Optimizing Grade Control: A Detailed Case Study

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Abstract

The most important task in daily life of an open-pit mining operation is to perform in-pit selection of ore and waste material. Oftentimes the process is complicated because subclassifications are required, for example through 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 contact dilution, which in turn lead to economic losses. In extreme cases, these losses can be serious enough to compromise the profitability of the operation.

A series of geostatistical conditional simulations can be used to predict the probability of ore occurrence at a given location. The set of grades obtained from these simulations are interpreted to be a posterior cumulative conditional probability function, in a Bayesian sense, for each location. These, in conjunction with in-pit economic parameters, can be used to minimize economic losses caused by imperfect selection. This method has been successfully applied to a number of precious metals and copper open-pit operations, of which one specific example is given.

This paper discusses the basic principles of the methodology, and describes the results achieved covering a 13-month period with the Maximum Revenue grade control.

INTRODUCTION

In many open-pit precious metals mines it is common to incur in ore loss and dilution at the time of ore/waste selection. It is often difficult to define accurately the position of the dig lines or dig boundaries prior to the loading operation, more so in cases were there are few or no visual markers and the higher grade ore is structurally controlled.

Traditionally, commonly used grade control methods included simple visual observations of the blast holes grades, some form of blast hole averaging, or polygonal methods. In more recent years, several forms of kriging have gained acceptance, including ordinary and indicator kriging. Even more recently, grade control methods incorporate the concept of Monte Carlo-based conditional simulations and economic losses.

This paper describes a conditional simulations-based grade control method, which, coupled with adequate economic loss functions, achieves economically optimal grade control. It is postulated that this method results in improvements with respect to more traditional grade control methods, including kriging, under the following circumstances:

- Ore and waste populations are significantly inter-mixed, and it is difficult to clearly identify separate ore pods without leaving ore blast holes outside the pods; similarly, the recognizable ore pods may have significant amount of waste within;

- No visual markers are available; even if higher-grade controlling structures are identified, there is never assurance that they are mineralized;

- Grade variability is significant; typically, the blast hole database will exhibit coefficient of variations (CV=standard deviation/mean) higher than 2.

The conditional simulation method described is based on the intuitive idea that errors will always happen; this imperfect pit selection is sometimes called mis-classification in the relevant literature (Goovaerts, 1997). The main objective of the method is to minimize the economic losses incurred, based on a given set of economic parameters and a given probability of occurrence of ore within a blast.

This paper presents details on a specific example that illustrates some of the practical aspects of implementing a simulation-based grade control method. For more other related details the reader is referred to Aguilar C. and Rossi (1996). The benefits of the method are presented based on production data, mine and mill reconciliation data, and cash flow analysis.

The case study is a now exhausted medium sized open pit gold and silver mine, which processed about 10,800 tons of material grading about 1g/t Au and between 4 g/t to 6 g/t Ag ore daily. The mine worked on 5m benches, and blast holes were used for breakage and to obtain samples from the pit. Blast holes are spaced about 4.5 m. and are sampled over the entire 5m bench height. Blast holes were drilled, sampled, and loaded with explosives on a daily basis, typically one blast of 300 to 400 holes per day. The "traditional" grade control method included plotting the blast hole samples on scaled maps; mine technicians would then 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 were passed on to the surveyors, who then would stake (mark) on the pit the ore and waste areas for the operators to recover or discard to the waste dump. The ore, after being crushed in three stages, is heap-leached using sodium cyanide, and Au and Ag is recovered by passing the enriched solution through six activated carbon columns. Finally, an Au and Ag doré is produced with approximately 27-30% Au. Up until the introduction of a new grade control method, the mine produced about 65,000 ounces of Au per year.

GEOLOGIC SETTING

Gold mineralization is very erratic, with a highly skewed distribution that makes grade modeling and resource/reserve prediction difficult at any scale. Gold and silver minerals are associated to a sub-volcanic intrusion, mainly consisting of rhyolite, breccia, quartz-feldspar porphyries, and occasional dacitic dikes. Alteration is typical of porphyry intrusions, zoning from a central potassic alteration, an intermediate alteration zone characterized by actinolite and epidotes, and an external halo of propyllitic alteration. Superimposed to these alterations a different sericite-quartz alteration has been identified, associated to veining and significant shearing.

