Integrating geometallurgical parameters into mining grade control at operating mines

Dr. William Shaw
Golder Associates, Toronto, Canada
Dr. Sia Khosrowshahi
Golder Associates, Perth, Australia
Dr. Andrew Richmond
Golder Associates, Brisbane, Australia
Michael McKevitt
Golder Associates, Perth, Australia
Dr. Marcelo Godoy
Golder Associates, Santiago, Chile

Abstract

Conditional simulation is now an accepted tool for managing ore block design at a number of operating mines. It provides a way to consider the quality of data, local continuity and economic risk in defining ore and waste across the cut-off boundary. In addition a computer based decision-making process can ensure consistency in making decisions to meet multiple criteria such as cut-off grades, minimum ore-block size and secondary criteria such as contaminant grades.

The development of a procedure for using multiple criteria now allows ore blocks to be defined using multiple alternative strategies depending on the specific production requirements. This has introduced the opportunity to define ore blocks for different destinations based on their material types and opens the way for geometallurgical modelling to be incorporated into grade control.

Contact details

Dr Bill Shaw
Principal, Ore Evaluation Services,
Golder Associates Limited, Toronto, Canada
wshaw@golder.com

Introduction

Mining grade control, sometimes referred to as “ore control” is the practice of differentiating between ore and waste. Ore is the material in a mine which is fed to the fixed plant (or “mill”). Good grade control occurs when the ore has been optimally delineated, measured and differentiated from the waste to maximise some predefined criterion, such as the net revenue from the mining operation. One method to measure the efficiency of the grade control process is to use conditional simulation (Khosrowshahi and Shaw, 2001; Shaw and Khosrowshahi, 2004) to optimise the generation of the ore block outlines (Khosrowshahi *et al*, 2009).

Ore Block Optimisation

Successful delineation of ore requires determination of the position of the boundary between ore and waste. The first obstacle to this is that the definition of ore can change over time as the costs and revenues change, thus altering the mining cut-off grade. The second obstacle is that, given a specified cut-off grade, the true boundary between ore and waste can never be known. Knowledge of the true boundary is constrained by the sampling resolution, sampling errors and the extent of any visual indications of mineralisation. Finally, even if the true boundary separating ore and waste was known, boundary design is still constrained by the mining method and the scale of equipment.

Khosrowshahi *et al* (2009) describes the logic involved in developing an optimised ore block including modelling the risk associated with predicting ore-waste boundaries and mining them in various ways. For a given conditional simulation or estimation model, the optimum mineable ore blocks can be determined. This requires the definition of costs and benefits for all the possible ore blocks that could be mined in a region, and the selection of the optimised ore block configuration. The advantages of such an approach are:

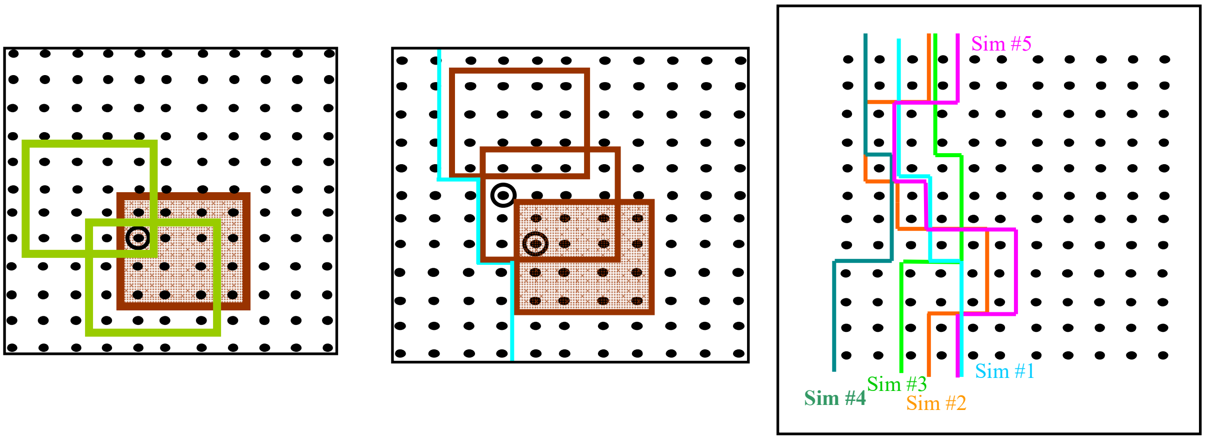
- The definition of ore blocks becomes more objective.
- The impact of changing mining strategies (e.g. selective mining *vs*. bulk mining) can be rapidly assessed based on the real economic value of the ore mined and the costs of mining.
- Misclassification between ore and waste at the ore block planning stage is reduced.
- Reconciliations between predictions and production improve dramatically.

