Integrating Machine Learning and Conditional Simulation for Geometallurgical Block Modelling: A Case Study from the Resolution Copper Project

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Block models used for mineral resource estimation and grade control are fundamental to mine planning and design. Traditionally, these models focus on revenue-generating metals and follow well-established industry standards such as JORC and NI 43-101. However, as orebodies become more complex and lower in grade, the need to consider non-revenue-generating geological features in block models becomes increasingly important. These include deleterious elements (e.g., arsenic), minerals that impede processing (e.g., talc), and physical properties (e.g., rock hardness) that influence recovery, throughput, and energy consumption. Geometallurgy addresses these considerations by linking geological characteristics to metallurgical performance and overall project economics.

This study introduces an integrated geometallurgical modelling approach applied at the Resolution Copper Project, focusing on rock hardness as measured by Bond Work Index (BWi). To overcome the challenge of sparse BWi test data, machine learning techniques were used to predict BWi values from well-sampled geological variables. A Gradient Boosting Machine (GBM) was developed using six key geochemical predictors (Al, Be, Cs, Mg, Mo, Zn) and lithology. The model achieved strong predictive performance ($R^2 = 0.75$; RMSE = 1.2 kWh/t).

To account for spatial variability and uncertainty, geostatistical simulations were conducted. Lithology was simulated using the Hierarchical Truncated Pluri-Gaussian method, while continuous variables were transformed via Projection Pursuit and simulated using the Turning Bands method. These simulations preserved multivariate relationships and spatial continuity.

The trained GBM was applied to the simulated datasets, generating a geometallurgical block model of BWi that captures both spatial variability and uncertainty. This model enhances predictive capacity for mill throughput and supports better-informed mine planning decisions. The study demonstrates how integrating machine learning with geostatistics enables the creation of practical and predictive geometallurgical models, adding substantial value to resource development and operational planning.