Recoverable resource estimation for an underground manganese project using multivariate conditional simulation with scenario reduction

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ERAMET is conducting a strategic technical study of the Mukulu deposit in the Kalahari Manganese Field in the Northern Cape Province, South Africa. The study aims to ascertain the feasibility of opening an underground mine to exploit two manganese ore units (the upper and lower bodies) in the Hotazel Formation.

Given the geometry of the two manganese orebodies, a 2D estimate for Mn and all secondary variables would seem appropriate strategy, but mining engineering considerations (*e.g.* economic optimization under the constraint of fixed mining widths) require three-dimensional analysis.

Following a succession of methodological studies carried out by Geovariances in collaboration with Eramet in 2014, a new iteration of the resource estimate based on an original approach was conducted in 2015 to be integrated to the Feasibility Study (FS) of the mining project.

The rationale for this final iteration of the FS resource model is to:

- Co-simulate Mn, Fe, and bulk density at the selective mining unit (SMU) level by direct block co-simulations
- Estimate the secondary variables (MgO, SiO_2, CaO, and P) at panel level (a panel is a multiple of SMUs assuring a sufficient quality of estimation given the drill spacing) and migrate the estimated values to simulated SMUs
- Select a series of realizations using a scenario reduction algorithm developed for the Eramet Group (S2RM) to summarize the most likely situation
- Post-process the selected realizations in order to compile the necessary grade-tonnage curve tables for FS evaluation integrating the underground mining technical constraints.

The paper presents the necessary theoretical elements for understanding the estimation strategy followed. It focuses on practical aspects of the case study, in particular the application of a scenario reduction algorithm to pick a representative subset of a few simulations to help appraise the risk attached to the downstream (reserve optimization, mine sequencing) phases of the project.

Keywords: direct block simulations, multivariate, scenario reduction, underground recoverable resources.

Introduction

ERAMET is exploring new potential manganese sources outside of its flagship deposit at Moanda in Gabon, Central Africa. As part of this diversification strategy, ERAMET is conducting a strategic technical study of the Mukulu deposit in the Kalahari Manganese Field (KMF) in the Northern Cape Province, South Africa in cooperation with Main Street 778, a black economic empowerment (BEE) company that owns the mining right

The Mukulu manganese orebody lies at a depth of more than 400 m, and the overburden includes at least 50 m of sands from the Kalahari cover. ERAMET is studying the feasibility of opening an underground mine to exploit two manganese bodies (the upper and lower bodies) in the Hotazel Formation.

The KMF is located in the Paleoproterozoic Griqualand West Basin. This sedimentary basin occupies the northwestern corner of South Africa and lies on the western margin of the Archaean Kaapvaal Craton (Figure 1). In this large region, the KMF represents only a small sub-basin located in the northern part of the Griqualand West Basin. The KMF is an elongated NNW-SSE trending basin approximately 40 km long and 15 km wide (Grobbelaar *et al.*, 1995).

