based. Expected values for the traditional and risk-based approaches were US$ $125.6 x 10^6$ and US$ $133.6 x 10^6$, respectively. The NPV for the predicted model (CU-OK LTM), the expected model (E-Type) and the real executed model (CU-OK STM) using the traditional mining sequence is respectively US$ $149.1 x 10^6$, US$ $125.6 x 10^6$ and US$ $135.5 x 10^6$. Thus, the actual differences of the predicted and expected models (simulations) compared to the real executed model are 10% and -7.3%, respectively. For the risk-based approach the predicted NPV is US$ $146.2 x 10^6$, the NPV for the expected model is US$ $133.6 x 10^6$, and the real executed NPV is US$ $139.6 x 10^6$. The real differences related to the predicted and expected models for this sequence compared to the executed model are 4.7% and -4.3%, respectively. Thus, there is a significant risk reduction and higher confidence towards achieving the defined goals. The executed NPV value considering the risk based sequencing is 3% higher in a year than the traditional approach.

6 Conclusions

The results showed a potential improvement in the predictability of technical and economical results in a copper mine using the risk-based planning methodology. It



(a)



(b)

Fig. 12 (a) NPV risk analysis for both methodologies, considering the minimum, maximum and expected risk values (E-Type), compared to the estimated value (LTM CU-OK); (b) Executed NPV risk analysis for both methodologies considering the predicted (CU-OK LTM) and the expected (Etype), compared to the real executed model (CU - OK STM).

Table 4 Results and differences (relative error) among the estimated model (ordinary kriging, budget reference), simulated models and the real executed model for both methodologies.

Model - Pushback	NPV (US$ x 10^6)	Difference Models / OK
OK - Traditional Sequencing	149.1	-
Etype - Traditional Sequencing	125.6	-19%
Min - Traditional Sequencing	86.6	-72%
Max - Traditional Sequencing	175.6	15%
Real Executed - Traditional Sequencing	**135.5**	**-10%**
OK - Risk Based Sequencing	146.2	-
Etype - Risk Based Sequencing	133.6	-9%
Min - Risk Based Sequencing	102.6	-42%
Max - Risk Based Sequencing	170.1	14%
Real Executed - Risk Based Sequencing	**139.6**	**-5%**

was also showed the ability to better manage the inherent risks related to grade variability for the mining sequencing. Note that the results derived from this methodology do not lead to an optimal solution. This conclusion reinforces the view that the production schedule can only be truly optimized when the geological uncertainty is fully integrated in the optimization process and operational mining sequencing at the same time, which is currently a difficult process. The results obtained in this application indicate that the proposed approach has the potential to significantly improve the economical result and better forecast the mine performance when compared to the traditional practice. The results not only indicated a potential increase in value of the project, but also provided a sequence that minimizes the chance of deviation from the goals at the processing plant and at the final product.

References

1. Dimitrakopoulos, R. and Farrelly, C.T. and Godoy, M.: Moving forward from traditional optimisation: Grade uncertainty and risk effects in open pit mine design. Transcript of the Institute of Mining and Metallurgy, Volume Section A: Minerals Industry, Number 111, pp A82-A89. (2002).
2. Halatchev, R.: The Time Aspect of the Optimum Long-Term Open Pit Production Sequencing. 30th. Application of Computers and Operations Research in the Mineral Industry, Littletown, SME. (2002).
3. Godoy, M. C.: The effective management of geological risk in long-term production scheduling of open pit mines. PhD thesis, 256 p, The University of Queensland, Brisbane. (2003).
4. Kirkpatrick, S. and Gelatt, C.D. and Vecchi, M.P.: Optimization by simulated annealing. Science, vol. 220, no. 4598, pp 671-680. (1983).
5. Geman, S. and Geman, D.: Stochastic relaxation, Gibbs distributions, and Bayesian restoration of images. IEEE Transactions on Pattern Analysis and Machine Intelligence, Volume 6, pp 721-741. (1984).
6. Farmer, C.: The generation of stochastic fields of reservoir parameters with specified geostatistical distributions. In S. Edwards and P. R. King, editors, Mathematics in Oil Production, pp 235-252. Clarendon Press, Oxford. (1988).
7. Strebelle, S.:Sequential simulation drawing structures from training images. PhD thesis, Stanford University, Stanford, 316p. (2001).
8. Metropolis, N. and Rosenbluth, A.W. and Rosenbluth, M.N. and Teller, A.H. and Teller, E.: Equations of state calculations by fast computing machines. The Journal of Chemical Physics, Volume 21, Number 6, pp 1087-1092. (1953).
9. Deutsch, C.V. and Journel, A.G.: GSLIB: Geostatistical Software Library and User's Guide. Oxford University Press, New York, 368p. (1998).
10. Morley, C.: Beyond reconciliation – a proactive approach to using mining data. in Proceedings Fifth Large Open Pit Conference, pp 185-191 (The Australasian Institute of Mining and Metallurgy: Melbourne). (2003).
11. Deutsch, C.V.: Annealing techniques applied to reservoir modeling and the integration of geological and engineering (well test) data. PhD thesis, Stanford University, Stanford, 306p. (1992)
12. Souza, L.E., Costa, J.F.C.L. and Koppe, J.C.: Uncertainty Estimate in Resources Assessment: A Geostatistical Contribution. IN: Natural Resources Research, vol.13, nº1,pp.1-15. (2004)