A MINING APPLICATION OF MULTIPLE POINT SIMULATIONS: MODELING OF MINERALIZED ZONES IN A HYDROTHERMAL DEPOSIT.

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SUMMARY

In open pit mining, the information collected during production is abundant and generally of good quality. Using a massive historical production information from a hydrothermal gold deposit, a realistic training image (TI) of the actual mineralisation has been developed in the mined-out area of the open pit. The objective of developing the training image in the context of Multiple Point Simulations (MPS) is to provide an analogue to simulate deposits in similar geological settings as well as exploring deeper extensions of the same deposit.

In this application, the training image is used also as a reference for comparison with the simulated images. A case study is presented and it is based on a complex geological system of a hydrothermal deposit characterised by a number of distinct facies (pod zones) with high local variability with non-stationarity.

Firstly, 50 mineralisation facies simulations have been performed, this is followed by a second stage 100 block gold grade simulations. The grade simulations are repeated for each facies independently with adapted parameters characterizing the statistical distribution and the variograms. The facies and grade simulations are finally merged by means of a cookie cutting procedure to get 100 realizations of the Au grade.

Two sets of boreholes corresponding to different drilling patterns of inclined boreholes typical of feasibility or new mining mineral resource definition drilling have been used to condition the simulations. The statistical analysis on the distributions of facies proportions and local statistics on similarities with the reality (i.e. the TI) are provided. The capability to delineate the mineralized areas is also addressed. Comparing E-type estimates calculated from the simulated gold grades with the actual in situ production grades based on grade control drilling allows quantifying the uncertainty associated with the different sampling patterns used for the alternative techniques.

INTRODUCTION

Simulations of ore bodies have multiple applications for the mining industry. The most important ones are linked to uncertainty assessment issues and sampling optimization. Geology and grade have to be simulated consistently with specific methods. Due to the high variability associated with the input parameters, eg, grade, the choice of the method for simulating the geology is critical as simulated models will reproduce quite different features depending on the method (eg, Object based simulations, Sequential indicator simulations, Truncated Gaussian simulations). In the case study presented in this paper, a geological model with sufficient level of detail and a high degree of confidence can be obtained from grade control data at the production stage, which provides a reliable training image to be used in the Multiple Point Simulation process (MPS) (Strebelle 2002).
In addition to the training image, conditioning data from sampling of existing boreholes were used to control the simulations of the geology. Grade simulations using turning bands method and conditioned by the same boreholes were then carried out to obtain realizations of grades for each geological facies. The comparison of the differences between simulated grades and grades of the training image, considered as the ground truth, allows quantifying the uncertainty as well as the precision and efficiencies based on the different sampling campaigns.

Based on the orientation study done within the mined out area of the pit, and based on recommended drilling pattern in the deeper part of the deposit, an E-Type block estimates as well as facies models would be developed from MPS/simulations in the same manner, particularly using the same training image from the mined out area of the deposit.

METHODOLOGY

Some Theoretical Considerations for Block Simulations Used in the Case Study

The Discrete Gaussian Model (DGM) (Chilès and Delfiner 2012) was used to generate directly block values, without going through an average of n points discretising the block.
Under the hypotheses of the Discrete Gaussian Model (DGM) we can simulate directly block values (Deraisme et al. 2008). This method is very efficient as it saves a lot of computing time compared to the "traditional " approach where the block values are obtained by averaging simulated points by discretizing the blocks. The key hypothesis in the methodology considers that a point randomly located within a block is on the average equal to the block value (Cartier's relationship). This property allows us to link point and block values by means of a linear regression between their Gaussian transforms Yx and Yv. It is illustrated by the schematic figure below (Figure 1).

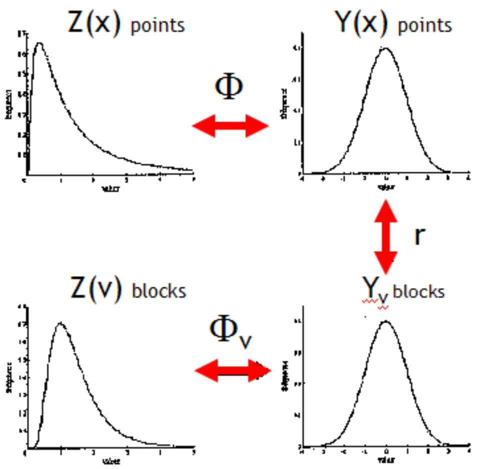

Figure 1: Scheme of the change of support by means of Gaussian anamorphosis between raw variable Z and its normal score transform Y.

