GRADE CONTROL USING CONDITIONAL SIMULATIONS AND ECONOMIC OPTIMIZATION

Mario E. Rossi GeoSystems International 479 Cascadita Terrace, Milpitas, CA 95035, USA

1.0 ABSTRACT

A crucial task in the every-day life of an open-pit mining operation is to perform in-pit selection of ore and waste material, sometimes sub-classifying it for stockpiles or different treatment facilities. Perfect in-pit selection (i.e., making no mistakes in deciding the destination of every ton of material mined out) is impossible. Sampling errors, estimation errors, limited or bad information, and operational constraints result always in ore loss and waste dilution, which in turn leads to economic losses. These losses can be serious enough to make the operation unprofitable.

Minimizing ore loss and dilution is therefore key to a successful operation. Every mistake made detracts from the maximum amount of ore that could, theoretically, be recovered from the pit and thus it is critical to optimize the recovery process. Conditional simulations can be used to derive conditional probability distributions, which, in conjunction with pertinent economic parameters, can be used to minimize losses caused by imperfect selection.

This paper discusses the potential benefits of the methodology, and illustrates the subject with a striking example from a gold mine in northern Chile, where in a period of 18 months this methodology has recovered 45% more tonnage, 1% less grade, for about 45% more ounces, if compared to the method previously used.

2.0 INTRODUCTION

Inversiones Mineras del Inca, a wholly-owned subsidiary of Niugini Mining Ltd., began to mine the San Cristóbal gold deposit in April 1991 [1], which is located in the Región II, northern Chile, approximately 100km east of Antofagasta. San Cristóbal is a small-to medium open pit mine, working on 5m benches, from which 10,800 metric tons of material grading about 1 g/t gold (Au) and between 4 g/t and 6 g/t silver (Ag) are extracted daily. Blast holes are used to blast the rocks and to obtain Au samples from the pit. Blast holes are located on a quasi-regular grid, spaced about 4.5 m., and they are sampled over the entire height of the 5m bench. Blast holes are drilled, sampled, and loaded with explosives on a daily basis, typically one blast of 300 to 400 holes per day. Traditionally, based on the blast hole samples plotted on scaled maps, San Cristóbal technicians would draw polygons based on the observed grades at each blast hole, and thus define areas of ore to be extracted. These maps with the corresponding polygons drawn in are passed to surveyors, who then stake (mark) on the pit the ore and waste areas for the operators to recover or discard to the waste dump. The mine uses two Carterpillar front loaders 992C and one 988 for loading, and transport is accomplished using seven Carterpillar 773B 50-ton trucks. The ore is passed through a primary jaw crusher, two secondary standard cone crushers, a third short-head cone crusher, and final an impact crusher that yields crushed rock 100% below 1.27mm. The treatment process is sodium cyanide heap leaching, using heaps of 11,000m² and 10m height, and the enriched solution is passed through six activated carbon columns, to recover the Au and Ag from the liquid. Finally, an Au and Ag doré is produced with approximately

27-30% Au. Up until the introduction of a new grade control method, San Cristóbal produced about 65,000 ounces of Au per year.

Gold mineralization at San Cristóbal is very erratic, with a highly skewed distribution that makes its modeling very difficult. In addition, the geology at San Cristóbal, although relatively simple and well understood, provide very few critical markers, and no visual indicators for the occurrence of gold. Gold mineralization is mainly structurally controlled, located within visually-evident veinlets; however, the occurrence of veinlets does not ensure the occurrence of gold, so that not all structures or veinlets have gold, nor all the gold is strictly confined to structures. The short- and long-term production reconciliations obtained until mid-1994 were relatively poor. The grade control method based on polygonal drawing was losing significant quantities of gold and processing significant quantities of waste. In late 1994, in an effort to remedy the situation and find a more optimal ore/waste selection process, a conditional simulation method, combined with economic optimization, was designed, tested, and implemented.

3.0 CONDITIONAL SIMULATIONS AS MODELS OF UNCERTAINTY

The theory of conditional simulations will not be developed here. The reader is referred to [2], [3], or [4], among several others. The idea is to build a model that honors the full histogram and variogram of the conditioning data, and therefore honors the spatial variability of the deposit as represented by the conditioning data. In the case of a grade control problem, blast hole data is used for conditioning, and, if available, direct coding of geologic features into the model also is used. This can be accomplished using an indicator technique to code geology, see for example [5] or [3]. Conditional simulations are built on very fine grids, as fine as possible given the hardware available, so that they correspond to approximately the support size of the original samples. By honoring the histogram, the model correctly represents the proportion of high and low values, the mean, the variance, and other statistical characteristics of the data. By honoring the variogram, it correctly portrays the spatial complexity of the orebody, and the connectivity of low and high grade zones. These are fundamental variables for the optimization of the ore/waste selection procedures, which depends mostly on a correct prediction of the variability of the high-grade/medium-grade/waste transition. When several simulated images are obtained, then it can be said that a model of uncertainty has been obtained, and as such, this paper shows it to be a good basis for grade control.