Mineralization occurs within discontinuous structures, oriented North to NW-SE, within a dilational zone ("jog") limited to the north and south by two shear zones; the structures hosting the mineralization are typically 0.1 to 1.0 m in width, gold present in a quartz-pyrite association. When the structures intercept more favorable lithologies, such as breccias, gold mineralization appears also disseminated into the host rock.

Although the geology is relatively simple and well understood, it provides few markers, with no visual indicators for the occurrence of gold and silver mineralization. The occurrence of the mineralized veins does not ensure the occurrence of gold, so that not all veins have gold, nor all the gold is strictly confined to structures. The short- and long-term production reconciliations obtained from 1991 (when the mine began operations) until mid-1994 were relatively poor. Estimation methods for long-term mine planning had been based on ordinary kriging estimates, controlled by the use of geologic/grade envelopes. A significant improvement was achieved by using Multiple Indicator Kriging instead of Ordinary kriging, still constrained a low-grade envelope. The grade control method used until 1994 was based on drawing polygons around ore blast holes. It was determined that the polygons were 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.

MAXIMUM REVENUE GRADE CONTROL METHOD

The Maximum Revenue grade control method is a two-step procedure:

- Initially, a set of conditional simulations is obtained from the blast hole data available; these conditional simulations provide information about the uncertainty (how much it is not known) about the grade at a specific point within the blast.

- Second, an economic optimization process using Loss Functions is implemented, to obtain the economically optimal ore/waste selection. The Loss Function quantifies the economic consequences of each possible decision.

Conditional Simulations and Loss Functions

For a general background of the theory of conditional simulations the reader is referred to Goovaerts (1997) or Journel and Huijbregts (1978). The simulations are used to build models that reproduce the full histogram and modeled measures of spatial continuity of the original, conditioning data. Therefore, they honor the spatial characteristics of the deposit as represented by the conditioning data.

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, it is shown to be a good basis for grade control.

For grade control, the simulation model is based on blast hole data. This paper assumes that the all-important issues of blast hole sampling, sample preparation and assaying have been satisfactorily resolved. At the mine described here, a detailed sampling heterogeneity study was conducted, and procedures and protocols implemented to achieve a target 15% fundamental sampling error variance.

Conditional simulations are built on fine grids, as fine as possible given the hardware available, so that they correspond to approximately the support size of the original samples. A reasonable grid for the simulation could be 1m by 1m by 5m, as is used in the case study presented here. Larger grid sizes may still be used sometimes because of the amount of computer time and hard disk space involved. Such a fine grid is possible because of the random aspects of the algorithms used (conditional simulations are 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 Rossi and Parker (1993). 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 (Isaaks, 1990) and Sequential Indicator (Alabert, 1987) simulations. The latter is more complicated, based on multiple indicator kriging techniques (Journel, 1988), and requires definition of several indicator cutoffs. The former is simpler and quicker, although more restrictive in its basic assumptions. Any available geological criteria can and 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.

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. When there is sufficient conditioning information, these simulated values for each block will not vary significantly; this is typically the case for grade control, where blast hole data is available on a relatively small scale.

Therefore, the idea is to initially develop a grade model of uncertainty for each point within the blast area, to later then apply a loss function to evaluate the possible economic consequences of each decision. The model of uncertainty can be described as (Journel, 1988):

$$F(z;x|(n)) = Prob\ \{Z(x) \leq z|(n),\ \alpha = 1,...,n\} \quad \textbf{(1)}$$

Here *F(z;<u>x</u>|(n))* represents the cumulative conditional distribution frequency curve for each point <u>*x*</u> of the simulated grid, obtained using the *(n), α=1,...,n* conditioning blast holes, and it provides the probability of that point in the grid of being above (or below) any grade *z*.

