Geometallurgical Modelling – Quo Vadis?

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ABSTRACT

Geometallurgical modelling is now a hot topic in deposit evaluation and in optimising mine performance; however, its history is long and varied. Historically metallurgical sampling has frequently suffered from a lack of data due to the cost of producing representative bulk samples. In the early 1990s geometallurgical modelling similarly suffered from a lack of data due to complex, time consuming and expensive sampling techniques. More recently, 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. However, most of the geometallurgical variables sampled are implicitly (and incorrectly) assumed to be additive when modelled by traditional geostatistical techniques, often leading to ill-informed and costly decisions. Geometallurgical variables are mostly non-additive so the current geostatistical challenge is to develop new approaches to dealing with this type of data.

This paper briefly describes a historical case study of geometallurgical modelling of the George Fisher Pb-Zn mine completed in the mid 1990s, then outlines some of the current misconceptions of geometallurgical data and modelling techniques regularly applied to it, and finally discusses some recent developments in geometallurgical modelling, with examples from a number of current clients indicating the direction forward.

INTRODUCTION

This paper asks a number of questions to provide a snapshot of what geometallurgical modelling means from a mining geology perspective, and where it is going. In developing mining projects the role of important disciplines such as geology, geostatistics, mine planning and metallurgy have long been clearly defined. Many operations now see advantages in forming cross-discipline teams to address questions like 'How can we optimise particle size reduction from the mine, through the mill?', or 'How can we ensure that studies of energy demands for a mine site are based on good data, interpreted correctly?'. Understanding where geometallurgical modelling is heading will allow us to collect better data now to solve future questions.

Traditional planning of mines and scheduling of production is largely based upon the modelling of ore grade. It is known, however, that grade is not the only characteristic that can be taken into account to maximise performance at the processing plant and efficiency of tailings disposal. Ore processing plants respond well to feed that is consistent over time and that has known physico-chemical characteristics, which can be used to improve plant design and performance through the management of plant variables. Ore texture complements grade and influences, or is a measure of, mineral liberation properties, ore grindability, concentrate properties, disposal characteristics, and other properties, which collectively characterise the metallurgical behaviour of the ore. Furthermore, in an operational sense, even with the most sophisticated plant control system and mining practices, a response lag occurs between the measurement of an ore processing characteristic and the corrective action required. During this lag time an opportunity exists to maximise the profit of the resource by introducing a predictive ore control strategy.

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A few of the geometallurgical variables currently being used or considered 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, and
- acid producing sulfides in waste piles.

For some of these variables it is reasonable to ask at what scale are these measurements representative. For example, is a flotation test a grain by grain determination, or is it influenced by the volume of the original sample? The answer influences how a 5 kg (bench test) result or a 100 kg (pilot plant test) result can be scaled up to a 5000 t mining block. We know that variables such as recovery, strength, liberation, texture, grain size and size breakage distribution curves have a different support to the usual grade samples that we model everyday.

In the 1990s approaches to dealing with geometallurgical information were generally related to one or two variables considered most critical to the metallurgical performance or a proxy (eg ore texture) that contained implicitly information on many aspects of mining, metallurgical and tailings disposal performance. With the more widespread collection of geometallurgical information such as hardness, grindability, throughput, SAG power index, bond work index, crushing index, mineral recovery and concentrate grade, geometallurgical modelling is becoming more mainstream. The authors have noted that these non-linear geometallurgical variables are typically (and incorrectly) modelled through the application of standard geostatistical techniques that have long been successfully applied to linear or additive grade attributes.

The issue of non-linearity of geometallurgical attributes can be demonstrated by considering the Kulbeka-Munk function for kaolin reflectivity, shown in Figure 1. In this example, the two direct reflectivity measurements of 60 per cent and 90 per cent would have a linear average of 75 per cent. However, in reality a mixture of kaolin comprising equal portions of 60 per cent and 90 per cent reflectivity results in a kaolin product with a reflectivity of around 69 per cent. The difference between assuming linearity (75 per cent) and reality (69 per cent) translates into an outcome of a saleable versus a non-saleable product.

