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Mine Planning Under Uncertainty

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Abstract

The aim of this study is to develop a methodology that can contribute to the construction of scenarios for mine planning and to evaluation of the impact of geological uncertainties provided by simulated models. The approach suggested here includes the definition of a methodology to control and incorporate the local uncertainties associated with the ore in order to improve mine planning, assess the sensitivity of financial return and while considering the variations and uncertainty related to the geological model and grade estimation.

Keywords: Mine planning; Geological uncertainty; Geostatistical simulation; Risk analysis

Introduction

From exploration to mine planning, methodologies for quantifying the risk associated with mineral deposits can dramatically improve the decision-making process in the mining industry. Small variations in boundary conditions can have a significant impact on the final return of the project. In this context, geological uncertainty can be a major factor contributing to eventual failure of a mining project. The need to quantify and manage geological risk for project evaluation and decision making can be translated into the need to assess the geological risk of any parameter at all stages, from resource quantification, through mine sequencing to exhaustion of reserves. In addition, geological uncertainty can be translated into financial risk, providing an analysis of the economic feasibility of a project. The need for quantification of geological uncertainty has been recognized by the mining industry since the 1970s, when local and global estimates were considered insufficient for optimization of production planning, mine sequencing and homogenization strategies. Therefore, stochastic simulation has played a crucial role in the construction of grade uncertainty models in mineral deposits, providing a tool to perform risk analysis.

Geological exploration, project development and mining itself, including mine closure procedures, are all driven by the need to delineate, understand, evaluate, and plan the extraction of mineral resources. The definition of a robust geological and numerical model for a mineral deposit is an essential tool to analyse the quality of the in-situ material and to calculate the masses that need to be moved, with their respective grades. With knowledge of the reserves and existing material in a specific location, geostatistical techniques can be used to provide consistent evaluation and planning and to determine the associated variability and even uncertainty Matheron [1], David [2], Journel & Huijbregts [3]. Traditionally, grade control and mine planning are done using a block model generated by a traditional estimator, usually ordinary kriging, which gives the best estimate (unbiased and with the least error) using the available samples. However, this procedure is unable to incorporate the uncertainty associated with the estimate, and the variability of the estimated values is lower than the variability of the original data Costa [4].

Unlike kriging, geostatistical simulation methods aim to reproduce the variability and the spatial continuity of the original data, generating equiprobable models, conditioned to the data, which reproduce the first- and second-order statistics of the sample data. Geostatistical simulation algorithms are based on delineation of the uncertainty range by generating multiple realisations of the considered attribute values distributed in space Goovaerts [5]. These models are fed to transfer functions with different degrees of complexity to generate a distribution of possible outcomes, and the range of variation of this distribution characterises the so-called space of uncertainty Costa [6]. The processes involved in mine planning can be seen as transfer functions, which are models used to describe the actual operations or systems Peroni [7]. In this case, an uncertainty model based on stochastic simulation allows evaluation of the sensitivity of economic development, taking account of the uncertainty levels and tonnages for both mathematical surfaces and mining envelopes, as in the cases of design and long-term sequencing Silva [8].

Planning of the optimal production sequence can be a complex procedure, considering the number of variables and constraints that might be involved. The mine planning process is primarily determined by defining a final pit through an optimisation algorithm, providing a logical block extraction sequence Whittle & Rozman [9], Peroni [7]. The subsequent determination of an operational sequence of blocks up to the final pit is defined as pushback. At this stage, it is possible to evaluate the direct impact on key performance indicators such as cash flow and net present value (NPV). Several methods for determining an optimal extraction sequence have been presented Crawford & Davey [10], Mathieson [11], Dagdelen & François-Bongarçon [12], Whittle and Rozman [9], Rozman & Dagdelen [13], Tolwinski [14]. According to Diedrich [15], the main difficulties encountered when attempting to solve the optimal extraction sequencing of blocks to be mined, taking the uncertainty into account, are as follows:

a) The number of variables involved in the stochastic optimisation processes (simulated models and parameters).

b) The complexity of the equations defining the profit function costs and revenues, taking account of the diversion of targets (due to stochastic optimisation).

c) The generation of scenarios that are operationally executable given the time needed to process each optimisation and considering the computational capacity and the need for speed in decision making.

