PINCOCK Perspectives

ISSUE NO. 102— May 2010

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How Good Are Your Resource (Block) Model Estimates?

Grade estimation of a mineral deposit may be the single most important determination of the asset value. Three dimensional block models are constructed using the analytical data available for a deposit. This article discusses various ways to validate the block model grade estimates.

Computerized grade estimation is a major part of a digital resource model in any modern mining project. Generally, drill-hole data are used in these models. The quality of the grade-estimates (say Fe content in an iron ore-deposit model) is highly dependent on the parameters used in grade estimation. Such parameters include, but are not limited to, the geological constraints, the size of sample (composite length), the sample spacing, the statistical parameters of the input data (skewness, dispersion etc.), search parameters, block size, etc.

The following examples demonstrate how different parameters can change the grade estimation and hence the grade-tonnage curves.

Example1: In modeling the total copper contents of a copper deposit, the high-grade boundary is determined from preliminary data analyses. A test was made by changing the high-grade Cu boundary and using a smaller search ellipse for the set of high grade data (a set of data in which a data point is greater than the high grade boundary). The result is illustrated in Figure 1. In this figure, the tonnage curve is fixed and grades are all reported for the same tonnage from different models. The grade curves changes substantially, based on the search parameter changes.

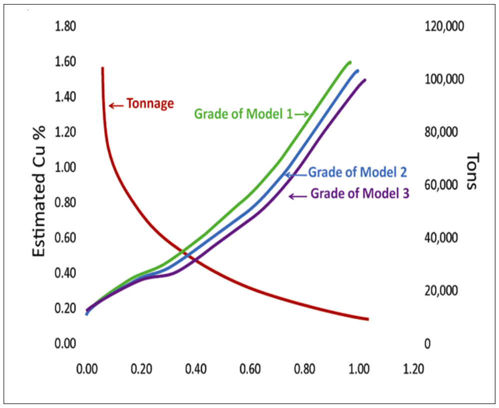


Figure 1: Grade tonnage curves as a result of restricting high-grade boundaries.
As can be seen in this example, for the same tonnage, Model 1 predicts higher grades than Models 2 and 3. Model 1 had no high-grade limit definition, hence no restriction of the search ellipsoids size; the Model 3 had tight search ellipsoids for high grade values. When compared with the blast hole data, Model 2 compared the best with the blast hole data, hence Model 2 better reflects actual copper grades. The high grade limit used in Model 2 is higher than that used in Model 3 and the search ellipsoids for the high grade values used larger for Model 2 as compared to Model 3.

Example 2: A similar test was made on using data from a zinc deposit. In the case of the Zn-deposit, the grade tonnage curves changed just by modifying the orientation of the search ellipsoids.

Example 3: In this project, estimates were made for gold content in a vein type gold deposit. The grade estimates changed substantially, using different high-grade boundaries and the size of the search ellipsoids.

In these cases, the model with the grade estimates closest to the composite data was chosen as the representative model. The drill hole composite data are the weighted average of contiguous assay data over a uniform length. This is a prerequisite in computerized resource modeling. Generally the grade estimates in the block-model are conservative compared to the other models created for the same deposit. However, the preceeding examples show how the grade estimates can vary based on modifying the parameters used in the estimation process. In order to ensure that the grade estimations are reliable, we often use various spatial and statistical checks per the following discussions.

Visual Validation Processes:

Cross-sections and plan views

Examine the vertical cross-sections and plan views: The vertical cross-sections and plan view with drill-hole data and block model estimates provide an excellent way of checking the quality of block model estimates. However, these checks can not quantify the quality of the block model. Additionally, the thickness representation of the cross-sections (perpendicular to mineralized structure is best), the color codes, and the orientation of the sections can influence the validation process.

Statistical Methods:

1. General statistics: The general statistics of the input data (drill-hole composites) are compared with those of the block model estimates. If the mean and standard deviations of the input data are close to those of the block model estimates, and the 90% or, 95% confidence intervals overlap, then one may conclude that the block model has similar characteristics to the input data; in other words, the block model is a reasonable global representation of the deposit. A similar comparison of the blast-hole data with the block model estimates may lead to even more confident conclusions on the representativeness of the model. However, this process has no spatial reference (geographic position). Accordingly, the statistical validation process can not be used for validating the estimates locally, i.e. at any specific location; the global statistical comparisons may differ widely from the local comparisons. The sample size, i.e., the number of composited data and the number of blocks compared, is a major issue in this process.

2. Statistical plots: The histograms and cumulative frequency plots of the block model are compared with those of the input data. Figure 2, shows a comparison of cumulative plots of the composite data and block model estimates for a copper (Cu) deposit. Such statistical methods provide a higher resolution comparison as well as a quantitative comparison.