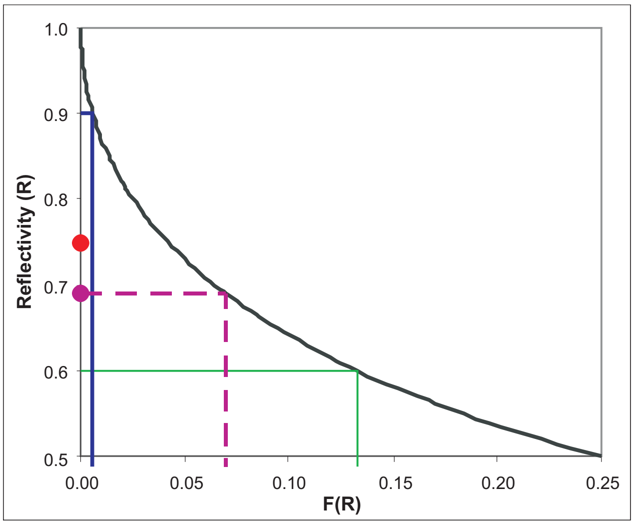

FIG 1 - Kulbeka-Munk function for kaolin reflectivity.

A 1990s APPROACH

The technical literature provides substantial information on the link between ore texture and metallurgical behaviour. If the metallurgical properties of ore and the ore's texture are intimately linked, then the time-dependent variability of ore behaviour in the mill feed is directly related to the space-dependent variability of textures in the orebody. If ore textures can be recognised, measured and quantified in spatial models, then ore texture models can form the basis for predicting, simulating and controlling the time-dependent variability of the ore behaviour in the mill feed.

Richmond (1998) presented an approach to the spatial modelling of ore textures from suitable measurements, thus potentially enabling predictive ore control strategies to be implemented for ore processing. The modelling framework was founded upon four factors:

1. definition of ore textures at a practical scale (mesotextures),
2. Characterisation of spatial continuity of mesotextures,
3. stochastic simulation of mesotextures at a fine scale, and
4. construction of predictive mesotexture models at the required mining scale from the simulated fine scale textures.

Figure 2 shows examples of ore textures at various scales at the George Fisher Pb-Zn mine in Queensland, Australia. Metallurgical and mineralogical investigations had clearly demonstrated that metallurgical behaviour was a function of ore microtextural composition. However, it was not realistic to collect and model ore texture data at this scale. Consequently, and based on substantial mineralogical work, it was assumed that ore mesotextures, independent of their spatial location, were composed of the same relative abundances of ore microtextures. This assumption allowed practical measurement of implicit metallurgical behaviour at the core scale, which could then be increased further to the mining scale through the application of appropriate modelling techniques.

For the simulation of ore mesotextures, a new sequential 'growth' algorithm extending the so-termed sequential indicator simulation or SIS was developed. The method mimics a natural process of 'informed' growth in a spatial pattern and generates geologically plausible patterns. Figure 3 shows two simulated models of nine mesotextures over an area of 90 m by 150 m, both based on mesotexture data identified in the core of the same drill hole fan at the George Fisher mine. The simulated model of ore texture in Figure 3 (left) is based on the off-the-shelf SIS method and was considered by the mine's geologists as unrealistic for the textures encountered at the mine. Figure 3 (right) is generated with the sequential 'growth' algorithm mentioned above. Visually, the differences in the two images are clear and due to the ability of the new algorithm to better account for complex, short-scale spatial relations among the ore mesotexture types. The modified SIS algorithm was shown to be suitable for implementation and excellent in performance, thus potentially assisting with the spatial modelling of ore textures and the implementation of predictive ore characterisation and processing strategies.

