Analysis of digital core to harness the upside of emergent selection and sorting technologies

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Rapid advances in sensing, selection and segregation technologies at several scales present material upside for mining and processing of ore bodies. This value can, however, only be harnessed if the information required to evaluate, select and successfully implement these technologies is available at the right scale and at the right time to impact on critical technology selection and process configuration decisions. As with many mining industry technologies, the earlier they are introduced into the design and/or operation, the higher the value that can be derived. This requires that the ore body characteristics be sufficiently known to quantify the value of segregation at face scale, pod scale and particle scale as early as possible in the lifecycle of a mining project. This study describes a methodology that uses continuous multivariate digitised cores to describe the variability of mineralised and unmineralised rock at different scales to evaluate the potential impact that segregation at sub-mining block scales may have on the value of the operation. A few approaches to deriving variables such as: 'In-situ heterogeneity' and 'Sortability indexes', are presented. These variables can be used to evaluate the modelling and simulation of a variety of selection and sorting technologies. They include face selection, post-blast shovel selection, truck selection, pod selection and particle sorting. Importantly, the method can enable projects and studies to investigate the way in which the characterised ore body lends itself to the generation of ore streams that are best suited to different processing routes (e.g., leach vs float). Correctly evaluating the potential value of the deposit and associated mining operation requires that the upside of selection and sorting at the sub-selective mining units scale is carried out synchronously with the preparation of cut-off grade strategies for the operation. The use of multivariate, multiscale and continuous data from cores acquired early in the project can facilitate the estimation of a variety of primary characteristics of the ore body at several scales. The use of these rock characteristic variables in mining studies, projects and operations has the potential to add material value to the mining industry.

Keywords: Project evaluation, sorting, selection, heterogeneity, primary variables, response variables

INTRODUCTION

"The Geometallurgical data we have will dictate the mine and process we envisage, and that vision will dictate the Geometallurgical data we require" (Kleingeld, 2008). The strategic evaluation and optimisation of mining projects and operations continue to evolve in the face of several emergent trends in the industry. These include increasing demand for a wider variety of products (e.g., rare earth metals), improvements in the scale and rate of data collection from orebodies, and emergent methods to use this data to emulate or simulate the ore body and operations and model relationships between rock characteristics, mining and processing technologies (Mc Niel *et al.*, 2022). This is driving an advance in the methods used to establish the pathways to value (Samis, 2007).

A variety of financial indicators are used to describe the value of the operation, and several approaches to these, such as net present value, utilise discounted cashflows (Smith, 2000). Over the life of the operation the methods used to select and classify parcels of rock as being either ore or waste will change and be influenced by the overall economics of the mining operation (Dowd, 1976; Asad, 2002; Cetin and Dowd, 2002; Akaike and Dagdelen, 1999; Lane, 1988). These economics will be influenced by the rate and cost of operations and the selling prices of products. Selection and segregation in mining are normally executed at a large block scale. The concepts and implementation of effective selection at the mining block scale have been well described (Lane, 1974, Dowd, 1976). As information at higher resolution (i.e., smaller distances between samples) and increased content becomes available earlier in the mining sequence, options for selecting and segregating mined materials increase. The classification decisions can now be considered in the light of emergent technologies that are capable of selection and sorting at higher rates to enable segregation at face scale, truck/shovel scale, belt pod scale and individual particle scale.

Some non-trivial aspects of managing grade and other rock characteristic data that must be kept in mind if it is to be used to investigate the potential for sorting and segregation, and thus add value to an operation include:

- the variability of the variables used to describe characteristics of in-situ rock will be related to the support of the sample that has been used to derive those variables;
- correct representation of the variability of several variables at different scales of measurement is important in the evaluation of selection and segregation;
- samples used to derive values for these variables are inevitably collected at much smaller volumes than the scale at which estimates of those variables are generated;
- samples used for rock characterisation may, in some cases, be spaced at distances greater than the semi-variogram range of the variables; and
- the values of these variables estimated in block models are typically smoothed as a result of some geostatistical interpolation methods.