Optimising material destination decisions using algorithms where the logic and parameters have been carefully considered is extremely valuable to any operation. This is because such a clearly defined process based on measurable parameters can better define risk, provide transparency and repeatability, and create an audit trail.

Defining the grade control selection logic as a sequence means that an algorithm, the Transfer Function, can be developed for any mine. This Transfer Function is then used to notionally mine the ore, waste and other material types, for each realisation of the conditional simulation model. Finally the local uncertainty defined by aggregating the ore blocks from the many different realisations is used to make risk based decisions to optimise the ore block for mining.

The approach used is first to build a conditional simulation model from appropriate sampled data and geological information (logging and mapping). This model is then examined using an appropriate "Transfer Function" to make decisions regarding the optimal position of the ore block boundaries. The specific Transfer Function used is a file that defines what is being optimised, the sequence of optimising, the various resulting mining products, and the imposed mining selectivity. While any number of products can be defined as part of the optimisation process, there are practical limitations such as the available data, and the number of ore destinations that can be realistically managed. Larger mines sometimes have less complexity due to their requirements to minimise mining costs by bulk mining. Smaller operations and those with very expensive processing costs (such as lateritic nickel projects) benefit more from increasing the number of ore types being defined.

An example of the optimising process is shown in Figure 1. The Transfer Function works by examining each realisation of the conditional simulation model in turn. For each realisation, every node is examined to determine whether the specified minimum mining block size (SMU) will meet defined criteria. Every possible configuration of the SMU sized volume around a node is tested. Once an optimal position is found, the next node is tested, and so on until all nodes have been examined. When all nodes have been examined, an optimal boundary can then be drawn. Repeating this process for all the realisations enables the variability within the conditional simulation model to be captured and used to defined the risk for ore blocking.



All SMU positions are examined **The optimal boundary is determined** **The process is repeated for all realisations**

Figure 1 Example of the process of optimising ore boundaries
(after Khosrowshahi *et al*, 2009)

Complex grade control strategies for ore blocking

Many operating mines make material destination decisions based on a single variable. Sometimes a combination of variables and factors is considered such as equivalent grade, or the potential impact of penalty variables (eg arsenic). Such derived variables may be quite artificial (eg the subjective logging of talc content) and while they no longer meet the purpose intended of any of the individual criteria, they may make the grade control process manageable.

The approach outlined above was first implemented at a porphyry copper project, which had two sets of selection criteria. The high arsenic scenario was used to maximise ore to the mill and the low arsenic scenario was used to minimise contaminants in the flotation concentrate. Different strategies were applied at different times in the mine, depending on customer requirements, available blending at the port, or feed-back as the concentrate stockpiles are building.

Some examples, detailed in Khosrowshahi *et al* (2009) and summarised here, indicate the flexibility of the ore block optimisation process.