For the case study described here, sequential indicator simulations were used. In this case, an indicator random function model is used, *I(x;z)* (Journel, 1983). 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 (Journel, 1988):

$$E\{I(x;z)|(n)\} = 1\ x\ Prob\{Z(x) \leq z|Z(x) = z_{\alpha},\ \alpha = 1,n\} + 0\ x\ Prob\{Z(x) > z|Z(x) = z_{\alpha},\ \alpha = 1,n\}$$

or

$$E\{I(x;z)|(n)\} = F(z;x|(n),\ \alpha = 1,...,n) \quad \textbf{(2)}$$

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 can and will likely occur. The loss function *L(e)* (Journel, 1988), is a mathematical expression that attaches an economical value (impact or loss) to each possible error, measured in, for example, dollars. By applying a loss function to a set of equiprobable simulated grade values (a conditional probability distribution, as obtained by conditional simulations, Equation (1)), then the expected conditional loss can be found by:

$$E\{L(z^* - Z)|(n)\} = \int_{-\infty}^{+\infty} L(z^* - z) \cdot dF(z;x|(n)) \quad \textbf{(3)}$$

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 Isaaks (1990), in grade control the expected conditional loss is a step function whose value depends on the operating costs, and the relative costs of mis-classification. This implies that the expected conditional loss depends only on the *classification* of the estimate $z^*(x)$, not on the estimated value itself. For example, the loss incurred when a block of leach ore is sent to the mill is a function of the difference in processing costs related to both leach and mill; it will, of course, also depend on the *true block grade,* but not on the *estimated block grade* value itself.

CASE STUDY

The work summarized here was initiated because the operation achieved very poor grade and tonnage reconciliations for a number of years. Traditionally, the block model used for long-term mine planning was blamed for the problem. Several attempts were made to improve the reserves block model, and after achieving was what believed at the time to be as good as block model as the drill hole data and the geologic knowledge would allow, called here the MIK model, attention was turned to grade control. It was evident that the intrinsic variability of the mineralization posed a significant challenge to the day to day operation, and grade control essentially determined operating profitability.

The case study describes changes introduce in the computerized handling and modeling of the blast hole data and the subsequent evaluation period, between March 1995 and March 1996 (13 months). All other aspects of grade control, including blast hole sampling, database creation, blasting practices, field demarcation, and operating practices are not affected by the change in grade control method.

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 an area-weighted average of the ore zone and the dilution zone.

Maximum Revenue Grade Control Method

In early 1995, the issue of grade control was studied in detail, and a new grade control method was developed and implemented at the site. As explained above, the method utilizes several geostatistical conditional simulations, based on blast hole data, on a blast-by-blast basis. These simulations are processed using a loss function defined as:

$$Loss = Actual\ Op.\ Profit - Potential\ Op.\ Profit \qquad \textbf{(4)}$$

The revenue equation, usually expressed on a per ton of ore basis, is given by:

$$Profit = (Price) \times (Met.\ Recovery) \times (Au\ grade) - (Treatment\ costs + G/A\ costs) \qquad \textbf{(5)}$$

The revenue function should include at least processing costs, and daily General and Administration costs assigned to the operation; alternatively, other attributable costs such as certain capital depreciation costs, or exploration costs for other company properties can be introduced, therefore artificially increasing the breakeven cutoff. Mining costs should not be included, since the blasted material will have to be moved regardless of its destination. Only if there are differences in transportation costs for different destinations, then a mining cost term will appear in Equation **(5)**.

Given Equation **(4)**, a matrix can be built based on the alternative material destinations. In this case, only waste and leach ore have been considered; therefore, a 2x2 Loss Function matrix is obtained. Extending this matrix to multiple destinations, such as mill and stockpiles, is straightforward. The Loss Function matrix expresses the concept of mis-classification, and it quantifies the cost in dollars of each possible mistake. Table 1 presents the simplest possible Loss Function, as used in this case study.

Each cell in Table 1 is identified as A11, A12, A13, and A14. Cells A11 and A14 are 0, because there the right decision is made, i.e., there is no loss. Cell A12 represents the loss incurred when waste material is sent to the processing facility, in this case the leach pad. The potential benefit is negative (since the true grade is waste), the only cost that should have been incurred into is the G/A cost of operating the mine; a negative profit is added to the potential operating profit, stemming from the processing of waste material. Cell A13 presents the case where material that is truly ore is estimated to be waste and thus sent to the waste dump. The potential benefit is the revenue that would have been achieved is the right decision was made; in addition, the G/A costs have to be added; obviously, the resulting loss in both cases is represented by a negative dollar amount, taking into account the opportunity cost, in addition to actual costs.