This paper therefore proposes the use of stochastic simulation as a method for assessing changes caused by the uncertainty associated with the attributes that define ore reserves and drive mine planning. It also proposes the introduction of risk associated with blocks, determining penalties within the mine planning that are transferred to the profit function and measure the impact on the project's economic results. The methodology is applied to a case study of a phosphate deposit located in central Brazil to demonstrate the application of this approach to a real deposit.

Objective

The goals of this study are as follows:

i. To model the uncertainty levels for a particular deposit using geostatistical simulation algorithms within irregular domains, contained within geological envelopes generated by the interpretation of sections.

ii. To compare the response of mining scenarios according to economic criteria.

iii. To introduce a risk analysis factor taking account of grade uncertainty and measure its impact on risk acceptance (or rejection), considering the probabilities given by the simulation algorithm.

Methodology

Incorporating geological uncertainty into mine planning

Using sequential Gaussian simulation (sGs), 50 realisations were generated for P_2O_5 grades. After running the simulation algorithm, 10 scenarios were selected, taking account of strategic aspects of mine planning, including the economic model constructed on the basis of the profit function targeting long-term mine planning. The blocks containing the economic values were imported into pit optimisation software (NPV Scheduler 4) to determine the final pit for each of these scenarios. The next step was sequencing the blocks to define a horizon of a medium-term range and define a smaller area considering the estimated value. The main goal of this work is to determine the impact of the variation given by the simulation scenarios. Besides the impact due to the simulation, the concept of risk acceptance (or aversion) is introduced. This criterion involves the adoption of a risk or uncertainty that the company will assume on the basis of a feasibility analysis related uniquely to the geological uncertainty. Therefore, an average scenario is adopted, represented by the mathematical expectation (E-type) of the P_2O_5 grade, with the appraisal of extreme scenarios determining the limits of variation of the project and the incorporation of criteria for risk tolerance. This information, when put together, allows one to delineate a mine plan or a set of mine plans including the variation of the size of the deposit to be mined or reported as reserves or to limit the project's feasibility under different risk tolerances Capponi [16].

Constructing the profit function

The construction of the profit function is equivalent to calculating the economic value for each block defining the cut- off grade and consequently the block selection between waste and ore. For those blocks recognised by geological contact as waste blocks, only mining costs are used to calculate the economic value. On the other hand, for those blocks within the ore zone, the decision whether the block is waste, or ore is made on an economic basis. The profit function is constructed in two stages: first, determination of the ultimate pit and selection of the study area using the average scenario (E-type results); second, use of the penalty factors given by the probability from the simulation. The following equations determine the conventional approach of evaluating a block model and the proposed modification with the introduction of a probability factor:

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PF = Revenues − Costs, (1)

PF = (S × G × R) − (M + P + G&A), (2)

where

S is the long-term selling price,

G is the grade of each block,

R is the process recovery,

M represents the mining costs,

P represents the process costs,

G&A represents the general and administrative costs.

The level of acceptance of the probability given by the stochastic simulation is defined by

PROB = 1 if prob i>= prob lim

PROB = 1 if prob i < prob lim (3)

Where:

Prob i is the probability of a block i calculated from the simulation

Prob lim is the probability limit chosen as the maximum probability level accepted

PROB is the categorical value assumed if the probability of a block i is greater or less than Prob lim.

and the inclusion of the probability within the profit function as a penalty parameter for the ore blocks after defining the probability limit to be used as risk acceptation or rejection is defined by

PF = S × G × R × PROB − (M + P + G&A), (4)

where

PROB is the probability that a block with grade G is higher than a specific cut-off grade.

Building the Optimal Pit

When building the optimal pit, the extent of mining and its sequencing are determined such that the best economic result is obtained. Figure 1 presents the hard boundaries used to generate the analysis. The pink boundary represents the horizontal limit of mineralisation of the deposit, the orange boundary is the current pit outline and the red line represents the area selected in this study, which comprises approximately a 15-year pushback. The main inputs to the final pit optimisation software were the initial topography (as at the end of 2011), the resource model classification taking account of the drilling density and the minimum data in the search strategy, geotechnical information, the long-term price for the phosphate rock and the estimate of the process cost. The final pit was defined using the Lerchs–Grossman algorithm Lerchs & Grossmann [17] through the implementation available on the NPV scheduler software according to Underwood & Tolwinski [18], Tolwinski [14].

