EVALUATION OF SAMPLING IN GEOMETALLURGICAL PROGRAMS THROUGH SYNTHETIC DEPOSIT MODEL

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ABSTRACT

The main purpose of geology is to develop a model to predict the variability in the mineral processing performance within the ore body. Geometallurgical tests used for developing such a model need to be fast, practical and inexpensive and include as an input data relevant and measureable geological parameters like elemental grades, mineral grades and grain size. Important in each geometallurgical program is to define the number of samples needed to be sent for geometallurgical testing to enable reliable metallurgical forecast. This is, however, a complicated question that does not have a generic answer.

To study the question on sampling a simulation environment was built including a synthetic ore body and sampling & assaying module. A synthetic Kiruna type iron oxide - apatite deposit was established based on case studies of Malmberget ore. The synthetic ore body includes alike variability in rock types, modal mineralogy, chemical composition, density and mineral textures as its real life counterpart. The synthetic ore body was virtually sampled with different sampling densities for a Davis tube testing, a geometallurgical test characterising response in magnetic separation. Based on the test results a forecast for the processing of the whole ore body was created. The forecasted parameters included concentrate tonnages, iron recovery and concentrate quality in terms of iron, phosphorous and silica contents.

The study shows that the number of samples required for forecasting different geometallurgical parameters varies. Reliable estimates on iron recovery and concentrate mass pull can be made with about 5-10 representative samples by geometallurgical ore type. However, when the concentrate quality in terms of impurities needs to be forecasted, the sample number is more than 20 times higher. This is due to variation in mineral liberation and shows the importance of developing techniques to collect qualitative information on mineral and ore textures in geometallurgy.

KEYWORDS

Sampling, synthetic ore body, simulation, geometallurgical testing framework.
INTRODUCTION

In developing the mineral resource estimates the information on the processability and its variability is collected quite late. Scoping studies deals almost only with geological data and the processing and mining information is considered only in pre-feasibility and feasibility study stages (The Australasian Institute of Mining and Metallurgy, 2012). Introduction of geometallurgy at early stages of the project can decrease level of uncertainty in the future project stages and consequently in production (Dominy, 2013).

Geometallurgy aims to develop a predictive model which combines geological and mineral processing information. This model is used in production planning, designing and management. It is expected to give benefits especially in low grade ores showing high variability in their processing properties. Such ores have high production risks which can manifest as low or negative profit margins if the operation is managed in a traditional way.

Development of a geometallurgical model requires access to a large number of samples that specify the processing properties. The basic knowledge and sample material collected by drilling, drill core logging and chemical assays is not sufficient. Additional characterisation techniques are needed. Geometallurgical tests, i.e. small tests which characterize the metallurgical properties and thus give quantitative information on the variability are commonly used. They need to be fast and inexpensive, they should use only small amount of sample but still they should reliably characterise processability. A number of geometallurgical tests are available for different areas of beneficiation. For comminution they include tests characterising crushability, grindability and forecasting throughput. Examples of such are geometallurgical comminution test (GCT) developed by Mwanga et al., (2015) and GeM Comminution index (GeMCi) described by Kojovic et al. (2010). For magnetic separation Davis tube test is frequently used (Murariu and Svoboda, 2003); for leaching different alternatives of leach performance test are available (e.g. Kuhar et al., 2011). For gravity separation the sample size is a problem, e.g. in the GRG test (Dominy, 2013; Zhou and Cabri, 2004). For flotation “shaker test” has been proposed by Vos et al. (2014) but it has not gained popularity.

Based on the test results a predictive model is created. As input parameters the model takes properties provided in the geological data set. Parameters like elemental grades (e.g. Cu wt%), mineralisation type and hosting lithology are commonly used. As an output the model gives production forecast: throughput, concentrate tonnages (mass pull), metal recoveries, concentrate quality parameters, tailing properties and economic key figures.

One problem in collecting such a data set is to select how many samples are needed for different assays and techniques to develop reliable geometallurgical model. If the number of samples is too small then the model can be inaccurate or even defective. By increasing the samples at some point the gain in prediction accuracy don’t justify the costs and time spent. Good sampling strategy is needed. It must take into account geological and metallurgical variability together with sampling (Gy, 1976; Minnitt et al., 2007), analysis and modelling errors (Bulled and McInnes, 2005).