The slope of the linear regression is the coefficient of correlation between both Gaussian variables. It is the so-called change of support coefficient r, it has been demonstrated (Emery and Ortiz 2005) that the square of r is the dispersion variance of the Gaussian variable regularized on the block (Y(v)):

$$r^2 = \operatorname{var} Y(v) = \operatorname{var} Y(x) - \overline{\gamma_Y(v,v)} \simeq 1 - \overline{\gamma_Y(v,v)}$$

The block Gaussian variable Y_v is nothing but the Gaussian variable regularized on the block *Y(v)* normalized by the change of support coefficient:

$$Y_v = \frac{Y(v)}{r} = \frac{1/v \int_v Y(x)dx}{r}$$

For the direct block simulation method the input variogram model is obtained from the regularized variogram of the point Gaussian variable by scaling it by the square of the r coefficient:

$$\gamma_{Y_v}(h) = \gamma_{Y(v)}(h)/r^2$$

Work Flow for the Case Study

The workflow is achieved in three main stages:

- 50 Facies simulations are obtained using MPS technique based on the "Improved Multiple-point Parallel Algorithm using a List Approach" (Impala) (Straubhaar, et al. 2011). Four levels of multi-grids were chosen to capture the main features of spatial continuity at different scales. The principle of multi- grids aims at achieving the simulations in successive steps starting from a sampling of the final grid taking in each direction one node every 2 or 4 … etc. Once the coarsest grid has been simulated, the nodes of the next grid are filled and so on. The non-stationarity of the facies is linked to the blocks proximity to footwall and hanging walls of the structural blocks. In order to account for the non-stationarity, the facies proportions resulting from the training image were transformed using the moving average of facies proportions calculated on the training image and applied to the simulated grid.

- 100 Grade simulations are generated using the turning bands simulation algorithm. A change of support model of 5mx5mx3m blocks was obtained from a Gaussian anamorphosis model applied to composited data and the variogram model of gold grade of each facies population.

- Both facies and grade models in the case study were merged. For each block and each simulation, the simulated grade assigned to that block and the simulation of same rank is the simulated grade of the simulated facies of same rank. For example if the simulation #1 gives the facies 1 and the simulation #2 gives facies 3, the simulation # 1 will have a grade from the grade simulation #1 of facies 1 and the simulation # 2 will have a grade from the grade simulation #2 of facies 3.To obtain get 100 grade simulations from only 50 facies simulations the following rule has been applied, 2 grades have been assigned to each facies simulation, i.e. grade rank equal to the facies rank and equal to the facies rank + 50.

CASE STUDY

Geology

The mine exploits oxide and fresh hydrothermal mineralization located in Tarkwaian sediments. The mineralization occurs in a Banket Sandstone formation split into 2 main Fault blocks. In each block gold mineralisation is concentrated in 3 to 4 facies also called pod zones with different characteristics in terms of grade distribution and variograms.
The model of gold concentration is illustrated in Figure 2.

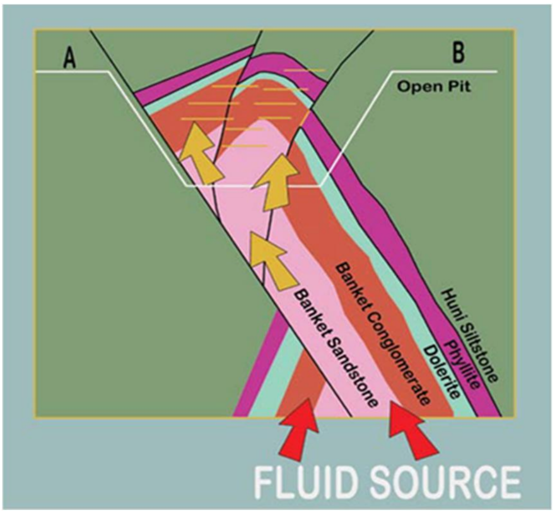

Figure 2: Schematic vertical section of the mineralization process.