This approach to mining and processing requires the solution of a so-called 'wicked problem' insofar as until certain aspects of the problem are assumed as defined and thus fixed to act as constraints, other aspects of project configuration cannot be solved as a closed-form solution. This suggests that an iterative approach may be preferred to finding the best selection of decisions and policies that deliver a 'better' or 'more robust' operational configuration. This type of problem is not too dissimilar to the planning of open pit operations that first require the determination of the ultimate pit, then an idealised sequenced set of pushbacks, and finally the application of a schedule to this material. To effectively model the benefits, risks and uncertainty of segregation will require a similar recourse to higher resolution models and simulations of the ore body and the processes used.

Emergent Selection and Sorting Technologies

Several emergent sensing and sorting technologies can be utilised to select and segregate mined rock at face scale, truck/shovel scale, pod scale and individual particle scale.

To evaluate these technologies requires the definition of the relationships between:

- the scale of selection and the variability of the mineralisation
- the scale of the estimate and the assumed continuity
- the effectiveness of the sensing technology in correctly representing the value of the content of the block; and
- the effectiveness of the separation that can be realistically achieved.

Selection happens at the scale of mining blocks or so-called selective mining units at the planning stage, where cut-off grade analysis is applied. The properties of these large blocks, which are usually the same size as the blocks in the model used to estimate their content, such as metal grade, are often based on estimates of the metal content derived from small samples extracted from the ore body. These estimates are unbiased for the entire block; however, the block may contain areas that are higher than the average grade and lower than the average grade. The dispersion of the grade and other content within the block can be exploited at the time of mining to generate rock streams with different grades and physical characteristics.

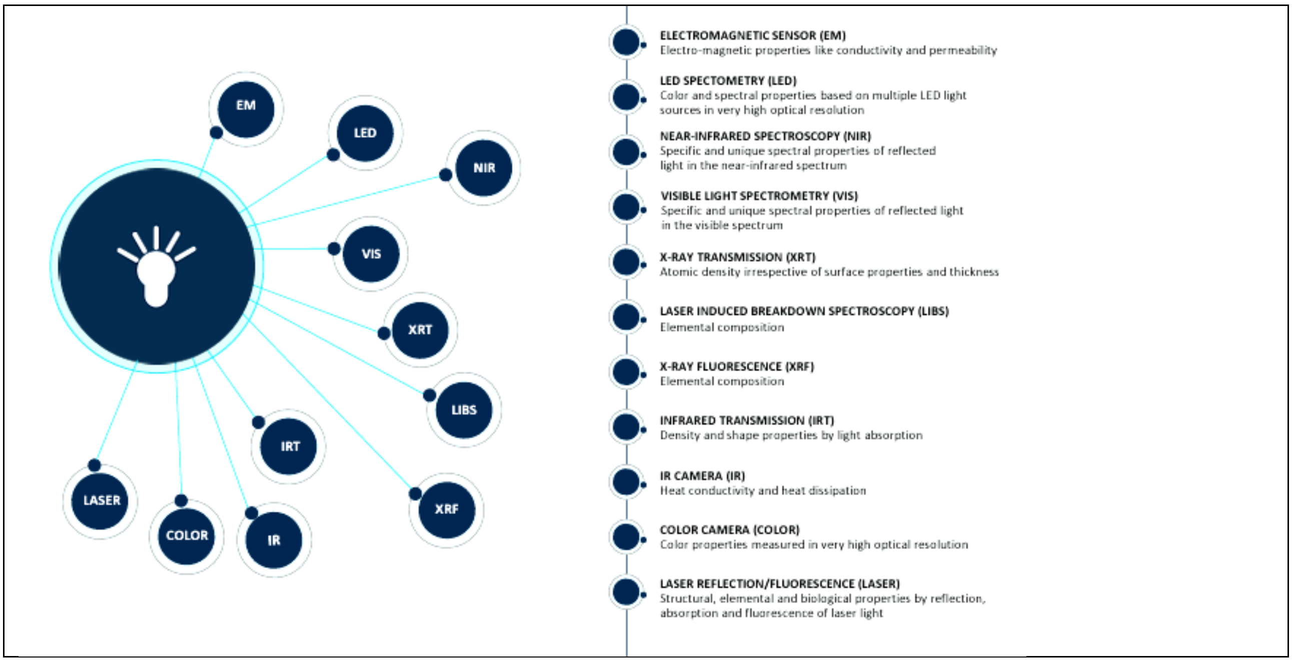

Figure 1. Description of sensors used across the spectrum of sorting and segregation (Tomra, 2023).