Number of required samples for different characterisation methods in geometallurgical programs is a widely discussed topic. David (2014) recommended up to 30 variability samples for metallurgical testing in different mine design stages. Williams and Richardson (2004) assumed several hundred of samples for metallurgical and geometallurgical testing, more than a thousand of samples for mineralogical study and more than ten thousand of samples for traditional chemical assays. In a mineralogical approach the mineralogical information: mineral grades and texture properties, are required for several thousand of samples (Parian et al., 2015).

Adequate geometallurgical sampling requires good knowledge of the ore body. Geological database and block model accompanied by internal company expertise on both ore body and beneficiation process often provide solid basis for planning and conducting sampling campaigns. Yet, the fact that geological information is mostly qualitative and its quality if difficult to estimate, is a challenge. Therefore
primary sampling, mainly by drilling, and secondary sampling for geometallurgical testing is often an iterative process. Geological information is used as default information in classification and domaining but they are critically evaluated against the results of the geometallurgical tests.

There are several unanswered questions around the development of a geometallurgical model. How many samples are required? How the samples should be assayed? What kind of geometallurgical tests should be used and how many samples are needed? How qualitative information can and should be used? Is mineralogical information needed or does it give some benefits? How the domaining should be done or is it really needed at all? How the modelling should be done? In what details the model should go? How to estimate the error in the whole chain? What kind of error can be accepted in different stages?

It is obvious that there are no universal answers to above posed questions but they vary from case to case. Studying different alternatives and finding feasible solutions is slow and tedious with real case studies. A synthetic ore body and corresponding geometallurgical system could provide an environment where different scenarios could be tested effectively.

Previously the sampling problem has been studied with synthetic geological data by and Malmqvist et al. (1980). The focus was in mineral exploration and sampling for mineral resource estimation of deep sited sulphide ore bodies. More recent examples of simulation for reproduction of complex geological structures and behaviour of the spatial geological data can be found in Chatterjee and Dimitrakopoulos (2012) and Mustapha and Dimitrakopoulos (2011). Modelling by simulation is a well-documented practice commonly used in the mining industry to evaluate alternative process designs (see Everett 2001, 2007; Howard et al., 2005; Everett et al., 2010, Jupp et al. 2013a). Such modelling is typically undertaken as an optimisation study to increase the efficiencies and productivity of operating mines where actual short-term grade variability data are available from production records. In these cases the real data is used as an input data into the simulation of different scenarios. Jupp et al. (2013b) created a synthetic ore body model and used it in geometallurgy to study the most effective way to reduce the variability in daily scheduling system.

In all the previous studies the modelling of the ore body has been restricted to lithology, density and elemental grades. The processing properties have been almost totally excluded and therefore as such they are not suitable for a test bed to study different geometallurgical questions listed earlier. A simulated synthetic ore body for geometallurgy must satisfy three conditions: it must include processing properties; it must show realistic variability within synthesised data and there must be spatial cohesion between data. Additional parameters, such as constraints of a mining method, processing performance, and economic response would produce more realistic output. A synthetic geometallurgical testing framework (SGTF) is described in this paper as a solution for answering different geometallurgical problems. The framework comprises of synthetic ore body together with processing and economic models to represent the major part of the mine-to-metal value chain. The aim of this paper is to describe a new technique for planning geometallurgical sampling, testing and model building by application of the synthetic framework. This allowed describing the effect of geological and metallurgical variability on sampling strategy. Malmberget iron ore deposit in Sweden (Lund et al., 2013) was selected for the ore type to mimic.

**METHODOLOGY**

A geometallurgical system is a complex value chain comprised of geological, mining, mineral processing and other metallurgical downstream processes. The simulation environment developed here for studying geometallurgical questions is called synthetic geometallurgical testing framework (SGTF). Three modules of the synthetic framework were used in this study: synthetic ore body, sampling & assay module and process simulation. Study conducted within the developed framework included three phases: sampling; geometallurgical testing; sample re-classification and metallurgical testing (see Figure 1).
Synthetic Ore Body

Synthetic ore body of the framework was developed in Matlab. It allows generating a geological model of an ore body using mineralogical approach (Hoal et al., 2013; Lamberg et al., 2013; Lishchuk et al., 2015b). Geological description is a spatial model represented by the cloud of points within a defined volume. The smallest units, points, are called voxels and their size should be smaller or equal than smallest possible sample to be collected by drilling and sampling from the synthetic ore body. Description of the geological properties is given for each voxel including information on lithology, mineralogy, chemical composition, mineral textures (textural archetype) and specific gravity.