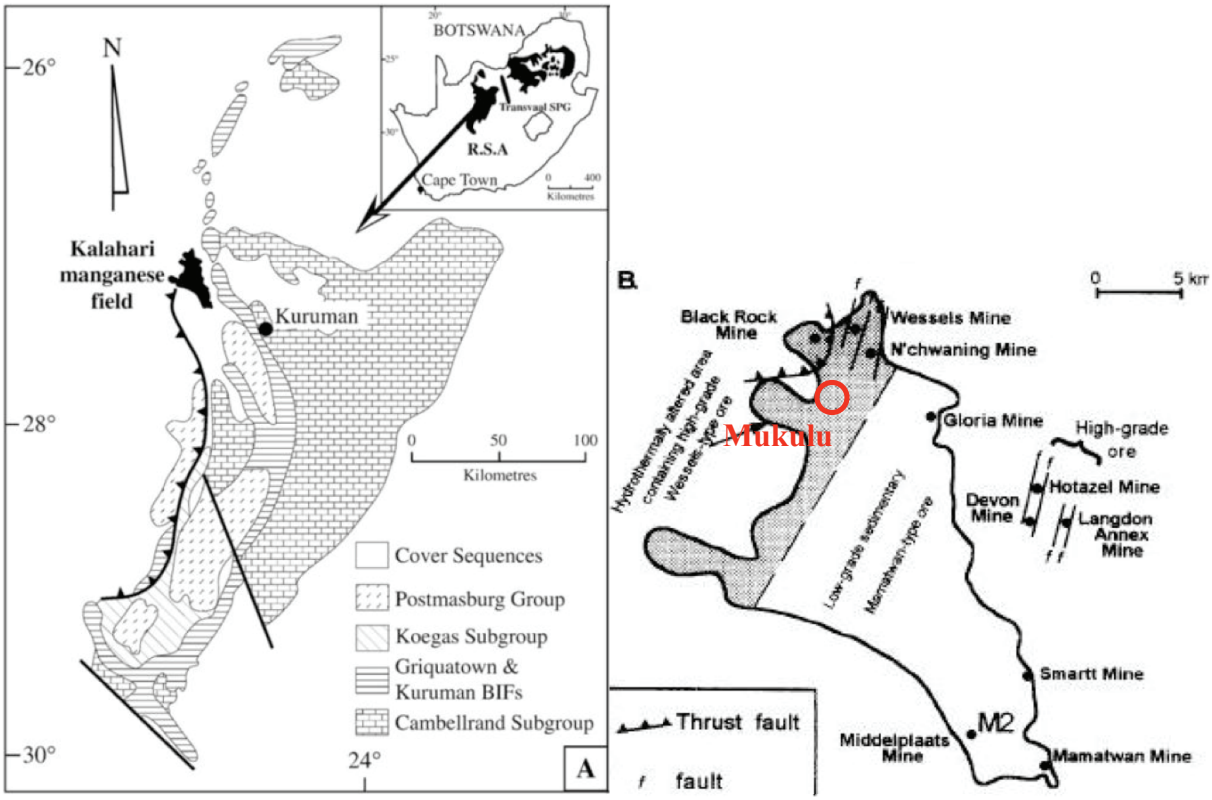


Figure 1 – (A) Location of the Griqualand West Basin on the Kaapvaal Craton (after Tsikos et al., 2010) and (B) Location of the Mukulu Mine and limits of the KMF sub-basin with the main structures and mines (Gutzmer and Beukes, 1996)

The Mn-bearing Hotazel Formation lies conformably on the Ongeluk Formation lavas (Polteau *et al.*, 2006 p. 264). The Hotazel Formation is composed of four banded iron formation (BIF) units alternating with three Mn-lutite bodies for an average thickness of 70 m. Of the three manganese bodies present in the Hotazel Formation only two layers have been modelled: the upper and lower body (referred to here as the UMO and LMO: upper manganese ore and lower manganese ore). The LMO ranges from 5 to 45 m in thickness and is of the most economic interest; the UMO is 5 m thick.

A series of methodological studies was carried out by Geovariances in collaboration with ERAMET in 2014 to reach pre-feasibility Resource status. A two-dimensional (2D) approach based on the estimation of mineralization thickness and accumulation appeared a robust choice of estimation method given the stratiform nature of the mineralization.

Projection of the 2D model for Mn and all secondary variables (Fe, MgO, SiO_2, CaO, and P) into three-dimensional (3D) space was required for mining engineering considerations. This was achieved as follows.

- Projection of the footwall surface upwards to form LMO and UMO hangingwall surfaces, using estimated thicknesses
- The hangingwall and footwall surfaces were then been used to select blocks of 50 cm height amenable to 3D estimation, using 50 cm composites.

Eventually, a post-processing based on convex analysis was implemented to characterize the grade-tonnage curve relationships attainable under certain mining hypotheses (minimum average manganese grade, minimum width mining cavities). The Convex Analysis functionality is a module of Isatis software, developed by Geovariances, and is designed to select from a 3D block model with estimated grades the blocks to be mined according to the following criteria:

- The metal quantity (Q) for a given extracted tonnage (T) is maximized
- The average grade is above a minimum target grade
- Simple mining constraints are fulfilled: the extracted ore at a given (X, Y) location is made up of a contiguous sequence of blocks within the footwall and hangingwall surfaces.

The optimization is based on convex analysis. If we consider a pile of n blocks from the hangingwall to the footwall, there are n possible 'projects' recovering from 1 to n blocks. These projects are nested because the project i+1 is the project i plus the next block at the bottom. The method consists of computing the $Q(T)$ representation of the pile and selecting the projects on the convex envelope for that curve meeting the criterion defined by the target mean grade of the considered mineral.

The kriging interpolator utilized to implement the 2D estimation method was unable to reproduce the true variability of grades, which translated into smoothed estimates. The application of an economic cut-off grade to the results resulted in dramatically reduced tonnages.

In a second study, localized multivariate uniform conditioning (LMUC) was used to better reproduce the true variability of estimated selective mining units (SMUs) (see Deraisme, 2011 for technical details on LMUC). However, the characterization of uncertainty is not available using the above method. This motivated a third study, where Mn and Fe were simulated through accumulation variables and density. Mining constraints were applied to five simulated scenarios selected to be representative of the whole set using scenario reduction. Scenario reduction refers to the methodology that allows the selection of a subset of realizations from a complete conditional simulation platform. The central idea of the algorithm is to characterize the difference between any two realizations by integrating, over all the panels, the difference in recoverable metal quantities between the two realizations for all the cut-offs. Once a dissimilarity matrix has been established for the simulation platform, a combinatorial based on k-mean clustering is used to select the k (here k=5) simulations that best capture the space of uncertainty as characterized by the total number of realizations.

In other words, the scenario reduction algorithm is built as follows:

- An appropriate way of measuring the distance between the initial set of scenarios and the reduced set (together with their associated probabilities) is first introduced
- A computationally efficient way of selecting the best set of k simulations out of the initial N simulations is then implemented in order to select the five simulations that best portray the range of possible outcomes.

A detailed presentation of the underlying concepts is given by Armstrong *et al*. (2013, 2014).

The results presented here come were obtained using the scenario reduction plugin (named S2RM) built in Isatis software (see Bleines *et al*., 2012).