A few value cases for selection and segregation can be described as follows:

Mining destination improvements:
- Classification of material based on the best destination, e.g., to different comminution circuits or to leach vs float process trains;
- Blending decisions;

Process feed management:
- Removal of a small mass of material that compromises downstream performance;
- Removal of a mass of low-value material prior to processing to allow for higher rates of mining, reducing plant feed mass, and or increase plant feed grade;

Discard materials management:
- Capturing valuable material from the discard stream;
- Separation of discard streams into material for later treatment; and
- Separation of discard streams into material storage types for long-term containment.

Technologies to execute selection and sorting include hyperspectral imaging that can scan faces exposed during mining. This information can be used to effect separation at the time of mining. In both open pit and underground operations, several truck and shovel sensors can now detect buckets and scoops' contents, e.g., kimberlite and waste detection using microwave resonance and base-metals sensing using X-ray fluorescence spectroscopy(XRF). Other sensors that exploit technologies such as near-infrared spectrometry, visual spectrum imagery, and XRF can be applied to the surface of broken materials. These can give indications of rock content with sufficient resolution and accuracy to support the classification of the contents into a ‘type’ and then to implement a destination decision for that parcel. On belt sorting technologies include the above, as well as methods such as prompt gamma neutron activation analysis, pulsed fast thermal neutron activation, magnetic resonance, radiometric, and X-ray transmission, among others, that sense material volumes as opposed to their surfaces (Duffy, 2015). Once the targeted section of the belt has been analysed, the material can be diverted to two or more different streams. Technologies designed to segregate particles, described by (Robben and Wotruba, 2018), are increasingly utilising combinations of sensors to enable the real-time collection and analysis of data and estimate multiple characteristics of the rock. This allows such operations to separate each particle based on its characteristics, thereby facilitating separate rock streams. These can be exploited in several ways, over and above merely sorting for higher and lower grades. The relationship between the characteristics of the separated streams and their associated value in the next and subsequent processes is becoming ever more complex.

Evaluation of Ore Body Segregation Potential

The characteristics of the data required to predict the value of a variety of configurations of selection and segregation require the prediction of the variables describing rock characteristics that are used in selection. The data must be provided at multiple scales, from millimetres to hundreds of metres. Further, the data needs to be of sufficient quality and resolution to inform decisions and choices, including the type of sensing, the locations in the flowsheet, the amenability of different lithologies, and their values in different places in the orebody. Traditional approaches to technology testing are often based on pilot-scale treatment of large (order of tonnes), often composite, samples deemed to be representative of expected run-of-mine material. These samples can be treated using sorting technologies set up in some fashion to enable the prediction of the performance of the selection and sorting technology on the specific sample. In many cases, such as flotation testing, the sample size is indicated by the length of time it takes for a process to reach steady state. For technologies such as face selection, it is challenging to validate the predictions without trial mining. Simulation of the processes used in mineral processing has advanced and continues to improve in speed and resolution (Nicholas *et al.*, 2008).

Underlying Concepts

To frame and evaluate the benefits and risk reduction that might result from the implementation of selection and segregation technologies, it is important to briefly consider the benefits and limitations of existing predictions of risk, uncertainty, and variability in the economics of mining projects. Selecting and implementing the best scale (mining rate and operation size) and cut-off grade policy for an operation relies on several assumptions (Dowd, 1976). These include assumptions of block grade accuracy, mining selectivity and active constraints over the life of the operation. The realised production performance will differ from the idealised plan to some extent, and some of this difference will be related to the miss-classification of blocks at the time of mining (i.e., classifying ore blocks as waste and waste blocks as ore). The misclassification will result from a variety of causes including smoothing effects of block scale estimation and execution challenges.

A typical grade tonnage curve for a deposit is provided in Figure 2.