The lithology is modelled as a set of geometric shapes enclosing voxels. The grade of each commodity mineral in any given voxel is defined based on spatial grade model:

\[
\tilde{M}^D = P + S + T \rightarrow \begin{cases} 
\tilde{P} = f_p(x, y, z), \min P = a_P, \max P = b_P \\
\tilde{S} = f_s(x, y, z), \min S = a_S, \max C = b_S \\
\tilde{T} = f_T(x, y, z), \min T = a_T, \max T = b_T
\end{cases}
\] (1)

where, \(\tilde{M}^D\) is mineral grade in a given voxel; \(P\) is primary, \(S\) secondary and \(T\) is tertiary component. \(P, T\) and \(S\) are functions of coordinates \((x, y, z)\) of the point, \(a\) and \(b\) are the minimum and the maximum values of each component. \(\tilde{\cdot}\) indicates that parameter was not scaled to the defined range and \(f_p(x, y, z), f_s(x, y, z), f_T(x, y, z)\) are trigonometric functions that describe \(P, T\) and \(S\). The commodity mineral can be represented fully independent on lithologies. The reason behind generating commodity minerals separately from the lithology minerals was to have capability to describe the grade distribution of important minerals accurately.

After defining the grade of the main commodity minerals in each voxel the remaining mass differing from 100% is filled with lithology based minerals. For each lithology the average grade and standard deviation is provided for each mineral present. This information together with normal distributed random numbers is used to complete the modal composition.

The textural information of each voxel is provided by textural archetypes. For each type full mineral liberation information in certain particle size (distribution) is provided in a global library. Chemical composition of minerals by lithology is also provided in library. Derivatives of voxels like chemical composition, specific gravity, magnetic susceptibility and other mineral based properties are calculated for each voxel from the modal composition and the library data.
Using Malmberget as a Case Study

Synthetic ore body for this study was created based on Malmberget iron ore deposit located in northern Sweden (Lund, 2013). Malmberget ore is comprised of several ore bodies, mainly of massive magnetite. Iron ore grade is high, 51-61 % Fe. Magnetite and hematite are the main ore minerals. Apatite and actinolitic amphibole comprise main gangue minerals. The accessory minerals include biotite, albite, pyrite, chalcopyrite and titanite. The massive ore, high in Fe and low in SiO$_2$, is surrounded by a semi-massive mineralisation. The semi-massive mineralisation can be several tens of meters thick, occurring as rims or as inclusions in the massive ore with a decreasing iron grade. The main gangue minerals of the semi-massive ore are silicates, i.e. feldspars (albite and K-feldspar), amphibole, quartz and biotite in various proportions.

The massive ore has broad variation of mineral-texture relations. Both fine- and coarse-grain textures exist. Mineralogically semi-massive ore is composed of several different mineral assemblages, i.e. lithologies, with more complicated textures than the massive ore itself. Lund (2013) identified two main textural types of the massive ore: Amp-(Ap-Bt) and Ap-(Amp), and one textural type of semi-massive ore - Fsp.

The synthetic ore body was created by using one commodity mineral, magnetite, and three lithologies (Fsp, Amp and Ap) equalling three textural archetypes. These are referred as geometallurgical ore types. Four gangue minerals (albite, actinolite, apatite and biotite) were included. The average modal composition of each lithology type without commodity mineral (magnetite) is given in Table 1. The average composition of the ore after modelling the full mineralogy is given in Table 1. Mode of occurrence of magnetite in one size fraction (75-150 microns) of an average ore is given in Table 1 to illustrate how mineral liberation information was included in the model. The chemical composition of the minerals was taken from Lund (2013) and was defined to be identical in all lithologies. Spatial distribution of lithologies, i.e. textural types, in Malmberget (Lund 2013) and in the generated synthetic ore body is compared in Figure 2. The synthetic ore body mimics reasonably well the lithological variation in Malmberget.

Figure 2 – Spatial distribution of lithologies, the left image is from Lund (2013) and the right image was generated within the synthetic ore body.
Table 1 – Average modal composition of lithologies and average modal composition of ore types and mode of occurrence of magnetite in one size fraction, 75-150 microns.