The method for this final iteration of the FS resource model was thus:

- Co-simulate Mn, Fe, and bulk density at SMU resolution by direct block co-simulations
- Estimate, using ordinary kriging, the secondary variables (MgO, SiO_2, CaO, and P) at panel level (a panel is a multiple of SMUs assuring a sufficient quality of estimation given the drill spacing) and migrate the estimated values to simulated SMUs. This approach was motivated by the lower density of information for the secondary variables and a need to ensure maximum performance of the geostatistical model used to simulate the primary variables
- Select a series of realizations out of the simulation platform using a scenario reduction algorithm developed for the Eramet Group (S2RM)
- Post-process the selected realizations in order to compile the necessary grade-tonnage curve tables for FS evaluation, integrating the underground mining technical constraints.

The SMU XYZ dimensions are 41.25 m × 62.5 m × 0.5 m, and the panel dimensions 165 m × 250 m × 0.5 m.

Estimation geometry by the flattening of data and grid

The tectonic framework of the KMF is such that the Mukulu deposit is disrupted by a N-S graben structure passing that has generated large vertical displacements of the mineralization (Figure 2). A series of secondary faults further modifies the mineralization geometry, without necessarily remobilizing mineralization (if remobilization occurs it remains localized near the main structures). As a consequence, the estimation geometry must be reconstituted by a flattening procedure that uses the footwall of both units as a reference marker (Figure 3).

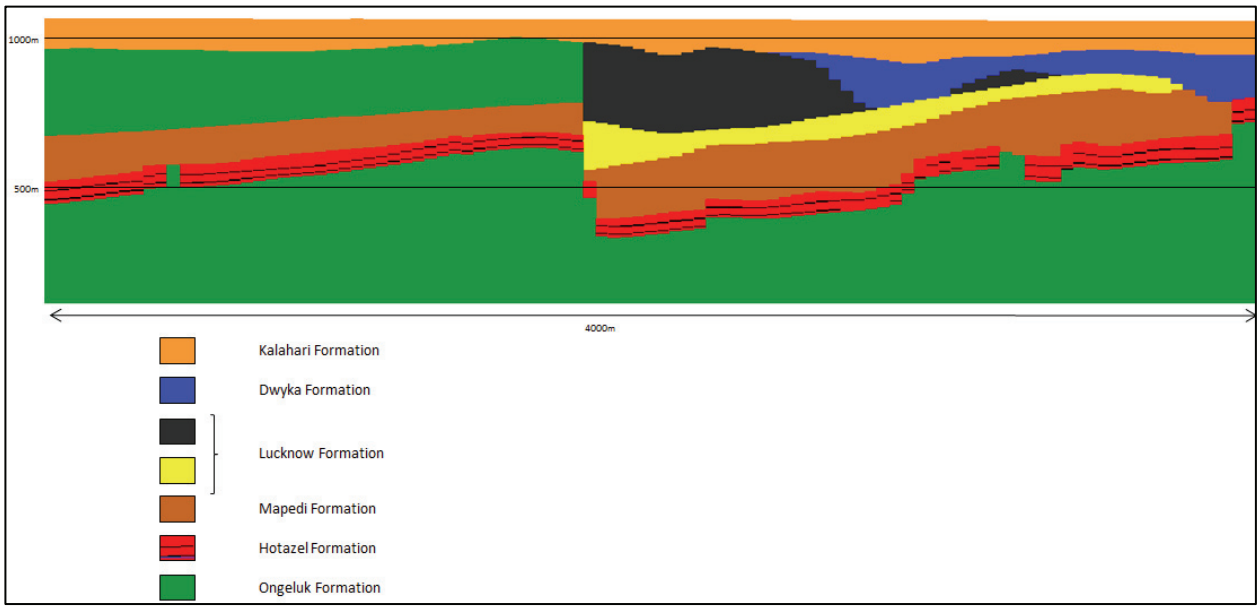


Figure 2 – Vertical displacements of the Hotazel Mn-bearing formation

For the LMO and UMO layers, kriging of the layer thickness is based on variogram models fitted to the experimental variograms, adjusting the nugget effect value to acknowledge the continuous nature of the variable. The nugget effect is fitted lower than the intercept of the Y axis given by a direct extrapolation of the variogram behaviour at short distances (Figure 4).

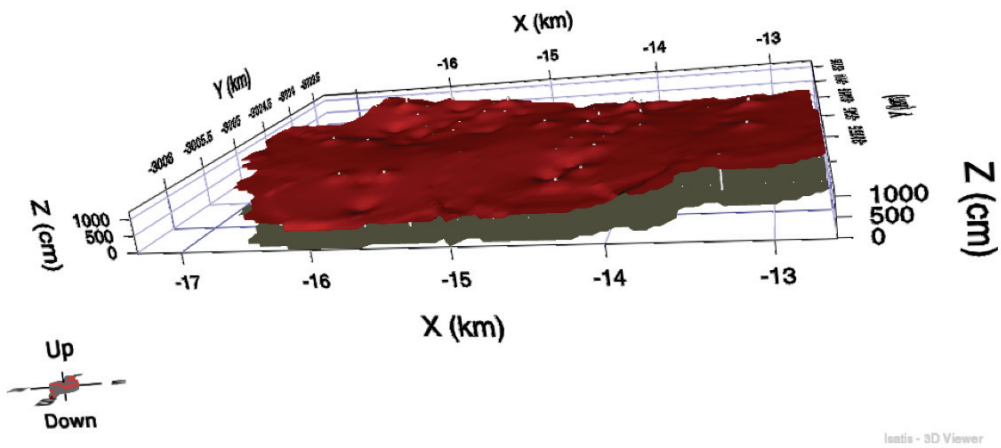


Figure 3 – Green surface represents the LMO footwall at Z=0 m, red surface is the estimated hangingwall in the flattened space

