Beyond Kriging: Applying Geostatistics to Geometallurgical Optimization

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A proper geometallurgical optimization of an ore deposit beneficiation process requires knowledge of a large set of relevant properties (from simple ore grade to complex textural parameters, from deportment to mineral grain size distributions) for all blocks of the deposit, not only their average values, but also their variability within the deposit and, even more importantly, their uncertainty. If a model of the monetary gain derived from processing each block via a particular method is available, then the expected gain for each possible processing can be approximated (integrating this uncertainty), and the best processing can be derived by selecting the option that maximizes the expected gain. This mathematical concept of geometallurgy can be applied to the entire deposit to derive the best global processing, but it can also be used to lead an adaptive processing structure if a spatially resolved block geometallurgical data base is available. This requires extending the geometallurgical measurements (e.g. data from MLA, Mineral Liberation Analyser) from the available samples to the whole deposit. This contribution proposes a workflow for this spatial interpolation task, integrating uncertainty derived from this interpolation process and thus enabling appropriate block gain calculation and informed processing choices.

Most of the work on the spatial interpolation of geometallurgical parameters is based on kriging techniques, i.e., the unbiased estimation of these parameters on un-sampled blocks. Unfortunately, given the non-linear nature of most useful gain functions, such unbiased property estimates lead to suboptimal processing choices as the gain estimates are biased. Our procedure is based on geostatistical simulation and on scale assessment principles and results in a better modelling of the geological variability of each parameter. This applies to data in percentages (mineral composition, chemical composition, element deportment, surface contact between minerals), to distributions (of particle or grain sizes), to textural information (e.g., spread of major axis orientation in schistose ores).

The procedure proposed is illustrated with a toy case study based on a high-grade iron ore deposit hosted by BIF (K-Pit, Koolyanobbing greenstone belt, WA). In a simplified approach, the existing geochemical information (spatially much denser than any possible MLA database) is transformed to the composition of four material types (hematite ore facies, deleterious minerals in hematite facies, chert and shale), and these are geostatistically simulated 10000 times over the whole domain. Then a processing model allowing four different combinations of processes (desliming on/off together with two different flotation cost schemes), is used to calculate the expected gain for these options, integrating over the simulations. The result is an optimal processing selection for each block (including no processing if all four gains are negative). These can be represented as a block model of which parts of the deposit should be sent to each of the four processing routes, and which left on place. Moreover, a comparison of the gains with those obtained from a naïve kriging procedure showed that the proposed procedure can be the key to the economic efficiency for an ore deposit.