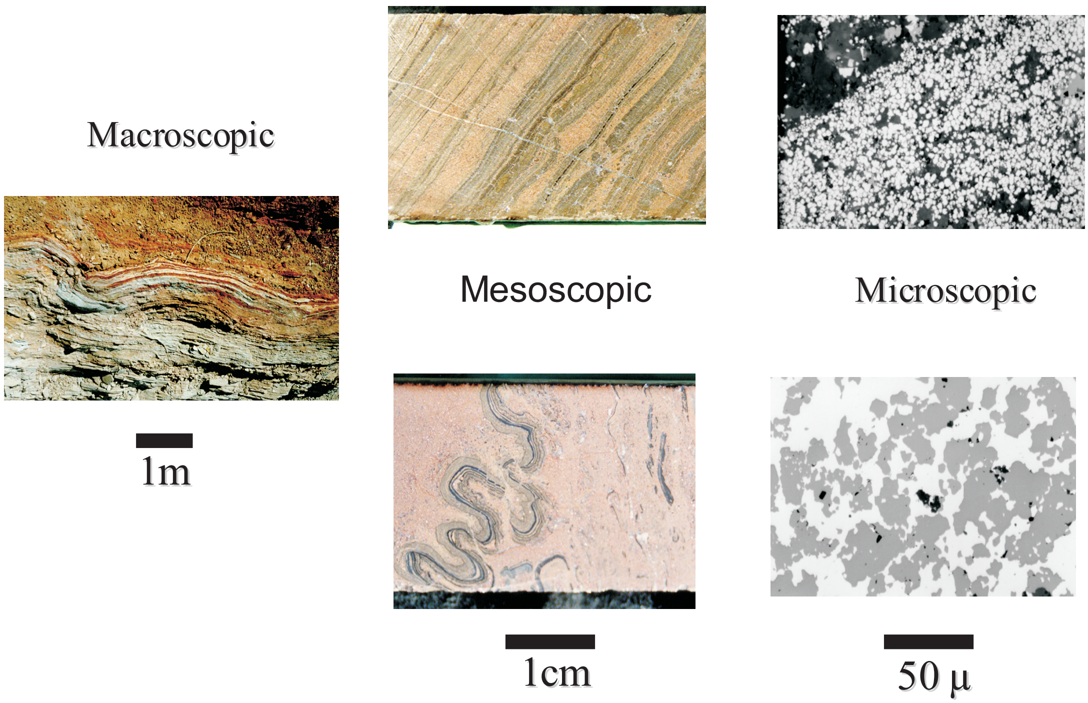

FIG 2 - Relationship between data and scale for ore textures at George Fisher mine.

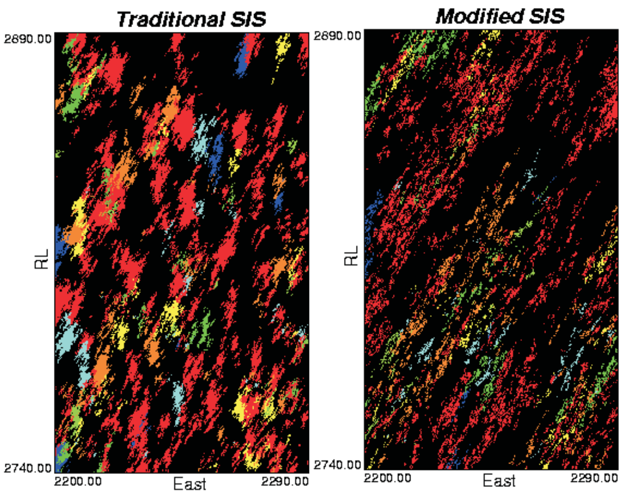

FIG 3 - Ore texture simulation generated by using: (left) the off-the-shelf SIS algorithm; and (right) the extended SIS algorithm with sequential 'growth'.

OTHER POTENTIAL MODELLING APPROACHES

Most well-known simulation algorithms (eg sequential Gaussian simulation, SIS, plurigaussian, turning bands, etc) reproduce only two-point statistics, leading to often poor reproduction of the true spatial characteristics of the phenomenon under consideration. The growth SIS algorithm described earlier improved implicitly the multiple-point statistics of the ore mesotexture simulations. However, simulation algorithms that consider multiple-point statistics explicitly (eg Strebelle, 2000) could be substituted if required. Alternatively, a pattern-based simulation algorithm (Arpat, 2005; Arpat and Caers, 2004) shows considerable promise for categorical variables such as ore textures.