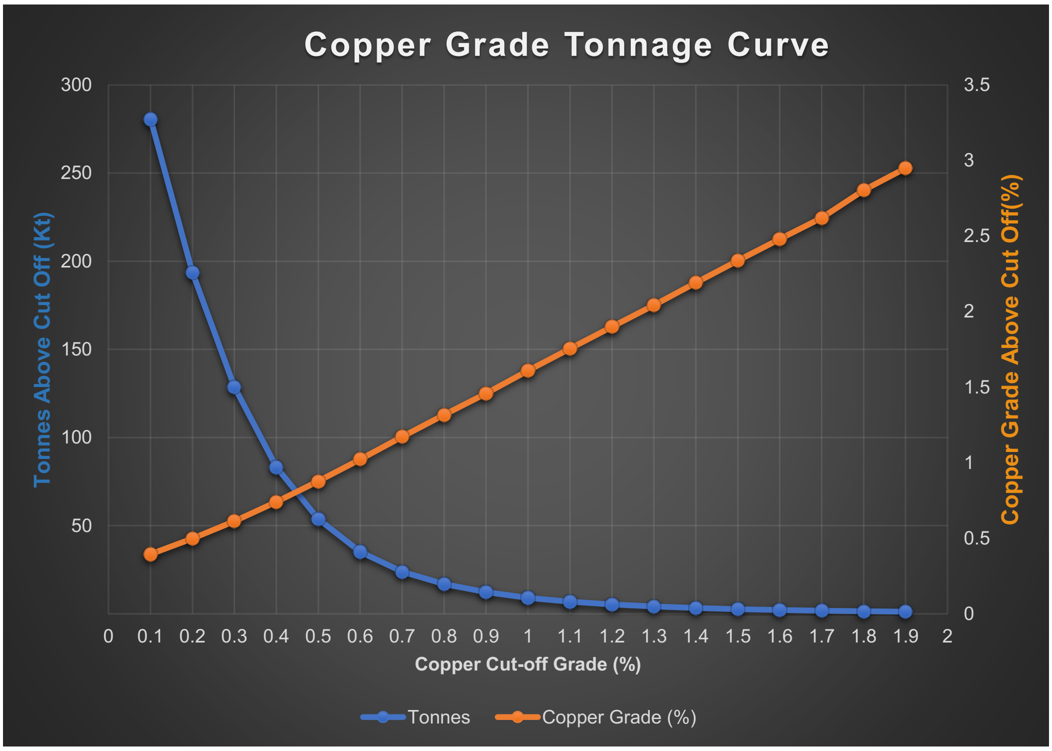

Figure 2. The relationship between cut-off grade, tonnage at cut-off and average grade above cut-off.

In this example, a section of the mine contains ~300 kt of ore above 0% copper cut-off grade. Assuming the cut-off grade has been determined to be 0.5% Cu, the pushback will deliver 50 kt of rock (blue line, left axis) at an average grade of roughly 1% copper (orange line, right axis) In Figure 3 the data is displayed with the x-axis representing the proportion of ore tonnage and the y axis reflecting the proportion of contained metal. A similar approach can be used to determine the relationship between the distribution of metal concentration in individual blocks and the expected mining outcomes.

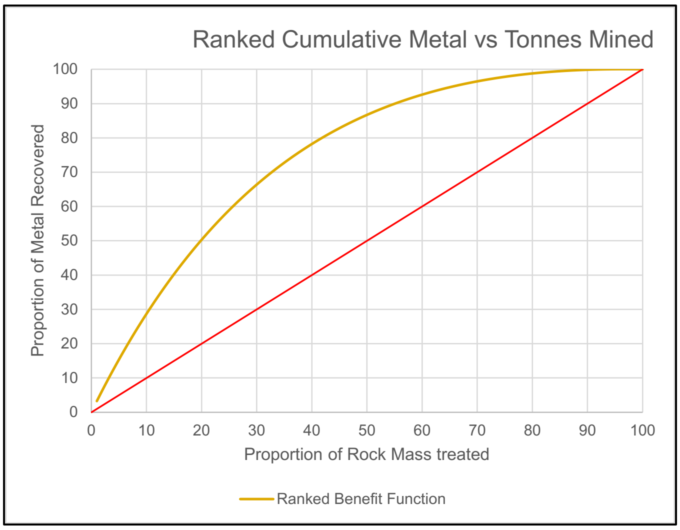

Figure 3. A ranked benefit function depicting the relationship between the possible tonnage treated vs proportion of metal delivered (45° line shown for reference as the hypothetical 'no-benefit' case).