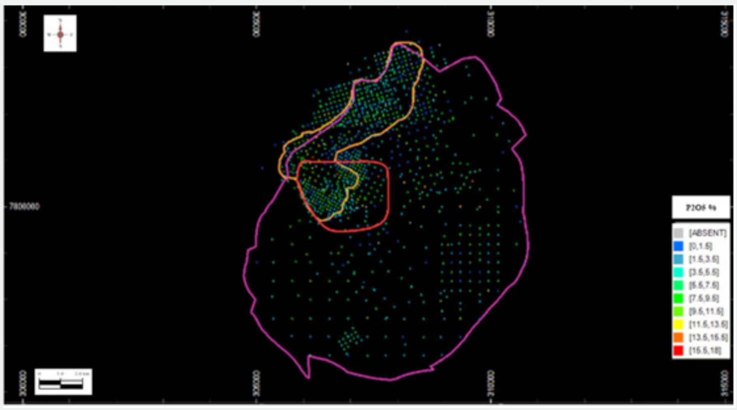

Figure 1: Hard boundaries and drilling pattern used to optimise and simulate the deposit.

Risk Analysis of Mine Planning

In the mine planning stage, the uncertainties related to the ore quality to be mined, as well as the profitability from the exploitation, are essential, because these will define the sequence of extraction of the ore with the project's earnings in mind. The planning process is complex, involving a number of uncertain variables with strong impact on the production outputs, and depends on the economic premises adopted. Depending on the stage of development of the project, the risk analysis will allow decision making in terms of the following:

a) Investment in additional information: incorporation of new samples, performance of new metallurgical tests, review of the limits and constraints of the target areas, and review of the concentration routes according to the characteristics of the ore.

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b) Development and commencement of mining operations, taking account of basic information based on equally probable scenarios.

c) Further development of the mine and investment in additional information, including consideration of further attractive projects, even in the minimum scenario when it is desired to reduce the dispersion of economic indicators.

d) Decision to abandon the project definitively or to delay start-up while waiting for technological improvements or for a better economic context.

At this stage, a risk analysis was performed, considering as ore those blocks with probabilities of being higher than the cut-off grade of 60–90% in 10% steps, applied to the E-type from the geostatistical simulation. The variable that was created was named PROBCUT and the cut-off grade considered was 5% of P_2O_5.

The uncertainty and risk analysis adopted in this work was applied as follows:

i. P90 – the conservative scenario, in which the P_2O_5 content of the considered block has a 90% probability of being higher than the 5% cut-off grade.

ii. P80 – the intermediate/conservative scenario, in which the grade has an 80% probability of being higher than the 5% cut-off grade.

iii. P70 – the intermediate/optimistic scenario, in which the P_2O_5 grade has a 70% chance of being higher than the 5% cut-off grade.

iv. P60 – the optimistic scenario, in which the P_2O_5 grade has a 60% probability of being higher than the 5% cut- off grade.

After calculating the profit function for each block, each selected scenario was imported again into the optimisation software to assess the economic result produced by each scenario after pit optimisation and mine sequencing. Figure 2 shows an example of an NPV graph for a given period: the curve points were plotted after classification of the results in descending order and cumulative probability. In this case, P90 was taken as the conservative estimate, P70 as intermediate and P60 as the optimistic estimate. Figure 3 shows the variation in ore masses generated by mathematical pits modelled by objective functions with higher probabilities to be feasible like P60, P70, P80 and P90 are shown in Figure 3. A relative mass difference of up to 60% can be seen in comparison with the expected mass of blocks at 90% probability that these blocks assume values above the stipulated cut-off grade.

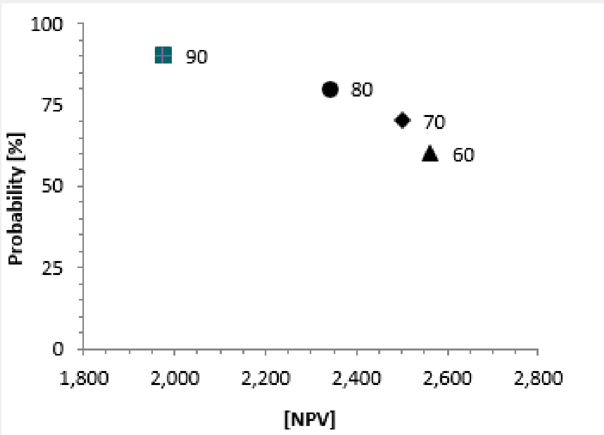

Figure 2: NPV of the project considering different risk acceptances.