Dealing with geometallurgical data of vastly different volume support is critical, especially when limited data is available for estimation. The authors typically see such information grouped together without due consideration or deliberate ignorance of the problem. Godoy (personal communication) 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) and relies on the selection of a model of coregionalisation that jointly honours linear data at all volume supports. 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.

For non-linear data one possible approach to geometallurgical modelling would be to retain the complete distribution of information using indicator-based geostatistical techniques. For these methods the probability of exceeding various thresholds is estimated. This has the benefit of turning non-linear data (when the full spectrum of data is considered) into multiple potentially linear data sets between adjacent thresholds, provided that the thresholds are appropriately spaced. At the very least, the poor outcomes that result from assuming non-linearity of the variable in question is minimised during any change of scale attempt. Single models of geometallurgical attributes can be generated by indicating kriging or one of its variants (probability kriging, indicator co-kriging, successive co-indicator kriging, etc). Alternately, multiple realisations of the attributes could be generated through SIS or more rapidly by successive co-indicator simulation (Vargas-Guzman and Dimitrakopoulos, 2002, 2004).

Kaolin brightness is a non-linear variable that has been successfully modelled for mining operations (Peroni, Costa and Koppe, 2000, 2003). For this work, data was transformed using the Kubelka-Munk function $(F(R)=[(1-R)2]/2R)$, then conditional simulation proceeded in transformed space. Finally the simulations were transformed back into real space with the Kubelka-Munk function. Critically, the Kubelka-Munk function is known to be scale (volume) invariant.

Power averaging based on experimental calibration has been applied successfully to averaging permeabilities in oil reservoirs (eg Deutsch, 1986; Journel, Deutsch and Desbarats, 1986). Power averaging is a non-linear averaging technique based on a power law, where $ave^w=ave(values^w)$.

CASE STUDIES

Without specifically mentioning the operations, the following examples show the range of issues that could be addressed by geometallurgical modelling and the consequences of insufficient understanding of the relationship between geology and metallurgy (or mineral processing).

Copper sulfide ores

During a major expansion of a copper project in South America there was extensive evaluation of the Mineral Resource, Ore Reserves and various other aspects that may affect the economics of the expansion. Extensive geometallurgical work was undertaken to evaluate the relationship between hardness, crushing and grinding. An unexpected consequence of the mine expansion was the appearance of more clayey ore in one corner of the pit. This was found to have a high talc content that resulted in suppressed copper recovery (quickly recognised and well managed) but also created more slimes in the tailings dam. Difficulties in dewatering such slimes would have a significant impact on water use, the volumes estimated for tailings storage, the environmental permitting to enable further tailings storage, and possibly the mine life. The geometallurgical approach to solving this problem was to consider the source of the problem material, map and model it in 3D and then integrate this material into the mine schedule in such a way that blending could reduce the impact of the material in generating slimes. The geometallurgical studies in this case included geology, mineralogy (using PIMA spectroscopy to identify the clay minerals) and bench scale metallurgical test work. The mining solution was a consequence of a better understanding of the orebody and how it behaved in the mill.

Magnetite ores

Magnetite ores are frequently defined using the Davis Tube test that determines the amount of mineral retained in a magnetic field after grinding and washing under controlled physical conditions. This retained material is then available for determination of the chemical composition of the material expected to be produced by the metallurgical processing plant. The value of doing many samples is that the relationship between magnetite and silica at mineral grain boundaries may vary locally in the deposit. This spatial variability can be defined using many small, equivalent samples, perhaps related to geological features in the deposit, and modelled using geostatistical estimation techniques. A Satmagan test is a physical test that defines the amount of magnetite in a drill sample but does not provide a concentrate for assay.