At Prominent Hill, South Australia, the first criterion for deciding material destination is uranium content. Regardless of other minerals, material above a specified uranium cut-off must be stockpiled separately. The next criterion is based on fluorine assays due to penalties incurred if excess fluorine was contained in concentrate. After this, the material is assigned to either of two categories for gold content if the copper grades were below cut-off. Finally the material is assessed for copper content and copper speciation. If copper is greater than cut-off, the following steps apply:

- Since barium assays indicate the presence of barite (BaS), the sulphur allocated to barite is subtracted leaving a residual sulphur content.
- Based on the ratio of copper to residual sulphur the copper speciation is determined.

The copper speciation is used to set metallurgical recoveries and concentrate quality parameters. The final process is to determine the net smelter return (NSR) of material based on ore type recovery, processing costs, royalties, transport costs, smelting costs, etc. Implementing this logic sequence into a Transfer Function has been demonstrated and results in ore blocking such as shown in Figure 2. Note that a further stage may be required to create appropriately smooth dig-lines for mining.

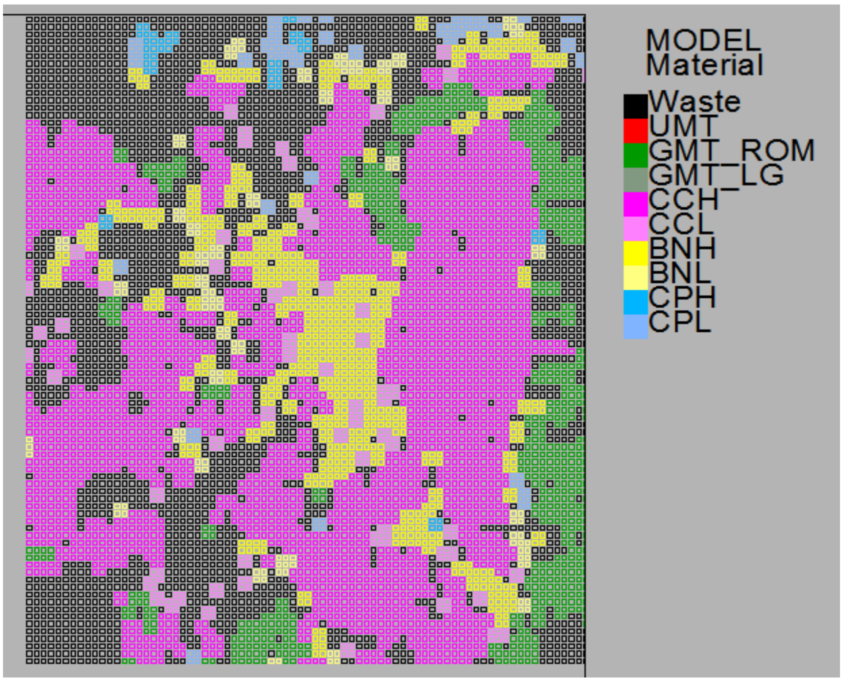


Figure 2 Optimised material types at Prominent Hill
(from Khosrowshahi *et al*, 2009)

At Rapu Rapu, Philippines the primary criterion for decision making was to determine whether the material was sufficiently oxidised to reject it from the sulphide flotation circuit. If oxidation was greater than 10%, the material was then assessed for its gold content and a determination was made whether to treat the material through a separate cyanide circuit. The next criteria for decision making were whether the material was below cut-off for zinc or copper but above cut off for gold. If above the gold cut-off, the material was stockpiled separately for possible future treatment. Finally the material was assessed for firstly zinc and then copper grades, both for high- and low-grade categories that have required zinc to copper ratios. The material type categories were critical to blending in the plant. The flotation circuit was designed to first produce a zinc concentrate then a copper concentrate. Gold credits were received in either concentrate but penalties were incurred for zinc in the copper concentrate and for copper in the zinc circuit. An example of the resulting ore blocking is provided in Figure 3.