A reasonable grid for the simulation could be 1m by 1m by 5m, as is used in San Cristóbal. Larger grid sizes may still be used sometimes because of the amount of computer time and hard disk space involved. Such a high resolution is possible because of the random aspects of the algorithms used (conditional simulations being Monte-Carlo-based techniques). In building a conditional simulation model, many of the conditions and requirements of linear and non-linear estimations apply, most importantly regarding stationarity decisions. Shifts in the attitude of the ore controlling structures requires the separation of the data into different populations, as would geologic or lithologic boundaries. Thorough knowledge of the behavior of the high-grade population is required to control high grades in the simulation, refer among others to [6]. Issues such as limiting the maximum simulated grade should be carefully considered.

The simulation method should be decided based on the type of the deposit, the available data set and the desired output. The first decision is whether to use a parametric or non-parametric approach. Examples of each are the Sequential Gaussian [7] and Sequential Indicator [3] simulations. The latter is more complicated, based on multiple indicator kriging techniques [8], and requires definition of several indicator cutoffs. The former is simpler and quicker, although more restrictive in its basic

assumptions. Any available geological criteria ("soft" information, see [5], or [9]) should be used. As with any estimation exercise, variograms should be estimated and modeled, and a number of important parameters need to be considered. These include: minimum and maximum data value and simulated value allowed, number of conditioning data to be used, search distances, anisotropies, etc.

Finally, it is critical to thoroughly check the simulated values. The histogram of the simulated data should be compared to that of the original conditioning data. Both should be similar in terms of simple statistics and overall shape of the histogram. The variograms of the simulated data should be similar to the input models, at least up to the search distance used. The original conditioning data and the simulated data should be plotted on maps at the same scale. Close examination of the two sets of maps will detect any possible deviations of the simulated data from the conditioning data. It is also instructive to observe what the conditional simulation produces in areas where there is little or no original (conditioning) data.

When a number of these conditional simulations have been run and checked, then, for each block defined in the grid, there are a set of equi-probable (by construction) grades available. These grades are interpreted to describe the model of uncertainty for that block, generally arranged as a posterior cumulative conditional probability curve. Preferably, a large number of simulations are needed to describe this curve better; however, and due to practical limitations, a much smaller number, perhaps as small as 10 simulations in the case of grade control, can be used as an initial approximation.

4.0 CASE STUDY

4.1 Traditional Grade Control Methods

At San Cristóbal, given the erratic nature of the mineralization, grade control essentially determines the profitability of the operation. In turn, proper sampling and assaying techniques are required to obtain representative samples from each blast hole. Detailed studies of Au distribution in the material drilled by the blast holes were carried out at San Cristóbal [10], which allowed to implement a sample preparation and assaying protocol that yields less than a 15% fundamental error variance.

Prior to 1995, the samples obtained from the blast holes were plotted in a plan map, and using visual inspection based on a processing cutoff (the grade that pays for processing plus general administration costs), a polygon was drawn, with the aid of geologic knowledge and operational constraints. The average grade of the polygon was estimated to be simply the average grade of the blast holes within the polygon. A dilution band of 1 or 2 m. was added, estimating its grade by averaging surrounding blast holes. Then, the overall grade of the polygon was estimated as a area-weighted average of the ore zone and the dilution zone.