<table>
<thead>
<tr>
<th>Lithology</th>
<th>Fsp</th>
<th>Amp</th>
<th>Ap</th>
</tr>
</thead>
<tbody>
<tr>
<td>Albite</td>
<td>52.1</td>
<td>9.6</td>
<td>7.7</td>
</tr>
<tr>
<td>Actinolite</td>
<td>25.5</td>
<td>68.7</td>
<td>8.6</td>
</tr>
<tr>
<td>Apatite</td>
<td>13.0</td>
<td>8.1</td>
<td>56.0</td>
</tr>
<tr>
<td>Biotite</td>
<td>9.4</td>
<td>13.6</td>
<td>27.7</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Geometallurgical ore type</th>
<th>Fsp</th>
<th>Amp</th>
<th>Ap</th>
</tr>
</thead>
<tbody>
<tr>
<td>Magnetite</td>
<td>75.7</td>
<td>71.6</td>
<td>75.8</td>
</tr>
<tr>
<td>Albite</td>
<td>12.7</td>
<td>2.7</td>
<td>1.9</td>
</tr>
<tr>
<td>Actinolite</td>
<td>6.2</td>
<td>19.5</td>
<td>2.1</td>
</tr>
<tr>
<td>Apatite</td>
<td>3.2</td>
<td>2.3</td>
<td>13.6</td>
</tr>
<tr>
<td>Biotite</td>
<td>2.3</td>
<td>3.9</td>
<td>6.7</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Geometallurgical ore type</th>
<th>Liberated</th>
<th>In composite particles with albite</th>
<th>In composite particles with actinolite</th>
<th>In composite particles with apatite</th>
<th>In composite particles with biotite</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fsp</td>
<td>95.9</td>
<td>2.2</td>
<td>0.5</td>
<td>0.5</td>
<td>0.4</td>
</tr>
<tr>
<td>Amp</td>
<td>94.5</td>
<td>0.5</td>
<td>0.8</td>
<td>1.9</td>
<td>6.5</td>
</tr>
<tr>
<td>Ap</td>
<td>89.2</td>
<td>0.8</td>
<td>6.0</td>
<td>0.9</td>
<td>3.0</td>
</tr>
</tbody>
</table>

Sampling and Assaying within the Synthetic Geometallurgical Testing Framework

Geometallurgical sampling within the synthetic geometallurgical testing framework implied two separate actions: primary sampling by drilling and secondary sampling by selecting parts of the drill cores. Simulated drill cores were created in MATLAB environment by giving the collar coordinates, final depth of the drill core, azimuth and dip of each individual drill core. Each drill core retrieved information available from the crosscut voxels of the synthetic ore body (Figure 3).

Voxels belonging to the same geometallurgical ore type, adjacent to each other and showing spatial continuity of metallurgical properties inside the ore body were referred to as domains (Hunt et al., 2014 and David, 2007). Assaying of simulated drill cores was performed by applying an error model for the chemical analysis. The error model was based on the precision and accuracy information given by Lund (2013) for XRF analyses. Standard deviation for each assay was computed as Hadamard product of elemental grades (G) and relative standard deviation (RSD) matrices (Equation 2). RSD for each element is given in equation (3).

\[
\begin{pmatrix}
G_{Al} & G_{Ca} & G_{Ti} & G_{Na} \\
G_{K} & G_{Mg} & G_{V} & G_{Fe} \\
G_{Al} & G_{Mn} & G_{P} & G_{S}
\end{pmatrix} \cdot \begin{pmatrix}
RSD_{Al} & RSD_{Ca} & RSD_{Ti} & RSD_{Na} \\
RSD_{K} & RSD_{Mg} & RSD_{V} & RSD_{Fe} \\
RSD_{Al} & RSD_{Mn} & RSD_{P} & RSD_{S}
\end{pmatrix} = \begin{pmatrix}
\sigma_{Al} & \sigma_{Ca} & \sigma_{Ti} & \sigma_{Na} \\
\sigma_{K} & \sigma_{Mg} & \sigma_{V} & \sigma_{Fe} \\
\sigma_{Al} & \sigma_{Mn} & \sigma_{P} & \sigma_{S}
\end{pmatrix}
\] (2)