The Database and Process Used

As mentioned above, using the massive historical production data from the hydrothermal gold deposit which has been mined for several years, a realistic training image of the actual mineralisation has been developed in the mined-out open pit. The application of MPS to the gold deposit has been carried out.

Basis for Assessing the Efficiency of the Alternative Techniques

By sampling these simulations based on different boreholes patterns, the experimental distribution of the estimation errors were obtained. It was therefore possible to quantify the ability of different borehole patterns to predict accurately the ore tonnage for the respective facies. The results of the analysis have been used to guide the additional drilling required in the deeper un-mined part of the deposit.

A numeric model of the mined out deposit is available at a fine resolution 5mx5mx3m with rocktype and mineralisation codes (or facies). This model is used for two purposes:

- as a training image driving the MPS simulations,
- as a ground truth reference or reality, i.e. “actuals” to which the different estimations and techniques were compared for their validity and relative effciencies.

MPS Analysis based on Typical Feasibility drilling data Configuration

Figure 3 shows the Fault Block 2 training image, which is characterized by strong non stationarity leading to a geographical separation between the areas where pod zones may occur.
Two borehole data sets were selected from the mined-out area on a regular pattern of 40mx80m and 20mx40m and were composited on 1.5m.
In total 7 pod zones were kept (three in the Fault Block 2 and four in the Fault block 3).

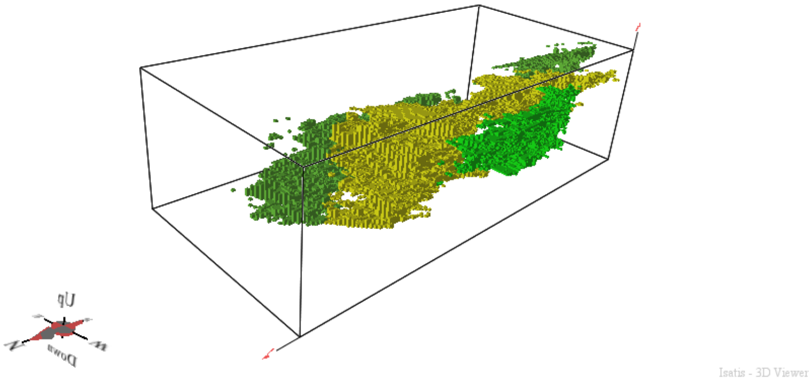

Figure 3: Perspective view of the training image of the Fault block 2 with 3 pod zones.

Table 1shows the comparisons of the pod zones proportions between the training image and the sampling based on the 2 boreholes data sets. Significant statistical differences are observed on the pod zones proportions between the training image and that estimated from the sampling of the 2 boreholes data sets and especially for the 40x80m grid.

Table 1: Statistics of the number of data in each pod zone of the Fault Block 2 from the training image and from the sampling by boreholes on 40mx80m and 20mx40m patterns. The complement to 100% is waste.

	Fault Block 2		
Pod Zone	Training Image	Composites data on 40x80 grid	Composites data on 20x40 grid
Rw2	33785 (11.6%)	118 (10.3%)	1547 (14.2%)
Re2	17785 (6.1%)	115 (10.0%)	898 (8.3%)
Rs2	5370 (1.85%)	9 (0.8%)	124 (1.1%)

MPS Results

Figure 4 shows an example of the simulation of one fault block conditioned by the boreholes of the pattern 20mx40m. It demonstrates a good reproduction of the general shape of the facies with higher variability at small scale.