4.2 Conditional Simulation-based Grade Control

The new grade control system implemented at San Cristóbal is based on the use of conditional simulations and loss functions [7]. The idea is to initially develop a grade model of uncertainty for each point within the mining area, and then to apply a loss function to evaluate the possible economic consequences of each decision. The model of uncertainty can be described as [11]:

$$F(z; x | (n)) ' Prob \{Z(x) \# z | (n)\}$$
(1)

At San Cristóbal, sequential indicator simulations were utilized, described in more detail in [3], [11], and [7]. If an indicator random function model is used, I(x;z), then it can be shown that the conditional probability function described above is given by the expectation of the marginal distribution of I(x;z), which is equal to the marginal probability distribution of the original variable Z(x) for each threshold *z* chosen:

$$I(x;z) | (n) \}$$
' 1 x Prob { $Z(x) \# z | Z(x)' z_*, "'1,n \}$ % 0 x Prob { $Z(x) > z | Z(x)' z_*, "'1,r \}$

or

$$E\{I(x;z) | (n)\} ' Prob \{Z(x) \# z | (n)\}$$
(2)

In grade control, the selection decision (which material is ore and which is waste) has to be based on grade estimates, $z^*(x)$. Since the true grade value at each location is not known, an error is likely to occur. The loss function L(e) is a mathematical expression that attaches a value (impact or loss) to each possible error. By applying a loss function to a set of equiprobable simulated grade values (a conditional probability distribution, as obtained by conditional simulations), then the expected conditional loss can be found by:

$$E\{L(z^{(\&Z)}|(n)\}' \stackrel{\%}{\longrightarrow} L(z^{(\&Z)}) @dF(z;x|(n))$$

$$N_{44}$$
(3)

The minimum expected loss can then be found by simply calculating the conditional expected loss for all possible values for the grade estimates, and retaining the estimate that minimizes the expected loss. As described in [7], p. 65, in grade control the expected conditional loss is a step function whose value depends on the operating costs, and the relative costs of misclassification. This implies that the expected conditional loss depends only on the *classification* of the estimate $z^*(x)$, not on the estimated value itself.

4.3 Results

Table 1 presents a comparison of tonnages, grades, and ounces predicted by the Multiple Indicator Kriging Long-term block model ("MIK"), with the corresponding tonnages, grades and ounces selected using the traditional method ("Polygonal Grade Control"), and the conditional simulation method ("CS Grade Control"). These quantities correspond to the period March 1995 through March 1996 (13 months). To protect confidentiality, they are presented as factors [12], where F1 corresponds to the comparison of the block model to the grade control, and F2 corresponds to the comparison between the material delineated in pit using grade control and the material actually received at the plant. As it is evident from Table 1, the improvements achieved with the conditional simulation method are very significant. The F2 factors in Table 1 reflect the tonnages actually selected and loaded to the plant using the conditional simulation method. A 10% unplanned dilution in a mine like San Cristóbal is very reasonable and mostly due to the operation itself, although it could conceivably be improved by enhancements to the grade estimation method. In addition, the F2 factor for the polygonal method is an estimated value, since no actual tonnage was recovered during this period using this method. The numbers in Table 1 reflect the assumption that the operation is indifferent to the grade control method used to select ore and waste, which in reality is not true. It can be proven that the polygonal-based

method presents characteristics that make the loading operation and selection in the pit much more difficult, which would make the resulting F2 factors for the polygonal method even worse.

Given the numbers presented in Table 1, the conditional simulation-based grade control method selects 34% more tons of ore, at a 10% higher grade, resulting in a 48% percent increase in selected ounces at the pit, if compared with the polygonal-based method. These results have had a major impact in the company's revenues, costs, and cash flows. Overall in-situ revenues incremented by US\$ 11.2 million in 13 months. When factoring in the ounces actually produced, along with actual costs, it is seen that an increase of about 50% in pre-tax net income has been achieved for the period.

	Tons of Ore	Au Grade	Ounces
F1 (Polygonal Grade Control/MIK)	0.84	0.91	0.76
F2 (Plant/Polygonal Grade Control)	0.75	0.81	0.61
F1 (CS Grade Control/MIK)	1.13	1.00	1.13
F2 (Plant/CS Grade Control)	1.01	0.89	0.90

Table 1:Comparison of the MIK Block Model, Minimum-Loss Grade Control Method, and
Polygon-Based Grade Control Method

5.0 CONCLUSIONS

Better knowledge of the geology at San Cristóbal allowed an understanding of the shortcomings of previously used methods of grade estimation. This lead to the implementation of a grade control method based on conditional simulations and loss functions [7], which has resulted in production records and significant economic improvements to the operation. The new method not only contributed to a higher recovery of ore and a better ore/waste selection overall, but also lead to other operational improvements, allowing for a reduction of the unplanned dilution.

The new grade control method, although more complicated from a mathematical standpoint, can be implemented so that it is easy for non-geostatisticians or specialists to operate and control. The method has been in use at San Cristóbal since February 1995, and is still being used with minimal supervision and only occasional revisions to the gold price, costs, and recoveries applied.

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7.0 REFERENCES

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