The grade control method consists of the following steps:

- A set of conditional simulations are obtained based on the blast holes of the current blast, plus surrounding sampled blast holes to obtain a series of conditional simulations on a small grid, typically 1x1m. These conditional simulations provide the cumulative conditional distribution function that quantifies the probability of each specific block of ore to be within each destination category (ore and waste, in this example).

- Apply to the conditional simulations the Loss Function as defined in Table 1; the resulting grid is therefore transformed into a series of codes (zeros and ones, for example) that define each block as either waste or ore; they represent the optimal selection in an economic sense.

- The codes within each blast are visualized on screen using adequate (sometimes simple) software tools, and a polygon is drawn on screen to select ore and waste; this polygon should be drawn by the grade control technician following operational constraints. Alternative, automatic algorithms can be and have been developed to produce an "automatic" cut, considering operational constraints; however, this author believes it is more appropriate to leave the final decision to the grade control technician. In addition, the geostatistical method allows for and benefits from geological knowledge, particularly in areas of sharp mineralogical or structural transitions, not always captured by statistical description of the blast hole data..

- An estimate is generally required for the tons and grade to be recovered from each blast; this estimate is typically the expected value of each block, i.e., the average of the simulations.

TABLE 1: Loss Function, obtained using Equations (4) and (5), in $.

	True Grade is Waste	**True Grade is Leach Ore**
Estimated Grade is Waste	A11 = 0	A13 = -G/A Costs -{Leach Revenues - Proc. Costs}
Estimated Grade is Leach Ore	A12 = {Waste Revenues - Proc. Costs} - G/A Costs	A14 = 0

Note that, as stated above, the decision of where to send each block or portion of the blast is made before any actual estimate of the grade is obtained. In fact, the decision only depends on the relative probabilities of each block of belonging to either the ore or waste category, and the potential cost of making a mistake.

RESULTS

From March 1995 through March 1996 both methods were carried out in parallel, allowing for a thorough comparison based on achieved production. The comparison demonstrated the remarkable improvement achieved by the Maximum Revenue Method.

To evaluate the performance of the methods prediction was reconciled to production. An F_1 factor is defined to compare block model results to grade control results. An F_2 factor is used to compare "loaded to heap" material to grade control predictions, see Rossi and Parker, 1993. The F_3 factor (F_3=F_1*F_2) is used to compare tons and grade predicted by the Long-term block model (MIK) to tons and grade loaded to heaps. Table 2 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 Maximum

Revenue method ("MR Grade Control"). These quantities correspond to the period March 1995 through March 1996 (13 months). Actual in-pit selection was performed using the Maximum Revenue method.