The impact of quantifying the risk associated with geological uncertainty generated from selected simulations can be seen in the design of the mathematical pit outlines shown in Figure 4. Section AA' indicates a variation of the pit limits for the northeast region of the area analysed. This uncertainty indicates a greater likelihood that the grades in this sector are closer to the cut-off grade. It can be seen, for example, that areas for the E-type scenario have a wide extent, but those for scenarios with low acceptance risk are contracted and have uncertain borders. Similarly, Figure 5 shows the pit depth according to the criterion of acceptance/ aversion to the risk; the areas with high uncertainty associated with the blocks are again highlighted.

Mine sequencing

According to Peroni [2], a pushback (also referred to in the literature as a cut-back or phase; see Hustrulid & Kuchta [19] can be defined as the stage in mine development that can be practically executed and mined according a logical extraction sequence. This means that the limits of a pushback and its predecessor must be separated by a minimum distance unless those limits coincide with the final pit limits. Table 1 presents the number of phases generated for each risk scenario. The cumulative quantities of ore versus sterile material by phase generated for each case analysed, as well as the expected-value E-type simulations, are shown in Figure 6. It can be seen that the curve gradient is the

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mine stripping ratio in the period. Thus, it can be assumed that the sterile ore ratio is directly related to the probability that the P_2O_5 grade is higher than the given cut-off grade. It can be seen that the uncertainty criterion does not give similar results to traditional approaches in terms of parameterisation prices or costs (revenue cost factor or revenue factor), where the ratio usually increases with the size of the pit: small pits with low ratios and bigger pits with high ratios. Here, the situation is reversed, and, for the scenario with high certainty, a small pit with a high ratio was made possible because the blocks were of high grade and so there was a high probability that the pit had grades above the selected cut-off grade of 5%.

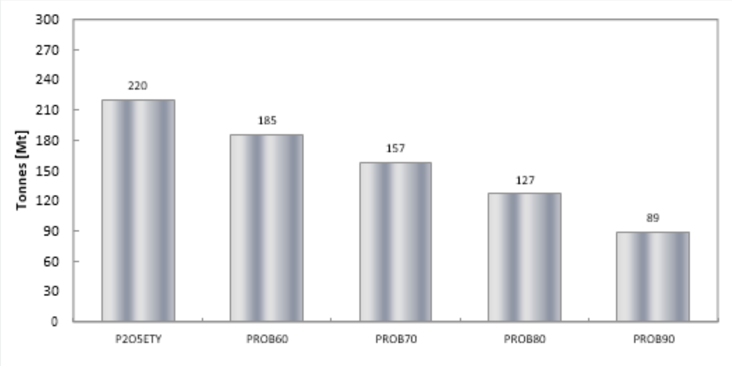

Figure 3: Total ore mass for each risk scenario, considering probability factor.

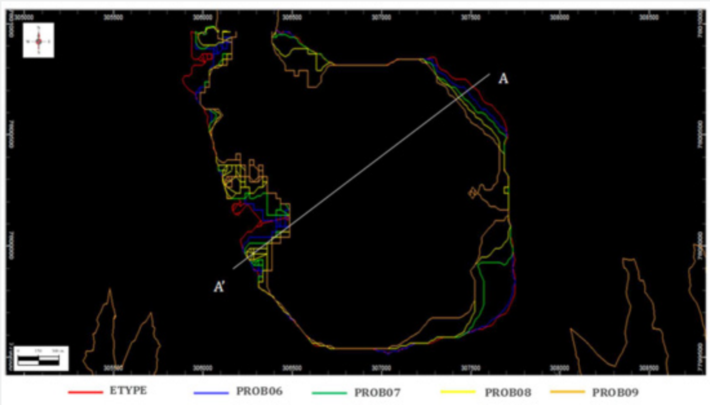

Figure 4: Plan view at the 1230 m level of the final pits for each risk scenario, taking account of the simulated block model associated with the probabilities shown by the differently colored lines.