\[
\begin{pmatrix}
RSD_{Al} & RSD_{Ca} & RSD_{Ti} & RSD_{Na} \\
RSD_{K} & RSD_{Mg} & RSD_{V} & RSD_{Fe} \\
RSD_{Al} & RSD_{Mn} & RSD_{P} & RSD_{S}
\end{pmatrix} = \begin{pmatrix}
1.0 & 3.2 & 1.0 & 2.0 \\
2.4 & 2.8 & 1.4 & 0.1 \\
2.0 & 1.1 & 0.7 & 6.5
\end{pmatrix}
\] (3)
Assays from the drill core samples were used to select the samples for geometallurgical testing. Initial hypothesis suggested that metallurgical performance can be linked to the lithology, i.e. geometallurgical ore types. Thus, geological parameters were isolated by clustering technique and assays of the drill core samples were classified by k-mean clustering algorithm (MacQueen, 1967). The Euclidean distance between the multivariate means of the \( n=2..N \) clusters was used as an indication of the difference between the geological parameters. Clustering for \( N=10 \) is presented in Figure 4, where elemental and mineral based approaches give almost identical results in classification.

Clustering was performed on normalised data by computing standard score for each input according to equation

\[
    z = \frac{x-\mu}{\sigma} \tag{4}
\]

where, \( \mu \) is the arithmetic average, \( \sigma \) is the standard deviation.

The results of the virtual Davis tube tests for selected samples were created using HSC Sim 7.1 process simulator (Outotec, 1974). For each sample sent for the virtual Davis tube test both modal composition and textural class information was provided. Based on this information the particle population of about 350 particles was generated in the simulator for given particle size distribution with \( \text{P}80=100 \) microns. For more information on how modal composition and liberation information of an archetype was combined for defining the feed stream see Lund et al. (2015). In the magnetic separation the separation of minerals was set perfect; for fully liberated minerals 100\% of magnetite was recovered into the concentrate and 100\% of gangue minerals ended into the tailing. For composite particles the simulator calculated the distribution value (recovery) based on recoveries of fully liberated particles and their mass proportions in a composite particle. The final outcome of the virtual Davis Tube test was the concentrate grade (Fe), its quality (P and Si contents), mass pull and iron recovery. Chemical composition of the concentrate produced was assayed by virtual XRF including the above described error model, thus the result generated in the virtual Davis tube included experimental error.

Real processing parameters were calculated in the same manner (but without experimental error) for all the voxels of the synthetic ore body since. These parameters are referred as “real parameters” or real case scenario (RCS). Geometallurgical sampling procedure was repeated several times by gradual increase.
of \( n \) from 2 to \( N \), until results from the test work converged with the real case (RCS). Results from the final iteration (\( N \)) were used to build a predictive geometallurgical model.

![Figure 4](image)

**Figure 4 – Classification of geometallurgical samples for mineralogical approach in top row (classification by magnetite (Mgt), apatite (Ap) and silica (Si) content); and for traditional head grade-approach in bottom row (classification by iron, phosphorous and silica content). Crosses show centres of different classes.**

### Geometallurgical Model

The main purpose of geometallurgy is to build a predictive model (Lamberg, 2011), and mineralogical approach is often used (Hoal et al., 2013; Lamberg et al., 2013; Lishchuk et al., 2015a, 2015b). In reality the Davis tube results are further scaled-up to forecast the full scale production results (Niiranen and Böhm, 2012). Here a simplification was made that Davis tube equals to the metallurgical result in a full scale process.

Two different approaches were used to build a geometallurgical predictive model: mineralogical – based on mineral grades; and elemental – based on elemental grades. Therefore, element to mineral conversion (EMC) (Parian et al., 2015) was done for obtaining modal composition for the ore body and Davis tube concentrate. Predictive model was based on the nearest neighbour algorithm and was predicting performance of each voxel based on iron, phosphorous, silica grade for the elemental approach and magnetite, apatite and silica grades for the mineralogical approach.

### RESULTS

A total of 200 sampling & geometallurgical testing campaigns were simulated ranging from 2 to 201 samples. Ten geometallurgical predictive models based on the nearest neighbour algorithm (for 2, 5, 10, 15, 20, 25, 30, 50, 100, 200 samples) were investigated and compared. Comparison was made for the prediction of concentrate quality and quantity, see Table 3. Prediction for iron recovery and total concentrate tonnages reaches acceptable level (<5%) already when 10 samples are used as a base of the prediction. Whether the estimate is done based on mineral or elemental grades does not show any significant difference. However, the prediction of the concentrate quality in terms of detrimental
components, i.e. phosphorous and silica, is much more sensitive. Even with 100 samples the error in the estimates of production of different quality products is quite bad, >5%. Only in 200 samples the required accuracy is reached.