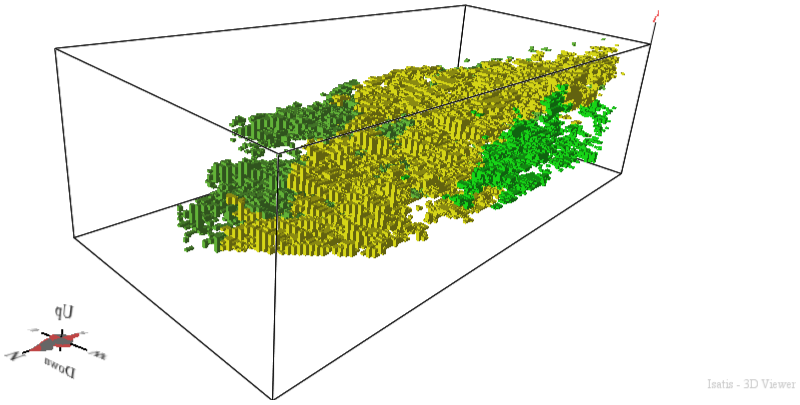

Figure 4: Perspective view of one simulation of the pod zones of the Fault block 2.

The distribution of the pod zone volumes from simulations conditioned by the respective sets of bore holes (Figure 5), is consistent with the expectation of a significant reduction of the variance around the mean value when more boreholes are used as input. The variance may be interpreted as the variance of the estimation error on the volume since the average of simulations can provide a non-biased estimate and each simulation is an equi-probable representation of the unknown.

Thus, the information provided by the simulations is the quantification of the error magnitude for the different sampling patterns.

In addition to the error variance, the confidence interval at any risk level can be calculated experimentally which is critical for capital intensive mining projects.

Table 2 and Figure 6 provide the tonnages calculated from the training image which are the ‘actual” tonnages, since the training image is considered to be the reality. It can be observed that the risk of bias is important, when a pod zone represents a small proportion of the total volume. This just points out that MPS does not guarantee that the simulated facies proportions will match those of the training image, hence the difficulty of estimating volumes without bias from sparse drilling. However, the denser grid ie 20mx40m) provides a more practical estimate. The average MPS simulated tons for all the facies combined based on the 20mx40m grid is within +/- 8% standard deviation with a probability of 90% (See Table 2).

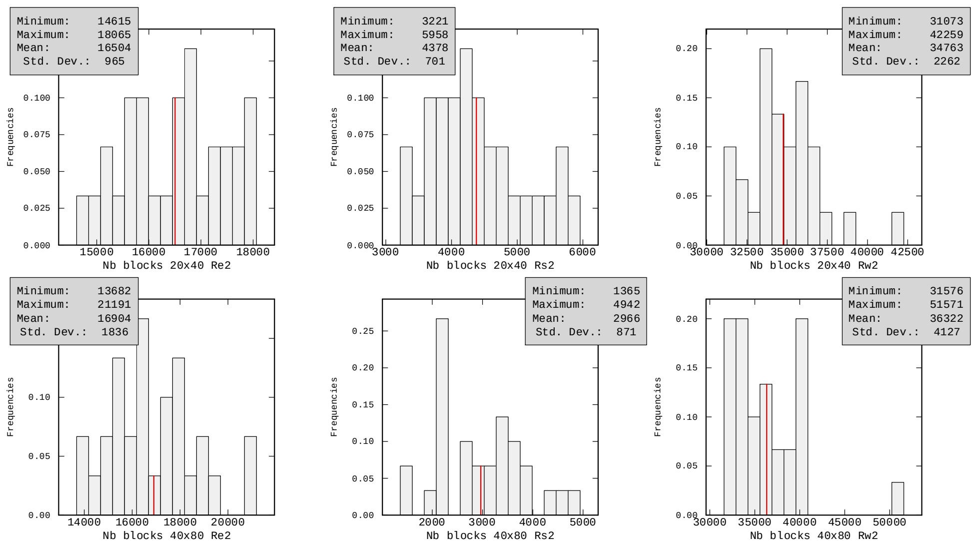

Figure 5: Histograms of the number of simulated blocks for each pod zone of the Fault Block 2 (from the 50 simulations with sampling pattern 20mx40m at the top and from the 50 simulations with sampling pattern 40mx80m at the bottom).

Table 2: Actual Tonnage, mean simulated Tonnage and Confidence Intervals at the risk level of 90% from 50 simulations of the different pod zones.