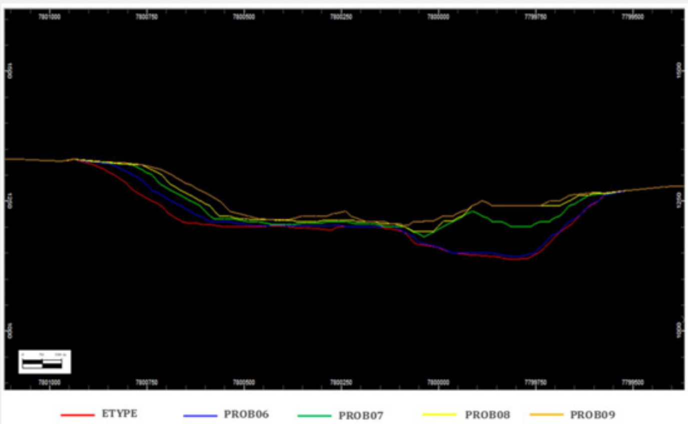

Figure 5: Vertical section (A', A) of the ultimate pits under different probabilities.

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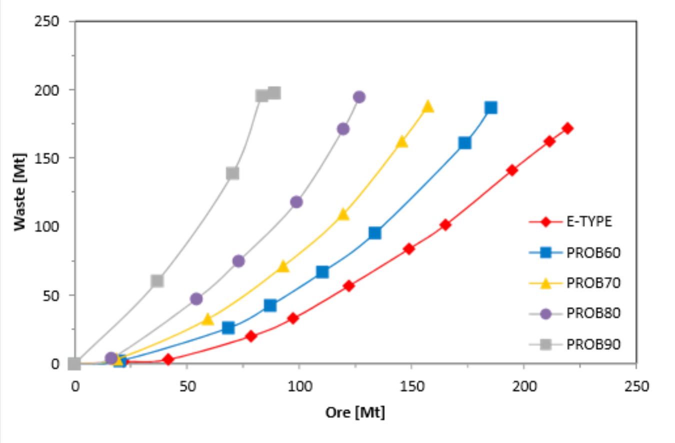
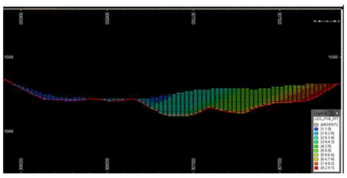
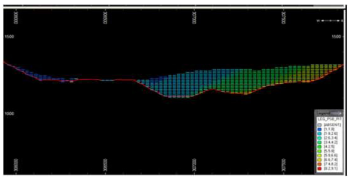
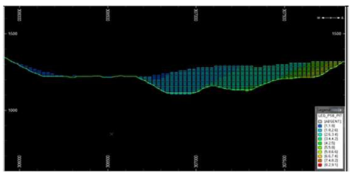
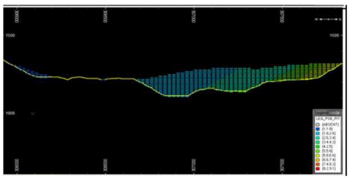
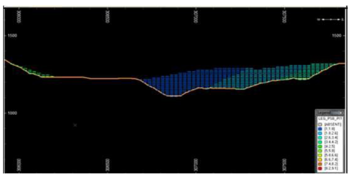


Figure 6: Curves of accumulated ore against waste masses for different acceptances of risk.

Table 1: Potential NPV for each phase, incorporating the risk factor.

Pit	Phase	NPV (MM$)										
		1	2	3	4	5	6	7	8	9	10	Sum
	E-TYPE	411	274	591	271	297	296	144	234	65	28	2611
	PROB60	404	839	300	301	293	380	55	-	-	-	2572
	PROB70	412	782	546	371	322	76	-	-	-	-	2509
	PROB80	386	824	342	419	319	63	-	-	-	-	2353
	PROB90	939	694	246	102	-	-	-	-	-	-	1981

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Pushback Generation

The risk analysis studies presented here were performed with optimised pits that can be used to determine the phases by application of the revenue factor Whittle [20] and consequently can provide useful information to define pushbacks and the mine sequence by generating tonnes and grades during the lifetime of the mine. It is important to note that head grade or tonnage requirements might not be met at every stage, since the stripping ratio might exhibit variations, which must be equalised later during the project operation. The impact on grade variation during mine sequencing of considering probabilities of P_2O_5 grades being higher than the cut-off grade is presented in Figure 7. It can be seen that the grade increases with the associated risk, which means that as long as the risk is rejected, the selected blocks have grades higher than the established cut-off grade. Figure 8 presents the NPV variation generated from the selected simulations. It can be seen that there is an absolute difference of US$619M when compared with the sequencing applying a PROB of 90% over the expected value.