Table 3 – Prediction on metallurgical performance based on 2-200 samples. Error gives difference between the real case scenario (100*forecast-RSC)/RSC.

<table>
<thead>
<tr>
<th>Samples N=</th>
<th>Prediction based on N samples % of ore gives Fe Rec, Conc, kt</th>
<th>Error compared to RCS % of ore gives Fe Rec, Conc, kt</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>HQ* 36.4 RQ* 63.6 LQ* 94.5 1244</td>
<td>-100 HQ* -46.5 RQ* 29.3 LQ* 1.1 5.1</td>
</tr>
<tr>
<td>5</td>
<td>9.7 19.1 71.3 89.1 1026</td>
<td>-62.7 -23.3 44.8 -4.7 -13.3</td>
</tr>
<tr>
<td>10</td>
<td>25.9 24.8 49.2 94.3 1208</td>
<td>0.0 0.0 0.0 0.9 2.0</td>
</tr>
<tr>
<td>15</td>
<td>22.0 22.2 55.7 93.9 1211</td>
<td>-15.1 -10.5 13.2 0.4 2.3</td>
</tr>
<tr>
<td>20</td>
<td>25.9 20.5 53.6 92.5 1158</td>
<td>-0.1 -17.6 8.9 -1.1 -2.2</td>
</tr>
<tr>
<td>25</td>
<td>25.0 21.6 53.4 94.0 1203</td>
<td>-3.6 -12.8 8.4 0.5 1.6</td>
</tr>
<tr>
<td>30</td>
<td>22.9 27.5 49.7 94.5 1211</td>
<td>-11.8 10.6 0.9 1.1 2.3</td>
</tr>
<tr>
<td>50</td>
<td>23.9 25.8 50.3 93.7 1186</td>
<td>-7.9 4.1 2.1 0.2 0.2</td>
</tr>
<tr>
<td>100</td>
<td>23.9 27.2 48.9 93.4 1179</td>
<td>-7.9 9.7 -0.7 -0.1 -0.4</td>
</tr>
<tr>
<td>200</td>
<td>24.7 25.0 50.3 93.6 1187</td>
<td>-4.7 0.8 2.1 0.1 0.3</td>
</tr>
<tr>
<td>RCS</td>
<td>25.9 24.8 49.2 93.5 1184</td>
<td>0.0 0.0 0.0 0.0 0.0</td>
</tr>
</tbody>
</table>

*HQ = high quality product, RQ = regular quality product, LQ = low quality product.

CONCLUSIONS

The effect of geological variability on geometallurgical sampling within the ore body was assessed within synthetic geometallurgical testing framework. Synthetic ore body, a part of the framework, was used to critically evaluate the number of samples needed for geometallurgical testing to create reliable production forecast. For the iron ore case study it was concluded that the number of samples varies based on the parameter to be forecasted. For iron recovery and concentrate mass pull already 10 samples gave a good estimate in a system having three different geometallurgical types. The difference between the types in iron recovery was minor, but still significant, however the nearest neighbourhood method used in populating back the forecast worked well because of clear difference between the chemical compositions of the types. When the product quality was forecasted the number of samples for reliable forecast increased to 200. It may be possible to improve this by using different deployment algorithm, like multivariate statistic or principle component analysis (e.g., Keeney, 2010). However, this indicates that more accurate geological information on mineral textures and liberation would be needed. This leads to a conclusion that there is significant potential to increase the quality geometallurgical forecast by collecting quantitative information on ore and mineral textures. Currently techniques available for this are either poor in quality (drill core scanning) or expensive to use (automated mineralogy). This is clearly an area where development is needed.

The case study shows the strength of developed synthetic ore model. This study differs in couple of ways from previously used synthetic data sets in geometallurgy (Jupp et al. 2013b). First the ore body modelling is taken into mineral level, both the modal composition and quantitative data on mineral texture is assigned to each voxel. Second, the mineral processing (here Davis tube) is modelled and simulated on mineral liberation level. This gives access into a variability level which is very significant for metallurgical response but very challenging to map in the ore body. Therefore it gives realistic environment to test different important questions in geometallurgy.
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