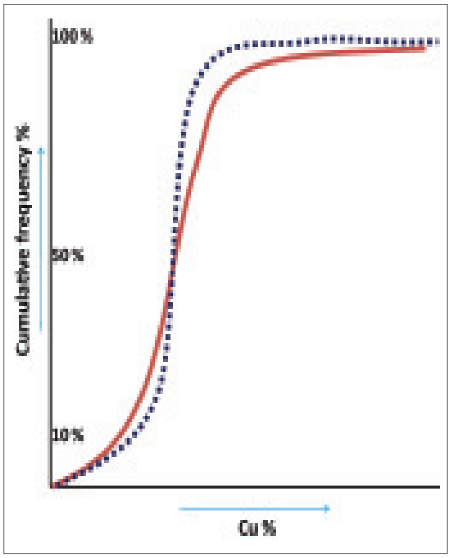


Figure 2: *Comparison of the cumulative frequency plot of the estimated copper grades (dotted blue line) in a resource model with the cumulative frequency plot of the composite samples (solid red line).*

Within a given range of grades the number of composite-samples and number of blocks may vary widely, which poses a statistical problem when comparing the average grades. Additionally, these comparisons lack a spatial reference. Therefore this method can not be used effectively as part of the local scale validation processes.

3. A nearest neighbor model: A nearest neighbor model is created by assigning the value of the nearest drill hole composite data (input data) to a block in a model. It is assumed to represent the deposit and the results are compared with the block model estimates. However, a nearest neighbor model does not represent the grade variation in the deposit, but rather smooths the grade distribution in areas of poor sampling. Therefore this technique is not always a suitable tool.

4. Swath Plots: Swath plots are the "comparison of the average of values within a limited space". As an example to explain a swath plot, Figure 3_a (page 3) illustrates the Au (g/t) grades plotted against depth in 50m intervals and in Figure 3_b, the Au (g/t) grades are plotted against coordinate easting on 20m intervals. In this plot (Figure 3_b), a number of data points (the block model estimates and composites) within 20m intervals are averaged and the values are plotted at location X_1. Similarly at location X_2, the averages of the block-model estimates and composites are plotted. It is important to note that the volume comprising of the number of samples / blocks should be the same or very similar. This will ensure an equal volume comparison of two sets of information at the same location. Otherwise, a smaller volume may tend to be biased because of selectivity of sampling at any given location.

An equal volume swath plot is a better than the other statistical techniques discussed earlier because it accounts for the same geographic location of the data compared.

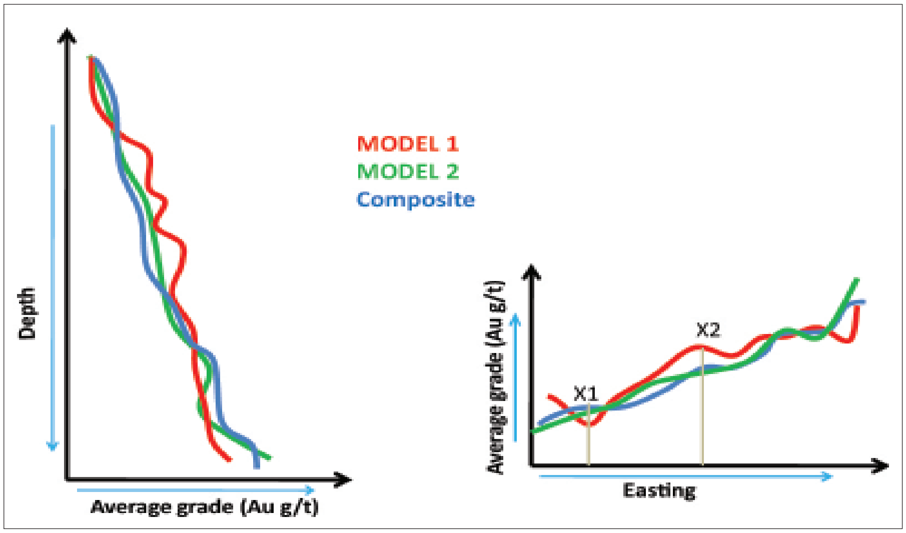
All preceeding techniques provide various ways to validate the estimates in a resource model. It may also be seen that more than one block model may be created for comparison purposes. All these models are compared with the raw drill-hole assay data or the composited drill-hole data, or the blast-hole data. In all these techniques, the block model estimates are treated as point estimates (not block, i.e., volume is ~ zero). Even though the nearest-neighbor (NN) model has equal support (volume), the use of the NN-model can be misleading. For example, in the case of clustered input data (e.g. abundance of drill holes around higher grade areas), the NN-model generates a model which is very smooth in areas of less dense data, which is unrepresentative. Using the NN-model for validation purposes is not logical.

Some of the techniques discussed are quite useful in validating the grade estimates. However, none of the above techniques address the volume variance relationship (the variance due block size)[1] and non-gaussian characteristics of the data-sets (i.e. the fact that most of the times the input data and grade estimates are not of statistically normal disribution[2]). So, to validate correctly, one should consider the effect of “size of block” and the skewness of the input data sets. The block dimension is one of the major variables that affect the grade estimation. The grade estimates are smoother and the error of estimation is larger for a smaller block size (Armstrong and Champigny, 1989)[3]. So, generally a block dimension equal to one quarter of the sample spacing along a plane (X and Y directions) is considered as industry standard, and may generate reasonable grade estimations. However, the dependency on the sample spacing creates a problem, as the samples may not be available in a regular grid pattern. Adding to the complexity of the situation, often the selective mining unit (SMU) is pre-determined when resource models are generated. The pre-defined SMU may not be the optimum block size for grade estimation.