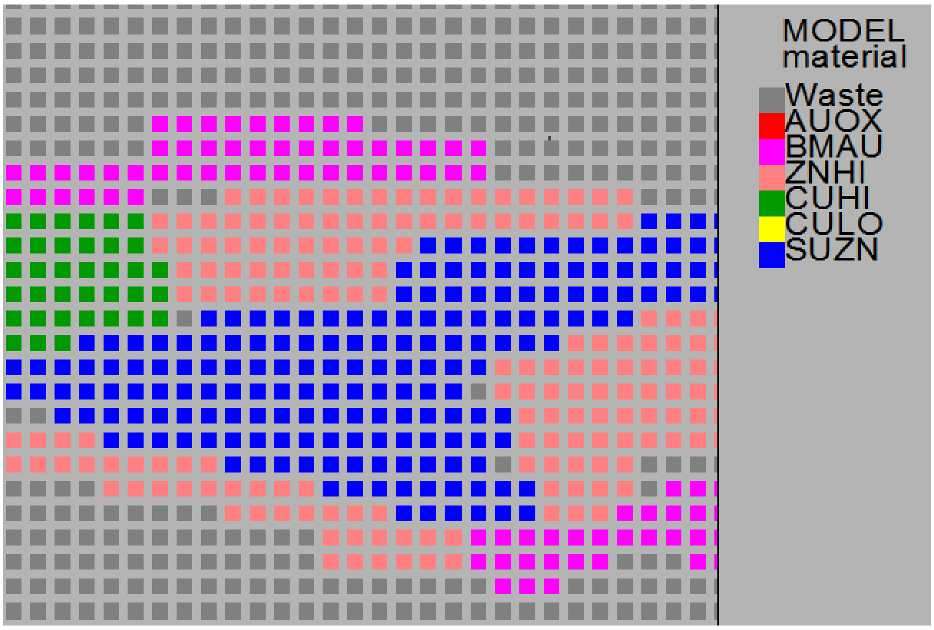


Figure 3 Optimised material types – Rapu Rapu

(from Khosrowshahi *et al*, 2009)

What exactly is Geometallurgy?

Broad definitions are often attractive and it would be easy enough to define the goal of geometallurgy as "to improve the understanding of resource economics by integrating geological knowledge, mine planning, operational design and mineral processing". However we run the risk in doing so that we are actually providing a new terminology for what we already do in most mines: optimise all the various known components of a mining operation to enhance the value of the ore that is mined and processed. For geometallurgy to add value, ie to enhancement profitability or knowledge, it must do a number of things:

- Create new information
- Change the linkages between current information
- Provide predictions that can be tested.

Without a clear understanding of how this can be done and the level of rigour required, there is a risk that "geometallurgy" may become discredited. Geometallurgical modelling provides a direct link from the orebody to the product that may be independent of the mining process or of the economics of mining. It is a consequence of this view that a scientific understanding of the orebody and an engineering understanding of the chemical and physical processes involved in extracting minerals from the orebody provides the real basis for the new science of Geometallurgy.

Geological versus metallurgical samples

Attempts to identify and characterise the availability and properties of ore in many different types of mines can be broadly classed as:

- Chemical, including estimation of mineral composition using normative mineralogy methods (eg Lipton, 1999).
- Quasi-metallurgical (eg doing bottle roll tests on drill samples to determine cyanide consumption, or using screen fire assays for gold to determine the proportion of gold that may be available in a gravity circuit).
- Empirical (eg the use of a pilot plant to test various zones so as to define the expected average upgrade).

Geological sampling is generally predicated on defining consistent domains (homogeneous zones to the geostatistician) within which a large number of minimally disturbed complete samples can be collected, compared and used to make predictions (estimations of tonnes and grade meeting various cut-off grade criteria). In the best cases this sampling can be considered to be complete, exhaustive, representative and unbiased. There is always a cost-benefit analysis that balances the number of samples against the risk of error, even if this is done informally. The samples are usually of small mass, such as those from a metre of halved NQ drill core (say 2 to 3 kg). They may be spaced on a nominal grid of 50 by 50 m but in a large mining operation this means there are usually thousands of samples to be considered. The low cost of sampling and assaying means that generally exploration and development drill samples would each finally cost in the range of $50 to $300.