In each of these cases, the cut-off grade is used as a proxy for the economic cut-off for further processing. At the time this decision is made in practice, many sources of flexibility have been surrendered. So, there is a 'staged' or 'time in project' component to this application and its relative benefit. For instance, during the design phase of the operation, the operational configuration can be adapted to account for changes in performance due to misallocation at a much lower cost than having to adapt the process once the mine has been built and commissioned. This can result in material value destruction if the magnitude and impact of misallocation on processing constraints are not correctly reflected in early-stage project evaluation models.

Early Project Estimates of Segregation Potential

In early-stage projects, the objective is to find a relatively simple method to assess the spatial dispersion of valuable components in the rock, with the aim of defining the potential upside or benefits that could be derived from idealised selection, segregation or sorting. It is possible to use composites of assays over entire domains and rank these to generate a distribution of the grade components of the orebody at the sample scale. This approach makes several assumptions about the relationship between the samples' characteristics and the ore body's characteristics. These include that the samples are contiguous through the ore body and that the heterogeneity in situ will replicate that of the samples at the sample support. Noting that the concept of support includes not just the size but also the orientation and geometry of the samples. The determination of the benefit function requires that samples are assigned to their domains and then within each domain samples are ranked from highest grade to lowest grade. In some cases where some of the samples in the domain are barren, the derived rank response curve will provide an optimistic view of the benefit of sub-block size selection. An approach to testing the stability of the derived function, at early stages in the project evaluation, is to recalculate the benefit function based on a sample set that discards lower grade samples i.e., below a cut-off grade that is a reasonable distance below the economic cut-off grade (e.g., equivalent to a 50% increase in Cu selling price). This attempts to reduce the possible biasing effects in the derivation of the selectivity function that would be introduced by assuming sorting will add value to blocks that are obviously either to be discarded as waste or selected as ore. (Note that this does not suggest that the samples be discarded for grade estimation). Using the derived functions, it is possible to assign the metal estimated (or simulated) into the blocks and subdivide this metal into, for example, four equal volumes or masses in each estimation block. Instead of assigning the mass of metal equally between the volumes, the estimated mass of metal is allocated to sub-blocks to replicate the distribution of metre-long composites. As shown in Figure 3, in which the vertical dotted lines for copper and sulphur indicate the four proportions.

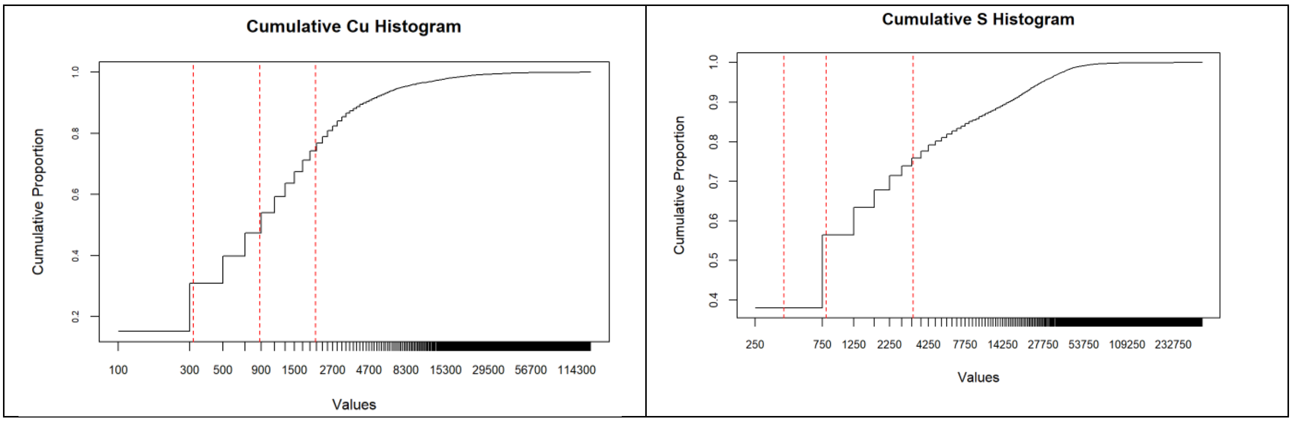

Figure 3. Cumulative Cu (left) and S (right) grades based on 1 m assay composites.