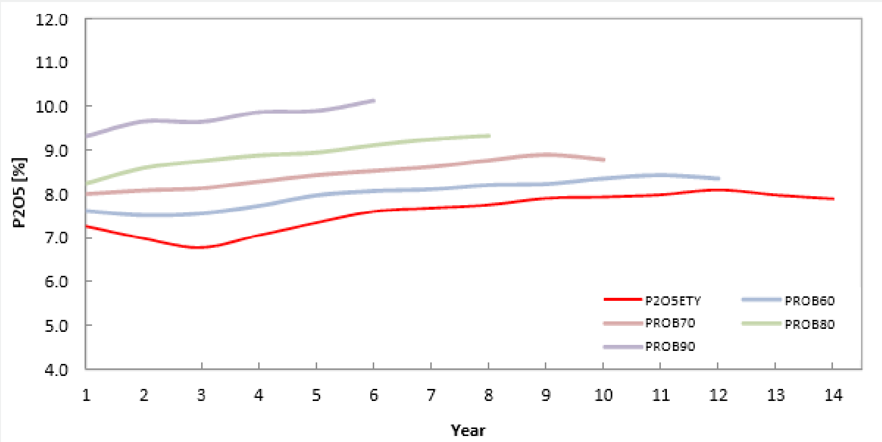

Figure 7: Average grade for each mining sequence for different probabilities.

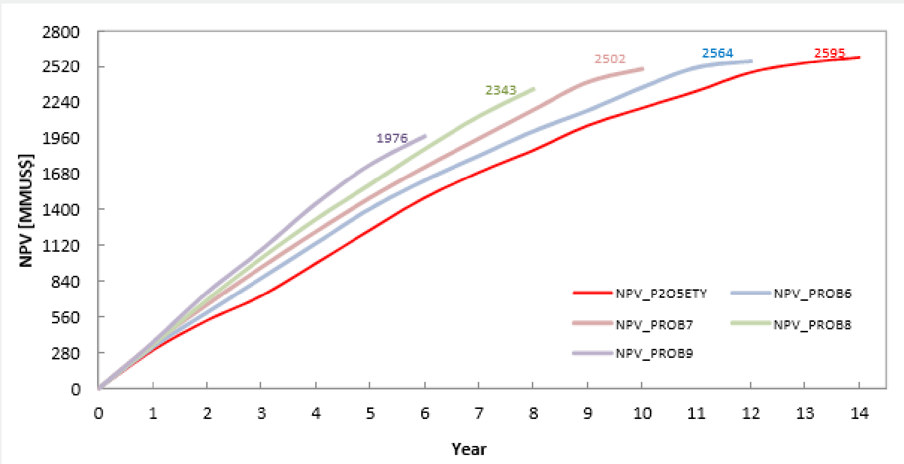

Figure 8: Cash flow analysis for each probability scenario.

Conclusion

The application of geostatistical simulation techniques has proved to be a fundamental tool in the uncertainty approach to geological variables. Traditionally, the mining industry has employed sensitivity analyses of other uncertain parameters such as costs, selling prices and process performance. Considering that geology and grades have a huge impact on a project's feasibility, the use of a tool like this can help to show that grades are variable and that this variation, or a lack of understanding of it, can have a significant impact on revenues. The incorporation of this

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variability allows its impact on the mine planning to be evaluated. Although in the study described here, the base case planning was based on the block generated by an average scenario, the impact on operational advances (pushbacks) could be seen, and, in the face of these variations, the mine plan could be altered by considering the different results from the probabilistic models. However, the purpose of this study was not analysis of the plan itself but rather measurement of the impact of the variations on the project's outcome. This impact was determined, and it was shown that the level of variability is an important aspect of uncertainty (due to lack of data, intrinsic variability of the deposit, quality of information, etc.) that needs to be considered. This uncertainty represents, for the case studied, something like 10% of the economic output of the project to the designated area.

a) Another aspect that has proved to be relevant for the application of the methodology is the observation of the deposit's behavior under scenarios of risk aversion/acceptance. In this study, the risk was measured by the probability that a given block has a grade higher than the cut-off value of 5% P_2O_5. When the risk acceptance was reduced, the presence of remaining portions of the deposit areas associated with higher grades where the uncertainty was actually smaller was confirmed by sample data or by the characteristics of the deposit in areas of low variability. The introduction of the uncertainty parameter in conjunction with the risk criterion allows the mining company to achieve the desired results while minimising errors and reducing the number of samples that need to be taken. This can be seen by comparing the results of mine planning based on the E-type model with those obtained using progressive probabilities.