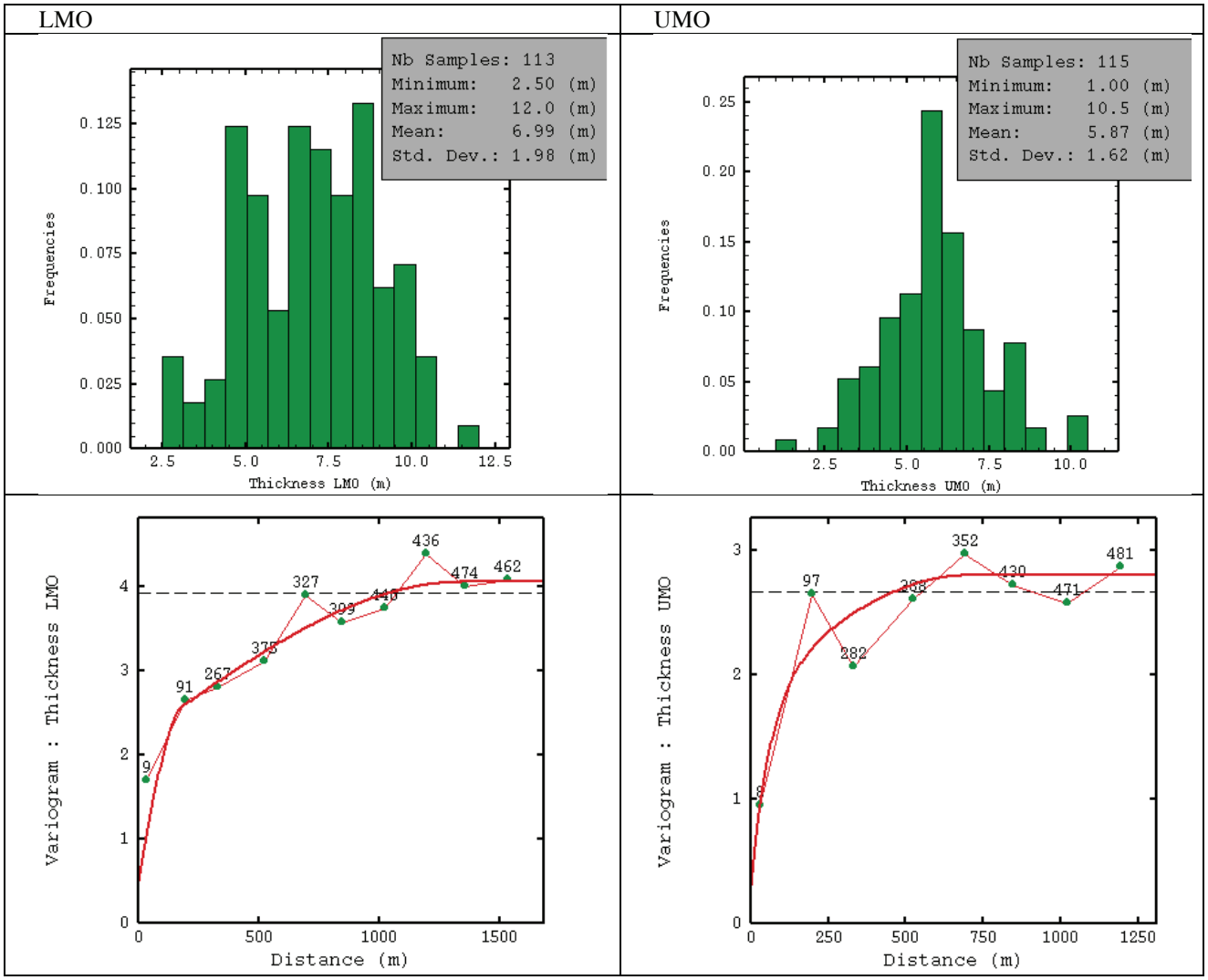


Figure 4 – Thickness histograms and variograms for LMO and UMO domains

Production and validation of the multivariate block simulations

Multivariate turning-bands block simulations (see Deraisme *et al*., 2008) were performed on the blocks (SMUs) for Mn, Fe, and density variables.

The steps used in this simulation workflow were (Figure 6):

- Transforming raw accumulation variables (product of grade and density) into their Gaussian equivalents through Gaussian anamorphosis
- Calculation of horizontal variograms and down-the-hole variograms on Gaussian equivalents
- Turning bands co-simulations on Gaussian equivalents
- Back-transforming of the Gaussian simulated equivalents into raw simulated accumulation variables
- Averaging of the raw accumulated variables to obtain raw block simulated values
- Calculation of grade simulated variables by computing the ratio (accumulation simulation)/(density simulation).

Variography was performed on Gaussian transforms. Gaussian model variograms were fitted before being back-transformed into raw variograms.