The benefit of this approach is that it does not require additional data other than the assay values. It is however reliant on the assumption that the sample distribution will resemble the sub-block distribution of grade. Using the redistributed metal, it is possible to then identify the proportion of blocks in each of the domains that will become economically viable if precise idealised segregation at this scale were to be implemented. At the same time, due cognisance must be taken for the case of blocks where the impact of uncertainty in the location of the contact and unintended ore loss and dilution by waste should be incorporated in the estimation of the characteristics of the mined material.

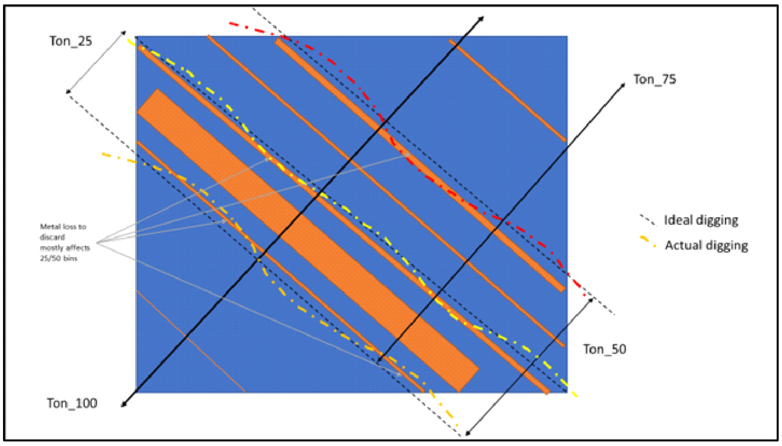

Figure 5. A cross section through an exposed face showing idealised and actual selection boundaries based on assumptions of digging accuracy.

These additional modifications to so-called contact blocks can be used to generate more plausible segregation predictions.

Derivation of Scale Dependant Heterogeneity

To enable evaluation of selection at finer resolutions requires data below the size of the assay composites. One approach is to use the volume variance relationship of grades in a domain and then extrapolate the variance into smaller scales (De Klerck *et al*., 2023). However, this method relies on the assumption that the change in the relationship with size will hold. Several scanning technologies can provide higher-resolution data; for example, the Orexplore GX10 instrument is capable of scanning cores with a resolution of ~200 µm. This data can be composited to different lengths, and the variance of the data collected can be analysed.

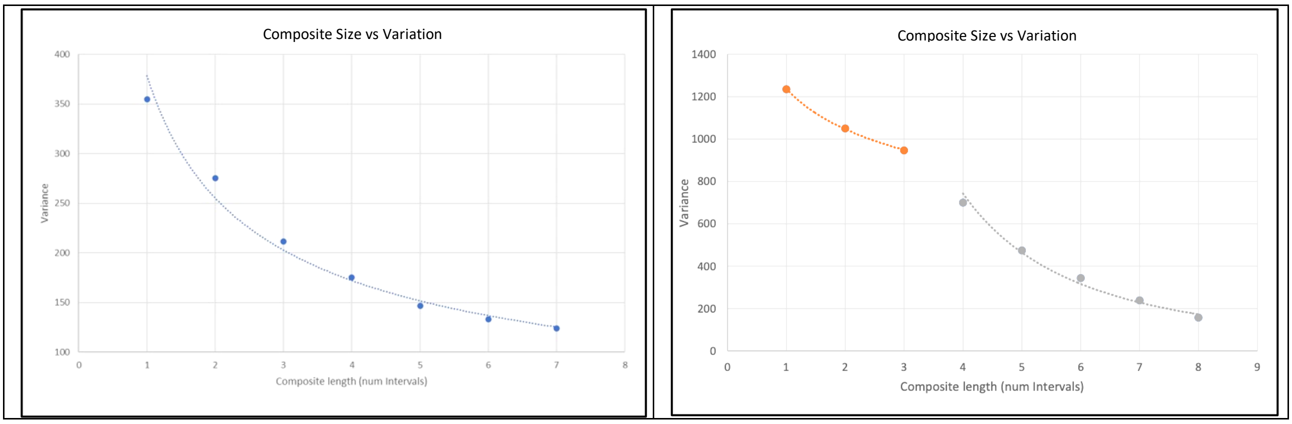

Figure 6. Comparison of composite size vs grade variation, a continuous case (left) and discontinuous case (right).