Metallurgical sampling by contrast is usually done by collecting large masses of material and combining them to make composites for bench-scale tests (5 to 50 kg), pilot plant tests (50 to 500 kg) or bulk samples (much larger, up to many thousands of tonnes). Collecting these samples is difficult and it may not be possible to establish that they meet the above criteria (complete, exhaustive, representative and unbiased). The way that these desirable attributes of a sampling regime are best proven is through comparison of a statistically valid number of blind replicates. In many cases this may be impossible due to cost and time considerations.

The objective of geometallurgical sampling is to find a middle way. Usually this is through the use of the geological samples themselves. For example, in bauxite studies the reactive silica and available alumina are determined in a small pressurised test vessel "bomb" from a small amount of each drill sample. Composites of many smaller (geological) samples can also be used, for example to determine the crushing characteristics of SAG mill performance index (SPi) and Bond work index (BWI) as currently being done by SGS Minerals Services. In addition to the criteria for good samples (complete, exhaustive, representative and unbiased) there are additional criteria to be considered:

- Geometallurgical samples may only be partial samples. For example the assays on the recovered concentrate from the Davis Tube tests on magnetite ores indicate expected grades of ore but they do not indicate contaminants or deleterious properties of the non-ore gangue material.
- Many copper deposits have both oxide and sulphide copper ores and there may be significant overlap in metallurgical characteristics due to the complex mineralogy generated by supergene enrichment. Often the total copper (CuT) and soluble copper (CuS) are determined at the assaying stage. The CuS value is a partial assay used to indicate the available copper for a specific digestion regime and is used to determine the proportion of the copper that is contained in oxide minerals (eg azurite and malachite) which will not be recovered in the flotation section of the processing plant. The sensitivity of various copper minerals to acid attack allows this technique to be developed to define mineral percentages of a number of copper mineral species, assisting in the geological definition of boundaries such as the base of oxidation (BOX) or the top of dominant sulphides (TDS).
- The geometallurgical test may be dependent on physical, chemical or other variables that need to be controlled. The ABAE test for available bauxite is dependent on the particle size of the sample, the concentration of the caustic soda, pressure, temperature and time, all which can influence the reaction kinetics. Old test rigs have been replaced by more sophisticated robotic rigs that enable these parameters to be more accurately controlled.
- The geometallurgical samples and apparatus are designed to replicate the characteristics of ore in the processing plant. There is a significant problem of scale since for example wet screening and heavy media liquid separation of small manganese ore samples must be done consistently for repeatability, whereas in the heavy media separation (HMS) part of the processing plant the flow rates, media density and product splits are being constantly monitored and varied as the ore feed varies.
- The processing of the geometallurgical samples may be done at the same time as exploration or development drilling, as part of the Feasibility Study. Changes to the processing plant will be made over time as the orebody varies and in particular feed rates and screen sizes will change.

The variable must be demonstrated to be linear and consequently additive. In simple terms this means that if we have two equally sized samples, one with 25% clay and another with 75% clay, combining and homogenising them will give two equal samples with 50% clay. If we are trying to predict the chemical composition midway between these two samples we would expect to get the average value (50%). However if the “stickiness” or some other attribute of the sample is not linearly related to the percentage of clay, then we need a non-linear estimator. Using the average value, or the kriged value, will not be correct for that attribute.

Many metallurgical results are non-linear, but are known functions of material characteristics that can be modelled. Examples of non-linear attributes in geology and mining are everywhere once we understand this:

- In rock mechanics the Rock Mass Rating (RMR) value used for characterisation of slope stability is categorical, not linear
- Texture classes may be similarly categorical (Richmond, 1998)
- Throughput as a non-linear function of hardness
- Unsaturated permeability of leach heaps as a non-linear function of fines content.