	Actual Tonnage (MT)	Sampling	Mean Tonnage (Mt)	q5-q95 Tonnage (Mt)
RW2	6,99	20x40	7,24	1,5
		40x80	7,5	1,87
RE2	3,73	20x40	2,82	0,49
		40x80	2,89	1,24
RS2	1,14	20x40	0,9	0,48
		40x80	0,63	0,64
RW3	7,33	20x40	5,96	0,58
		40x80	6,89	2,86
RE3	1,66	20x40	1,62	0,24
		40x80	1,2	0,6
RS3	0,74	20x40	0,75	0,18
		40x80	0,36	0,73
RF3	3,48	20x40	3,88	0,35
		40x80	3,47	1,48
TOTAL	25.07	20x40	**23,17**	3,94
		40x80	**22,94**	9,7

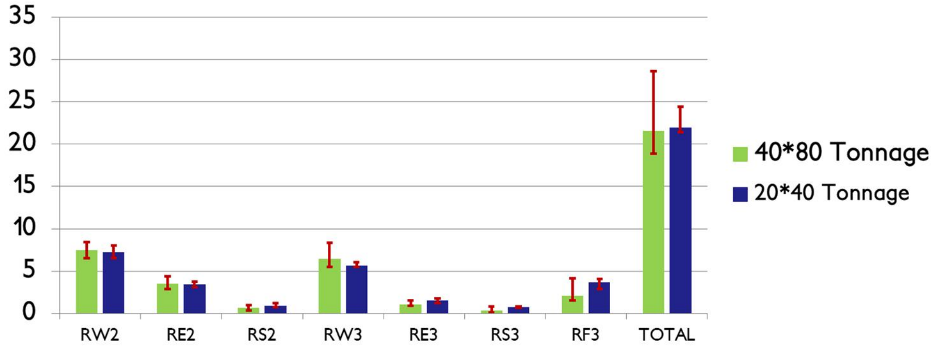

Figure 6: Comparison of average tonnages per facies with q5-q95 intervals from simulations conditioned by both drillholes patterns.

Additional Useful Uncertainty Analysis

We can also calculate the probabilities of the pod zones conditionally to reality, i.e. the assigned pod zone in the training image (Table 3). More precisely two conditional probabilities may be calculated:

- Type 1: knowing a block is in a pod zone according to the training image, what is the probability that the simulations have assigned it to the same pod zone.
- Type 2: knowing a block is NOT in a pod zone according to the Training image, what is the probability that the simulations have assigned it to that pod zone.

These probabilities give an important indication on errors at a local scale, while the previous statistics were global. The type 1 conditional probability is almost twice higher for the dense sampling pattern than for the sparse one. For the type 2 conditional probability the advantage is less.

Table 3: Probabilities of blocks to be in same pod zone as in the training image (left columns) and to be in another pod zone (right column).

	Block in SAME facies as in TI		Block in OTHER facies than in TI	
	40x80	20x40	40x80	20x40
Rw2	0.29	0.5	0.1	0.07

Re2	0.2	0.38	0.05	0.04
Rs2	0.11	0.19	0.01	0.01
Rw3	0.33	0.43	0.16	0.1
Re3	0.13	0.35	0.03	0.03
Rs3	0.09	0.37	0.01	0.01
Rf3	0.19	0.52	0.09	0.06
Average	0.19	0.39	0.06	0.05

Direct Block Simulation Results

The direct block simulations of 7 grade distributions for each of the 7 facies have been carried out. Generally the statistics and variograms are reproduced satisfactorily as shown in the example of Figure 7.

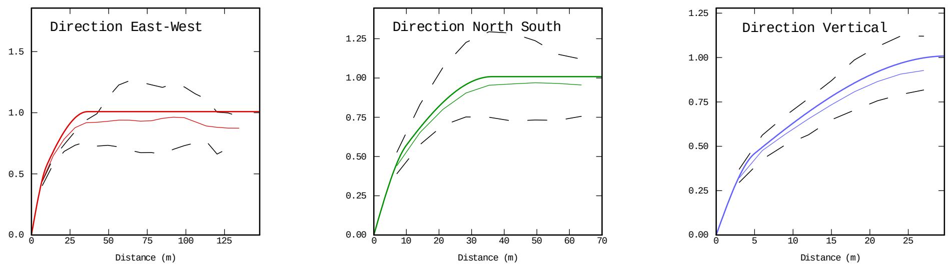

Figure 7: Example of variograms on Gaussian grade for one pod zone: the double line is the model input in the simulation process, the single line is the average of the simulated variograms , the dotted lines show the envelope of the simulated variograms.