References

1. Matheron G (1971) The Theory of Regionalized Variables and its Applications, Les Cahiers du CMM. Fasc No 5, ENSMP, Paris pp. 211.
2. David M (1977) Geostatistical Ore Reserve Estimation. Elsevier Scientific Publisher, Amsterdam pp. 364.
3. Journel AG, Huijbregts CJ (1978) Mining Geostatistics, Academic Press, London pp. 600.
4. Costa JF, Koppe JC, Zingano AC (1997) Uncertainty Analysis of Stripping Ratio and Enhanced Coal Mine Planning, in Proceedings of the MineIT'97. First International Conference on Information Technologies in the Minerals Industry (Internet), Athens, Greece.
5. Goovaerts P (1997) Geostatistics for Natural Resources Evaluation. Oxford University Press, New York, USA, pp. 483.
6. Costa JF (1997) Developments in Recoverable Reserves Estimation and Ore Body Modelling, Ph D. Thesis, The University of Queensland, Australia pp. 333.
7. Peroni RL (2002) Análise de Sensibilidade do Sequenciamento de Lavra em Função da Incerteza do Modelo Geológico. Tese de Doutorado. Programa de Pós-Graduação em Engenharia de Minas, Metalúrgica e de Materiais (PPGEM), Universidade Federal do Rio Grande do Sul pp. 126.
8. Silva NCS (2008) Metodologia de planejamento estratégico de lavra incorporando riscos e incertezas para an obtenção de resultados operacionais. Tese de Doutorado - Escola Politécnica da Universidade de São Paulo. Departamento de Engenharia de Minas e de Petróleo pp. 118.
9. Whittle J, Rozman L (1991) Open pit design in 90's. Proceedings Mining Industry Optimization Conference, Aus IMM, Sydney.
10. Crawford JT, Davey RK (1979) Case study in open pit limit analysis. Computer Methods for the 80's in the Mineral Industry, SME-AIME pp. 310-318.
11. Mathieson GA (1982) Open pit sequencing and scheduling. Honolulu, Hawaii, SMEAIME p. 1-15.
12. Dagdelen K, François-Bongarçon D (1982) Towards the complete double parameterization of recovered reserves in open pit mining. 17th APCOM Symposium, SME-AIME, Denver, Colorado pp. 288-296. 177.
13. Ramazan S, Dagdelen K (1998) A new pushback design algorithm in open pit mining. Proceedings of the 17th International Symposium on Mine Planning and Equipment Selection, Calgary, Canada, AA Balkema, Rotterdam pp. 119-124.
14. Tolwinski B (1998) Scheduling production for open pit mines. 27th APCOM Symposium, IMM, London, England pp. 651-662.
15. Diedrich C (2012) Incorporação da variabilidade dos teores para análise de risco de recursos minerais e sequenciamento de lavra. Dissertação de mestrado. Programa de Pós-Graduação em Engenharia de Minas, Metalúrgica e de Materiais (PPGEM), Universidade Federal do Rio Grande do Sul pp. 188.
16. Capponi LN (2012) Introdução de parâmetros de controle de incertezas para planejamento de lavra, Master´s Thesis, Programa de Pós graduação em Engenharia de Minas, Metalúrgica e Materiais p. 148.
17. Lerchs H, Grossmann I (1965) Optimum design of open pit mine. CIM Transactions, Volume LXVIII, CIM, Montreal p. 17-24.
18. Underwood R, Tolwinski B (1998) A mathematical programming viewpoint for solving the ultimate pit problem. European Journal of Operational Research (107): 96-107.
19. Hustrulid W, Kuchta M (1995) Open Pit Mining Planning & Design. AA Balkema, Rotterdam pp. 636.
20. Whittle D (2011) Open-Pit Planning and Design, In Mining Engineering Handbook, Ed. Peter Darling Published by Society for Mining, Metallurgy and Exploration, Inc pp. 877 -901.

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