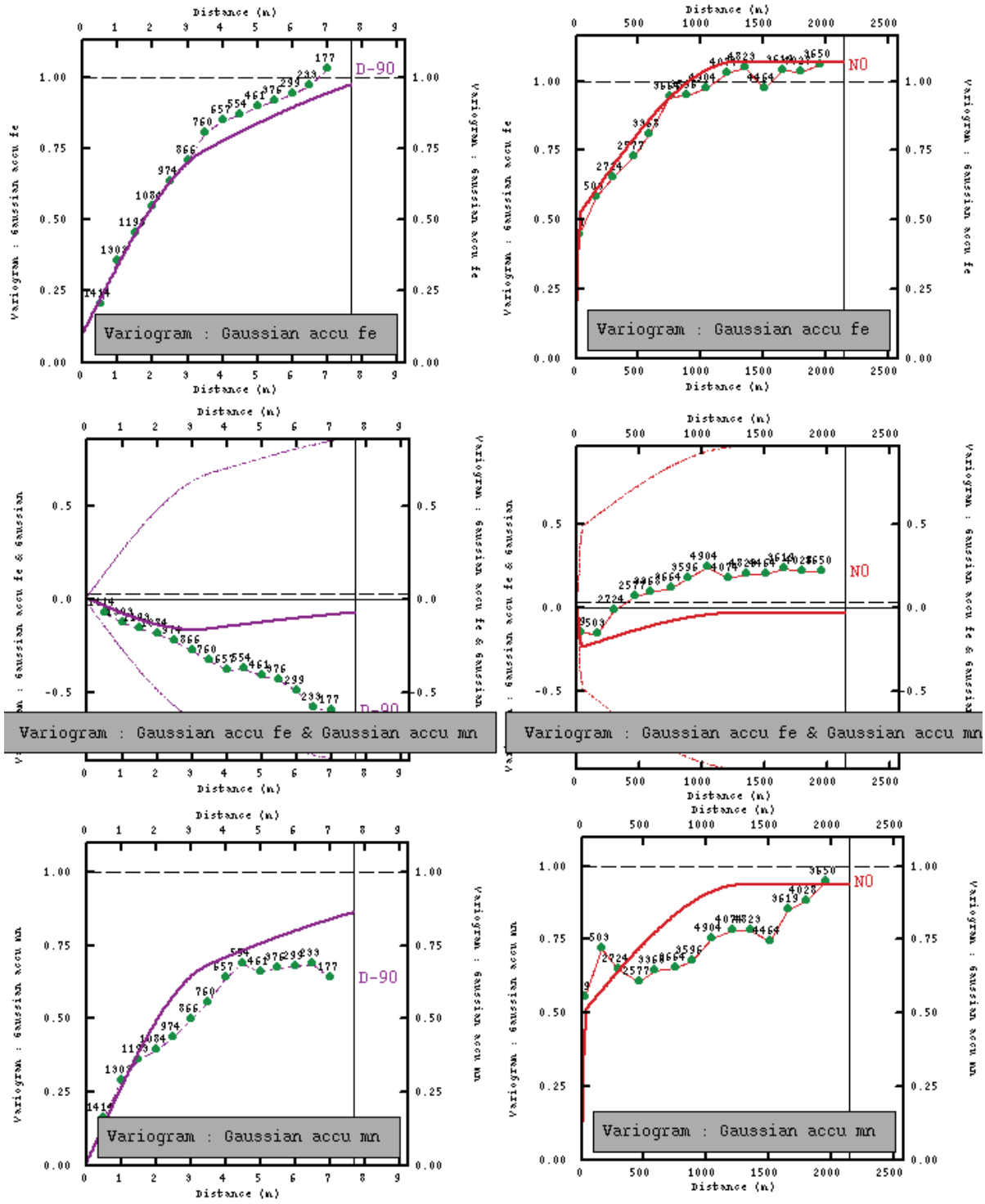


Figure 6 – Model of the Gaussian transforms of accumulation Fe (first row), accumulation Fe-Mn (second row), and accumulation Mn (third row) for LMO. Horizontal plane (first column) and vertical direction (second column) are represented

One hundred simulations were generated per unit using 1000 bands and a conditioning neighbourhood of 40 composites found within the following ranges of 700 m × 700 m × 15 m.

A statistical validation process was performed on the produced realizations. Basic statistics, histograms, and directional swath-plots were computed. The latter show a very satisfactory reproduction of key input parameters by the simulations, as evident in Figure 7.