Figure 6 shows the change in variance with the change in scale of the inferred concentration of sulphides in the core scanned. In the left-hand panel, we see a case of a continuous relationship between scale and variance, in the right-hand pane we see a case where there is an inflection point between composites 3 and 4. This suggests that in some cases the volume variance relationship can be difficult to model effectively assuming a monotonic relationship. This will arise from the complex geological interactions of mineralisation effects interacting with so-called ‘pockets’ and ‘patches’ in the mineralising environment that are more or less amenable to becoming mineralised and will lead to different sizes (and orientation) of regions of elevated concentration. This can to some extent be addressed through application of multiple domains and using defined models of regionalised variances in each. This same fine-scale data can also be used to generate grade tonnage curves or so-called benefit functions at different scales. The continuous scan data has been used to evaluate the dispersion of smaller segments of core in larger segments of the core. It is possible to evaluate the variation of mineralisation inferred from element concentrations in each hole that is scanned. In this specific case, it has been assumed that the sulphur in each interval is a fair proxy for the variability of mineralised and non-mineralised portions of a block. In Figure 7 the results of sorting 10 cm increments from a drill hole are displayed. In the left-hand panel, we have fitted one curve to a single collection of 100 segments at a single location in a drillhole. In the right-hand panel, we show a collection of curves that have been fitted to many increments down the hole.

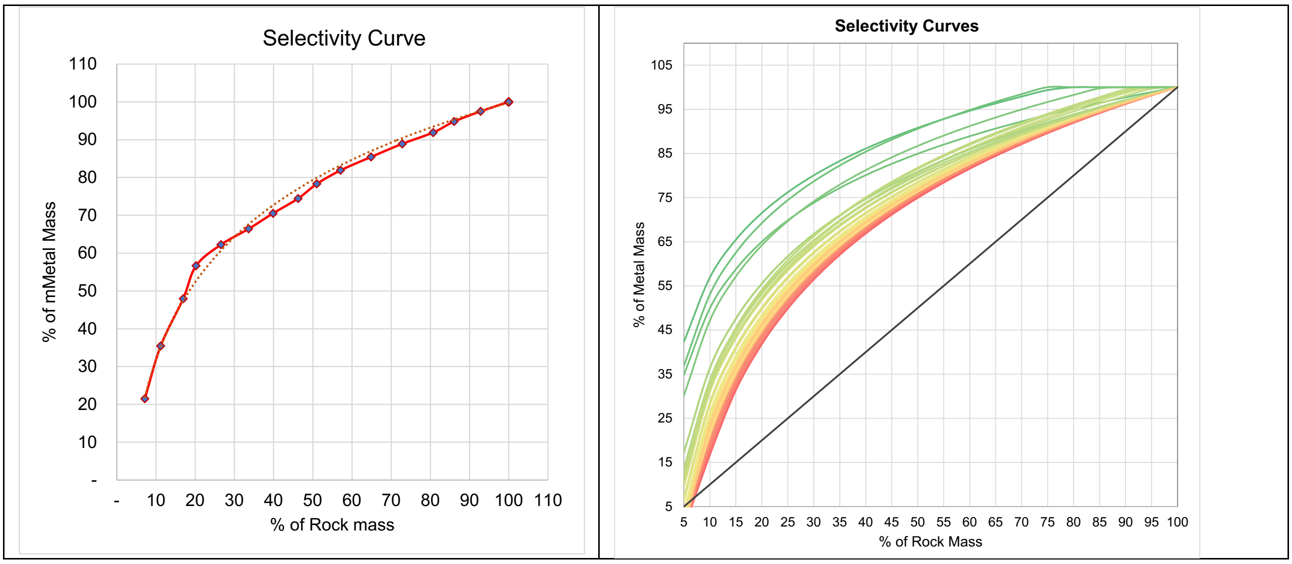

Figure 7. A cumulative proportion of mass vs proportion of metal model derived from 10 cm composites over a 10 m length (left) set of fitted curves fitted to 10 m benches (right) where the green curves indicate a higher degree of selectivity than the red curves.