The skewness of the input data and block grade estimates is another major issue. Most of the time, the input composite data are skewed, which leads to the grade estimates in a block model showing a similar statistical distribution. Due to skewness of the input data and the grade estimates, it is almost impossible to estimate the confidence intervals of the block model (because a normal distribution is required for confidence interval estimation). However, in many cases, a normal distribution of values is assumed for practical purposes.

Two different geostatistical techniques have been developed which are used to address the preceeding two issues. The most popular one is often known as the **HER**mitian **CO**rrection (HERCO) model, which is the same as the hermitian polynomial change of support model or, discrete Gaussian model (DGM) discussed in Journel and Huijbregts’ book, Mining Geostatistics (1978). The DGM or, HERCO uses a change of support coefficient (*r*) and Gaussian transformation of the input data and the block-model estimates (such as an ordinary kriging estimate of copper). The HERCO or, DGM grade-tonnage curve (Figure 4) is the theoretical grade-tonnage curve that is achievable from the same deposit.

The grade-tonnage curves of the estimates are compared with the DGM or HERCO model. The goal is to achieve a block model with the grade-tonnage curves close to the DGM, or HERCO grade-tonnage curves. As shown in the Figure 4, the Model 2 is the best model



3_a 3_b

Figure 3: Equal volume swath-plots. At each location (such as X1, X2 etc) of the above two swath plots, the total volume of space occupied by Model 1, Model 2 and the composite samples are the same.

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[1] http://www.kriging.com/PG1979/Chapter_3/Part3.htm

[2] http://en.wikipedia.org/wiki/Normal_distribution

[3] Armstrong, M.and Champigny, N., 1989. A study on kriging small blocks, in CIM Bulletin, Vol. 82, No. 923, pp. 128-133.

based on the close proximity of these curves to the HERC/ DGM curves. One of the limitations of this technique is that, being an advanced geostatistical technique, it requires specialized tools and training in geostatistics. Also, the HERCO, or DGM, does not provide grade estimates of the blocks. However, it is a handy tool to validate the grade estimates of a resource model.

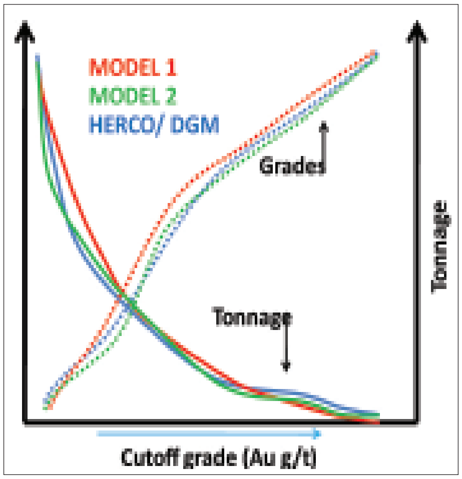

Figure 4: *An example of a HERCO grade-tonnage curve or, Discrete Gaussian Model along with the two grade-estimate models represented by two grade-tonnage curves.*

The other technique is a more advanced geostatistical technique, known as Uniform Conditioning. This technique can be used to validate the global and local scale grade estimations at different cutoff grades. This technique can also be used to optimize the SMU size. Recently, multivariate techniques have also been developed[4].

Conclusions:

Grade estimation within an individual deposit depends on various parameters, as discussed. These parameters are evaluated during the preliminary data analyses. Therefore, substantial time should be spent during the preliminary data analyses, in order to achieve grade estimates which are globally valid and can be used locally to predict the grades. However, the quality of input data (drill-hole data, survey information, etc.) are of equal or more importance to the grade tonnage estimates.

The choice of the grade estimation validation technique will depend on the stage of the project, quality of data, and grade estimation method. For example, a resource model at an early stage of estimation may not use geostatistical estimation methods, hence the HERCO and UC may not be applied, and swath plots may be suitable. In an advanced stage of the project (say, pre-feasibility, feasibility stage, or in an operating mine) there may be good quality data (closely spaced drill-hole data, geostatistical resource models, etc.) available for developing the HERCO diagrams or suitable for UC analyses.

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Acknowledgement:

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Thanks to Barton Stone, Ernie Bohnet and Richard Addison for their feedback and suggestions for improving the quality of this article.

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[4] Jacques Deraisme, J, Rivoirard, J and Castelli P C (1988) Multivariate Uniform Conditioning and Block Simulations With Discrete Gaussian Model: Application to Chuquicamata Deposit in the Ortiz, J. M, and Emery X (eds) Proceedings of the GEOSTATS 2008, Santiago, Chile

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