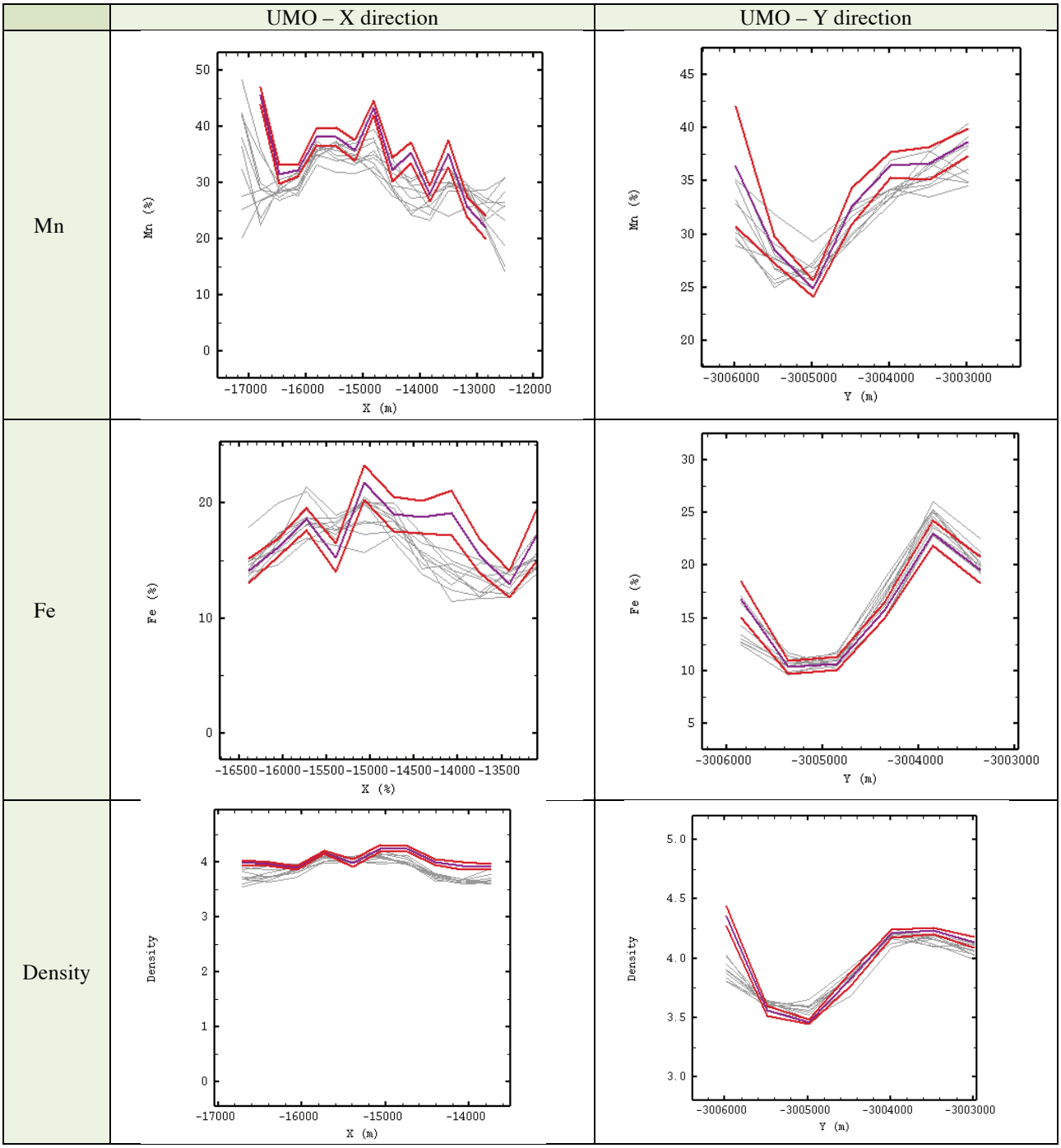


Figure 7 – X and Y directional swath-plots for Mn in UMO. Purple solid and red solid lines: data average, average +1 standard deviation, and average -1 standard deviation; grey lines: block simulations

Selection of a representative subset by simulation reduction

In order to post-process a manageable number of aptly selected realizations, the Isatis software scenario reduction algorithm (S2RM) (Bleines *et al*., 2012) was implemented on the full realization sets for each unit. The goal of S2RM is to allow the selection of a small group of realizations that is representative of the whole set of simulations. It was decided to select five representative realizations for both the LMO and the UMO.

To improve the selection efficiency a sampling of the combinatorial using genetic sampling (see Armstrong *et al*., 2014) was implemented. Different choices for the genetic sampling computation (number of parents, number of generations, number of mutations *etc*.) were tested (16 different combinations).

For each of the 16 combinations, the set of the five best realizations was selected, with the probabilities associated to each realization. As different sets of best simulations were created, it was necessary to find a way to select the scenario. The scenario eventually selected was the one offering the best sampling of the range covered by 100 co-simulations on the global grade-tonnage curves. Overlays of the grade-tonnage curves from the 100 simulations with the five best simulated scenarios were generated (see Figure 8 for the LMO unit) for each combination to facilitate the decision.