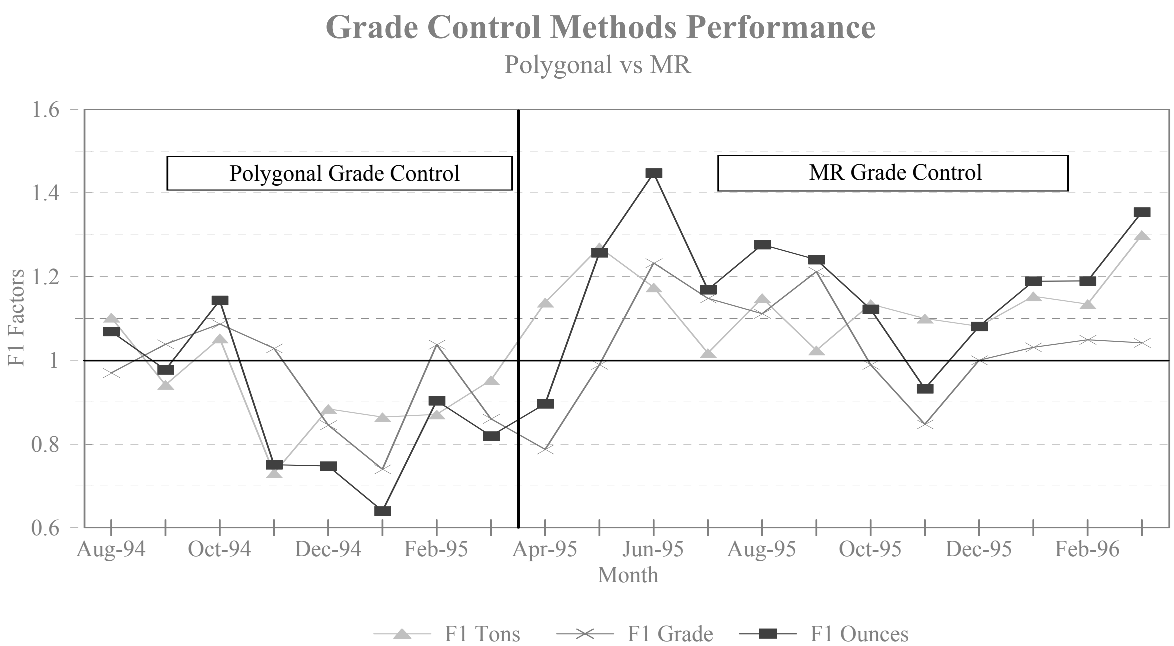

Figure 1: Monthly Grade Control vs Long-term Block Model Factors.

Figure 1 shows the F_1 factors for the period, on a monthly basis; the introduction of the Maximum Revenue grade control method is evident. Note that this was the only change introduced in the operation at the time. Table 2 shows the improvements achieved with the conditional simulation method. The F_2 factors averaged for the 13-month period in Table 2 reflect the tonnages actually selected and loaded to the plant using the conditional simulation method. A 10% unplanned dilution in ounces in an operation with an extremely erratic mineralization is quite reasonable. The results presented in Table 2 is that they assume that the loading 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 loading and selection in the pit much more difficult, which would make the resulting F_2 factors for the polygonal method even worse. The fine grid used by the MR method allows for an operational cut that incorporates less dilution. Another important conclusion is that in reality the Long-term block model (MIK) was conservative in tons and about unbiased in grade, and most of its perceived shortcomings were not in fact an issue.

Table 2 can be translated into economic gains. For this particular operation, the Maximum Revenue method resulted in 34% more available in-situ tons, a 10% increment of available in-situ grade, for an net increment of 48% in-situ metal. These results had a major impact in the company's cash flows, operating revenues, and costs. Overall in-situ revenues incremented by US$ 11.2 million in 13 months. The associated net increase in cash flow was US$ 4.8 Million, or a monthly average of US$ 370,000, without including gains in diminished stripping cost, recall that the final, Long-term optimal pit shape was unchanged. Overall production jumped from approximately 65,000 ounces annually to about 80,000 ounces.

TABLE 2: Comparison of the MIK Long-term block model, Maximum Revenue grade control method, and polygon-based grade control method, March 1995-March 1996.

	Tons of Ore	Au Grade	Ounces
F_1 (Polygonal Grade Control/MIK)	0.91	0.94	0.86
F_2 (Plant/Polygonal Grade Control)	1.34	0.82	1.10
$F_3 = F_1 * F_2$ (Plant/MIK, Polygonal GC)	1.22	0.77	0.95
F_1 (MR Grade Control/MIK)	1.13	1.00	1.13
F_2 (Plant/MR Grade Control)	1.01	0.89	0.90
$F_3 = F_1 * F_2$ (Plant/MIK, MR Grade Control)	1.14	0.89	1.02

CONCLUSIONS

When trying to model and operate on difficult and erratic ore deposits and grade distributions, such as gold, alternative methods exist based on geostatistical conditional simulations. In particular, for grade control, significant improvements have been achieved at several operations. The example delineated in this paper shows that the Maximum Revenue method achieves significant improvements with respect to more traditional (polygonal-based) grade control methods. The new grade control method, although more complicated from a mathematical standpoint, was implemented so that it was easy for non-geostatisticians to operate and control. The method was in use at the mine for about three years, and allowed extending mine-life for at least one year. The method requires strict geologic supervision (as it should always be), and revisions to the gold price, costs, and recoveries were applied as required.

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