After having populated the simulated models with gold (Au) grades, some simple statistics can be calculated like E-type estimates, standard deviation between simulated values and "actual" values. The bias observed in the facies simulations when the data are too sparse (boreholes patterns of 40mx80m) is still very pronounced on grades (Table 4).

Table 4: Average tonnages and grade before and after cut-off from 100 grade simulations and actual figures.

		Mean Tonnage (Mt)	q5-q95 Tonnage (Mt)	Mean AU Grade (g/T)
0 cutoff	20x40	21.37	21.93-25.87	2.22
	40x80	21.56	18.89-28.59	1.84
	Actual figures	**22.26**		**2.24**
after cutoff	20x40	19.78	18.21-21.5	2.55
	40x80	20.72	16.84-25.04	1.93
	Actual figures	**21.43**		**2.31**

The actual grade profile per level can be plotted and compared with the E-type estimate of gold grade calculated from the 100 simulations and the percentiles at 5% and 95% risk. Figure 8 shows an acceptable match.

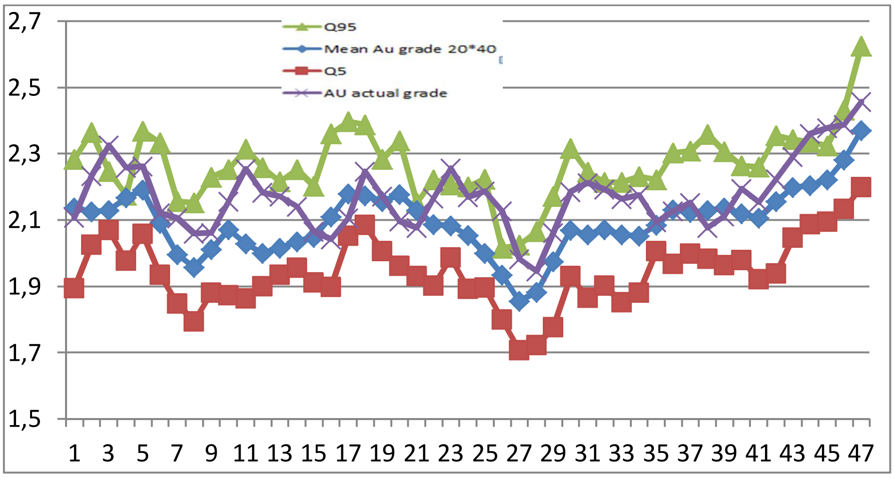

Figure 8: Vertical profile of actual grade, simulated mean grade and percentiles at 5% and 95% for each level 3m (level 1 at the pit bottom).

CONCLUSIONS

The application of MPS to mining data has proved to be efficient to produce images of geological variables characterized by their extreme non stationarity. The main historical challenge of MPS application which is often pointed out, relates to deriving geological training images, which does not apply to the case study presented in this paper, as the training image in this case has been obtained from a massive production grade control data. In this particular application the training image was used twice:

- to calculate probabilities of different spatial patterns between different facies
- to provide a reference for comparison with the simulated outcomes.

The MPS methodology aims at reproducing geological shapes and transitions between facies at different scales but there is no guarantee that the statistics of the facies proportions will match those of the training image especially when only limited drilling data is available for the MPS modeling which could be the case for very early feasibility mining projects. The study showed that the comparison with the training image makes sense especially on a local scale, only if a sufficient number of drillhole data is available for conditioning the simulations.

The study further showed that when a reliable geological/mineralisation training image is available and adequate representative sample data have been drilled in similar geological unmined extension areas, MPS and block simulations could assist in providing facies tonnages and grade models for feasibility/ new areas where mining is yet to be extended. MPS could also assist with sample pattern optimization when a training image is readily available. . Though computer time has remained historically a bottleneck, currently, this seems to being overcome as the required results are achievable timeously with most of software implementation of the simulation algorithms. Additional mining application case studies of MPS is further recommended as the use of the methodology has important applications for new exploration projects as well as mining extensions into similar geological orebody settings.

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