Bauxite ores

Bauxite ores are easily defined in terms of their whole rock chemistry and mineralogy; however, predicting the performance of ores in a plant using the Bayer process depends on the demand for caustic soda. So geologists spend considerable time trying to determine and predict the reactive silica ($RxSiO_2$) and the available alumina (ABAE), which varies depending on the temperature adopted during measurement.

Various

The need to predict the particle sizes or agglomeration characteristics for heap leach operations (gold projects in Western Australia (WA) and laterite nickel project in Queensland); the relationship between talc, arsenic and nickel (sulfide nickel projects in WA); or the impact of narrow subvertical enargite veins on arsenic grades in Chilean porphyry copper deposits indicate the many interacting factors that may impact on plant performance.

CONCLUSIONS

There are many cases in mining where identification of the geology, chemistry and the ore minerals is relatively simple, but the prediction of the behaviour of the whole rock in the metallurgical process is very complex. As geometallurgical modelling becomes more mainstream we need to ensure that the mining community does not become disillusioned with the results due to poor modelling practices. The authors have audited several geometallurgical models in which non-linear variables have been treated as linear implicitly by the selection of estimation method. These and other geometallurgical models have commonly been discredited during reconciliation studies. For example, Ashley and Callow (2000) described several case studies in which poor geometallurgical investigations led to inadequate plant design. All of these examples were traced back to poor sample selection and representivity issues.

The current challenge is to gain widespread acceptance of geometallurgical modelling using robust geostatistical techniques. Some key issues include:

1. Cross-discipline teams are typically required to address all components.
2. The issue of non-additive data is considered explicitly in the modelling process.
3. Few estimation techniques are directly applicable to geometallurgical attributes.
4. Geometallurgical models need to be generated at a suitable mining scale.
5. Procedures used for change of scale are either in linear space or are scale invariant.
6. The geometallurgical models are initially required to support long-term strategic planning. However, strategic metallurgical decisions will only have value if the same decisions can be made tactically in the grade control environment.

The question is how are we are going to get there?

REFERENCES

Arpat, B, 2005. Sequential simulation with patterns, PhD thesis, Stanford University, 166 p.

Arpat, B and Caers, J, 2004. Multiple-scale, pattern-based approach to sequential simulation, in *Proceeding 2004 International Geostatistics Congress*, Banff, 26 September - 1 October.

Ashley, K J and Callow, M I, 2000. Ore variability: Exercises in geometallurgy, *Engineering and Mining Journal*, 201(2):24-28.

Deutsch, C V, 1986. Estimating block effective permeability with geostatistics and power averaging, SPE paper 15991, 32 p.

Godoy, M, 2002. The effective management of geological risk in long-term production scheduling of open pit mines, PhD thesis, The University of Queensland.

Godoy, M, **YEAR**? Personal communication.

Journel, A G, Deutsch, C and Desbarats, A, 1986. Power averaging for block effective permeability, SPE paper 15128, 6 p.

Peroni, R, Costa, J F and Koppe, J C, 2000. New mine planning strategies applied to kaolin deposits, in *Proceedings Sixth International Geostatistics Congress* (eds: W J Kleingeld and D G Krige) Cape Town, pp 798-806.

Peroni, R, Costa, J F and Koppe, J C, 2003. Considering *in situ* grade variability during mining sequence, in *Proceedings 31st APCOM 2003*, 4 p (Southern African Institute of Mining and Metallurgy: Metallurgy).

Richmond, A J, 1998. Multi-scale ore texture modelling for mining applications, MSc thesis, The University of Queensland, 190 p.

Strebelle, S, 2000. Sequential simulation: Drawing structures from training images, PhD thesis, Stanford University.

Vargas-Guzman, J and Dimitrakopoulos, R, 2002. Successive conditional simulation of random fields by residuals, *Mathematical Geology,* 34(5):597-611.

Vargas-Guzman, J and Dimitrakopoulos, R, 2004. A new spatial stochastic simulation method for modelling ore textures, SMI research grant 12, final report part 1.