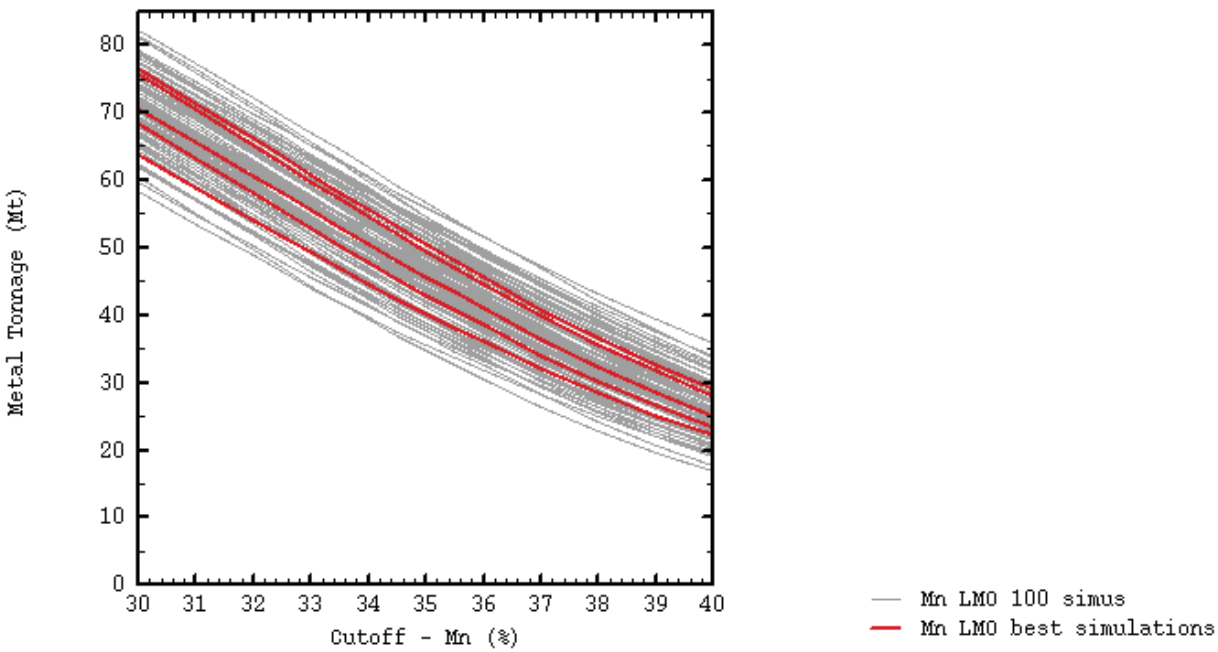


Figure 8 – Overlays of grade-tonnage curves for LMO unit. Grey curves are the 100 simulations; red curves are the five best selected simulations by S2RM

The five realizations (numbered by their Isatis software index) finally selected were:

- For LMO: 51, 53, 63, 65, 94 with associated S2RM probabilities, which indicate the representativeness of each realization, of 38%, 1%, 49%, 11%, and 1%
- For UMO: 6, 27, 33, 40, 79 with S2RM probabilities of 41%, 12%, 13%, 34%, and 1%.

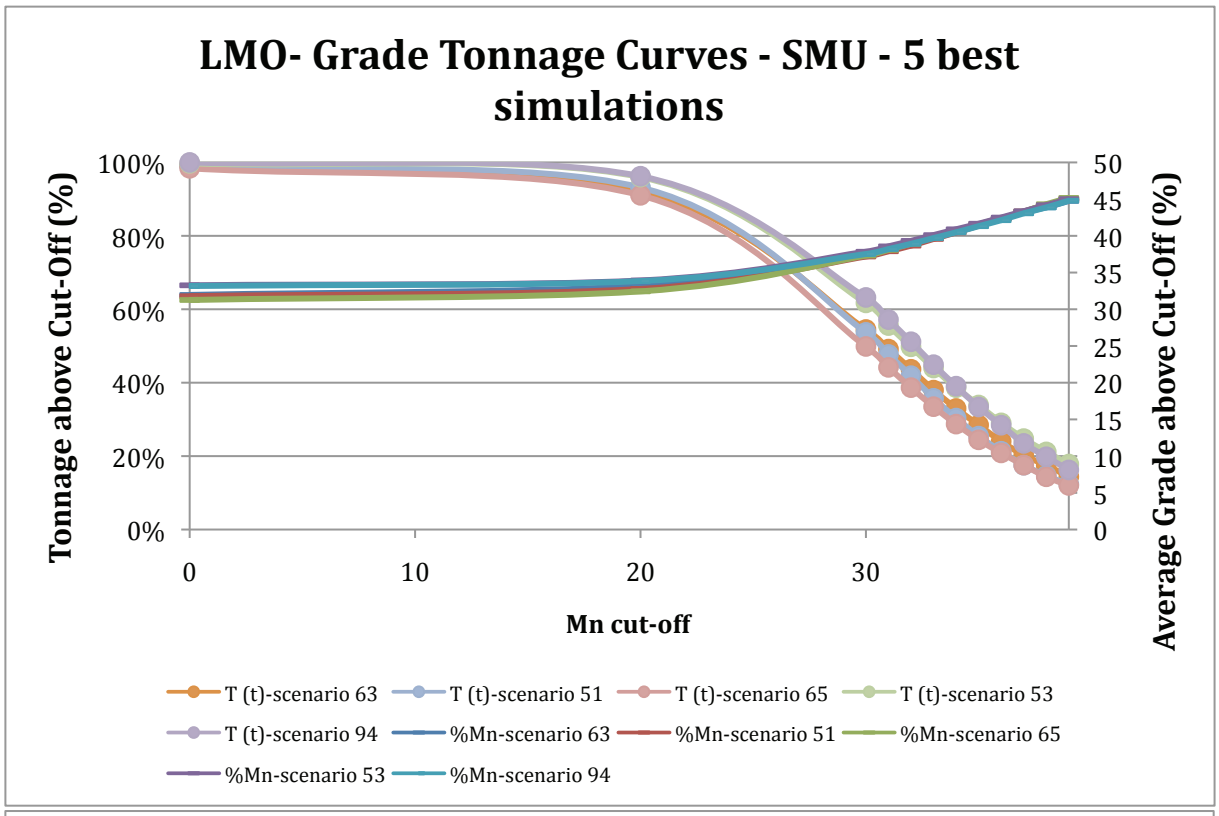
Estimation of the four secondary variables (CaO, MgO, P, SiO_2) via the ordinary kriging estimation of their accumulation values and density was performed on 3D panels (165 m × 250 m × 0.5 m) prior to being migrated on the SMU model.