Changing from point samples to predicting the attributes of blocks is the biggest challenge in mining and is addressed theoretically in geostatistics using Change of Support conventions. These rely on specific assumptions (that the data is representative, that the region being estimated is consistent, and that the variable being estimated is well-behaved). The last point is the most important for geostatistical modelling of geometallurgical data and is the most contentious. These issues are discussed further in Richmond et al (2009), where some interesting questions are posed about variables such as recovery, strength, liberation, texture, grain size and size breakage distribution curves which have a different support to the usual grade samples that we model.

Dealing with geometallurgical data of vastly different volume support is critical, especially when limited data is available for estimation. One of the authors (Godoy) has developed an estimation technique, called bulk kriging, for dealing with data of vastly different volume support. Bulk kriging is analogous to the well established direct block simulation algorithm (Godoy, 2002). A method such as bulk kriging is critical in dealing appropriately with data of different volume support, however, it also relies on linearity of the data.

Incorporating geometallurgical parameters

Simple and relatively cheap tests for geometallurgical variables such as hardness, grindability, throughput, SAG power index, bond work index, crushing index, mineral recovery and concentrate grade have become widespread. The cheaper sampling has resulted in relatively large geometallurgical databases.

A few of the geometallurgical variables currently being used or considered in long-term modelling include:

- Ore mineralogy
- Gangue mineralogy
- Textures and liberation
- Grindability

- Hardness and size distribution
- Bond Work Index
- SAG Power Index
- Tonnes per hour throughput
- A*b
- RMR rock mass rating / Barton Q Index
- Davis tube recovery
- Hydrothermal alteration - “Clay” mineralogy and abundance
- Acid-consuming mineralogy / Cyanide consumption
- Concentrate grade and quality
- Solubility ratio
- Trace element geochemistry/mineralogy – deleterious elements or by-products
- Acid producing sulphides in waste piles.

Optimising ore blocks using geometallurgical data

In any multi-element deposit there is some degree of complexity in the relationship between the different metals. A simple example is provided here based on total copper and soluble copper assays, which illustrates how in optimising the ore block boundaries using geometallurgical data will add to the complexity. Figure 4 illustrates that in using a criterion to change the ore block destination depending on whether the CuS/CuT ratio is above 0.2 or below 0.2, the method of estimating the block attribute (in this case the proportion of soluble copper that the plant can handle) may impact on the results. Again it is stressed that the linearity of variables being used should always be tested.

Total copper grade (CuT %)

2.02	0.29	0.95	4.56
2.96	0.74	0.38	0.43
1.65	1.42	1.06	3.13
2.30	2.94	1.45	4.80

Block average 1.94

Soluble copper grade (CuS %)

0.33	0.06	0.29	0.77
0.03	0.30	0.09	0.12
0.24	0.64	0.50	0.67
0.72	0.32	0.14	0.52

Block average 0.36

Ratio (CuS/CuT %)

0.163	0.207	0.305	0.169
0.010	0.405	0.237	0.279
0.145	0.451	0.472	0.214
0.313	0.109	0.097	0.108

Block average of ratios 0.230

Ratio of block averages 0.185

Figure 4 Care must be used in dealing with multi-attribute Transfer Functions. In this example the ratio of averages of CuT and CuS grades in an ore block is not the same as the average of the ratios.

Conclusions

Mining grade control can benefit from development of an algorithm that replicates the decisions used in defining ore blocks for mining. Multiple elements and other criteria can be incorporated into the process and the resulting system, applied to a conditional simulation model through a Transfer Function, can be used to make complex decision-making transparent, repeatable and auditable.

The incorporation of geometallurgical data into short-term planning and grade control systems is possible using this approach and is a logical development as grade control systems better perform their primary task of predicting the mineable grade. Attention to the data quality (of course) and the linearity of such attributes (often not considered) are both necessary.

Multivariate simulation is beyond the scope of this paper. There was considerable attention paid to this in a number of papers at the recent Geostats 2008 Conference in Santiago, Chile. There is still much work to be done on this and effective grade control modelling will benefit as new workable approaches are developed.

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