In order to compute the metal quantity (*Q*), ore tonnage (*T*) and mean grade (*M*) above cut-off based on the S2RM realizations it was necessary first to post-process each of them for the creation of mining selections.

The five S2RM realizations per unit were treated to perform mining post-processing aimed at selecting the SMUs satisfying dual operational constraints: economic cut-off applied on Mn and minimum width of the mining operation. That operation was performed by Eramet geologists using Surpac software. The flagged simulations were then used for *QTM* compilation at the following economic cut-offs: 20, 30, 31, 32, 33, 34, 35, 36, 37, 38, and 39% Mn.

Figure 9 display the cumulative grade-tonnage curves for Mn in both units for:

- The recoverable resource estimate obtained by weighting the processing of each selected realizations by S2RM probabilities
- Each selected realization (five per unit).



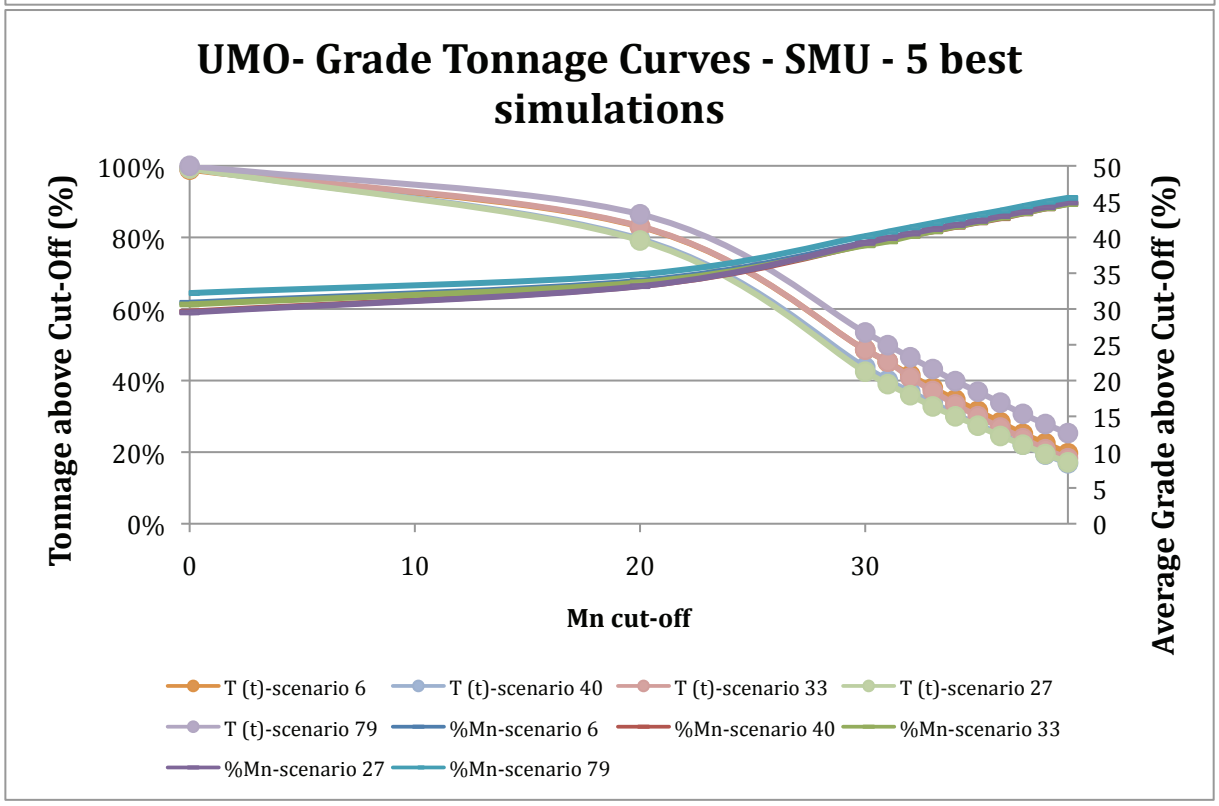


Figure 9 – LMO and UMO grade-tonnage curves for Mn recoverable resource estimate and each of the five scenarios selected with S2RM

Key results and conclusion

An interesting case study combining multivariate block simulations followed by scenario reduction and mining post-processing has allowed the characterization of the recoverable resource, the impact of the cut-off grade on the mining width, and the associated uncertainty of the Mukulu underground Mn deposit to be used as an input to the Feasibility Study.

The simulation platforms for both Mn units investigated were built for the key variables only, as they are more densely sampled than the secondary variables and inclusion of the secondary variables in the coregionalization would degrade the quality of the model for the main variables. The combination of simulated primary variables with estimated secondary variables at a different scale is a common feature of numerous resource estimates and did not represent a major challenge.

What proved to be interesting at this stage of the project evaluation was the ability to characterize the uncertainty around the central estimate provided by the simulation platform and the possibility of testing appropriately selected mining scenarios on each of the selected plausible realities. The corporate risk profile in particular can be safely integrated in that resource characterization process by relying on the probabilities calculated by the scenario reduction algorithm. This should allow the project steering committee to reach a decision using scenarios based on clear and robust estimates of the unknown mineable reality.

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