The parameters of the fitted power curve can be located at intervals associated with the scanned core. These variables can be estimated into the block model so that each block then carries the parameters of the ranked heterogeneity curve that can be applied to distribute the estimated metal mass in the block using the parameters of the modelled curves. To do this in a feasible time suggests that only three or four points on the curve should be selected, as in the use of quartiles. The resulting distribution of metal in the sub-blocks, which can be down to sizes that can be used to estimate the efficiency of particle sorters, can then be used to estimate potential metal and mass yields for each stream in an idealised ‘perfect’ selection case. To estimate a more realistic outcome, it is necessary to adapt the curves to the loss that will be incurred due to the inaccuracy of the sensor and sorting mechanics. This can be achieved by flattening the curves used to ensure they resemble curves from actual operations or the results of bulk test sorting. To calibrate these curves may, in some cases, require selected test work on selected sections of cores or from data gathered from similar operations. This approach is analogous to the use of partition curves in dense media separation processes to predict the proportion of misplaced or misclassified material that will be realised during the selection and segregation operation.

Particle-Based Sorting Indicators

In cases where the high-resolution data contains information that is analogous to the sensed data that will be used in the selection and sorting implementation, it is possible to build a model that will directly reflect the operation of the sorting device. In the case of X-ray tomography-based sorting devices, the three-dimensional core tomograph may be projected back into two dimensions to resemble the images that the sensor in the sorter will collect. It is possible to characterise different size pucks of rock through the mineralised zone. The tomogram of the rock contains the values for attenuation at every voxel. The data in each of the core segments can be scaled to a voxel size similar to that used in sorting sensors and projected as a two-dimensional image. This image can be used as an input to the sorting algorithm, which is used to process the image and provide an accept or reject signal.

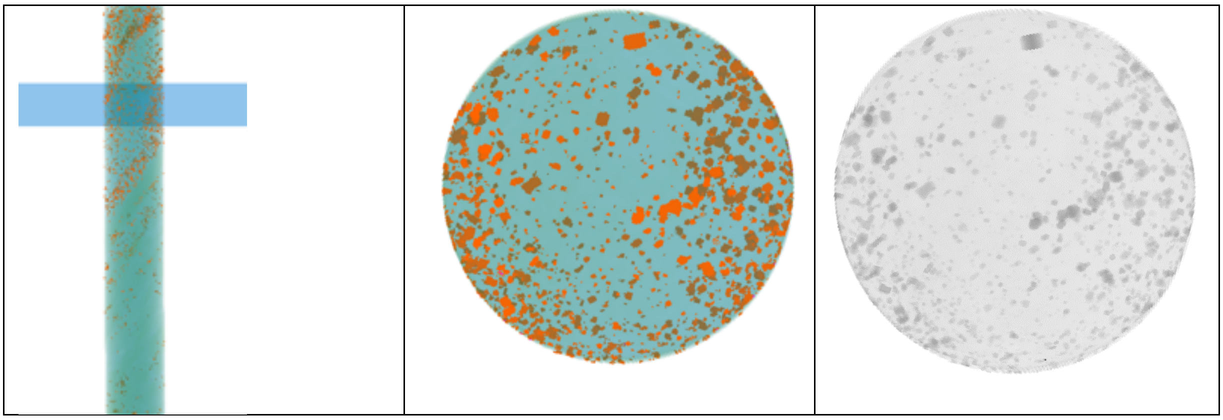

Figure 8. A depiction of the false colour image of the core (left) the false coloured section of the core viewed down the axis of the core (centre), and the rescaled two-dimensional image used for sorter emulation (right).

This approach assumes that resulting fractured particles will resemble the intact rock textures and will be independent of the location of the mineralisation. Further work investigating the impact of different orientations can be achieved using other projection axes. To validate predicted sorting outcomes will require experiments on core samples that are scanned, crushed, sorted and the particles rescanned.

In Figure 9 the scan results of processed particles are presented. The scan shows the mixture of feed particles, the reject and concentrate streams. The data from these scans is used to calibrate segregation curves for the sorting device, which can then be applied to the so-called 'virtual particle stream' that is derived from core scans and can be used to make realistic predictions of the characteristics of the products that will result from particle sorting.

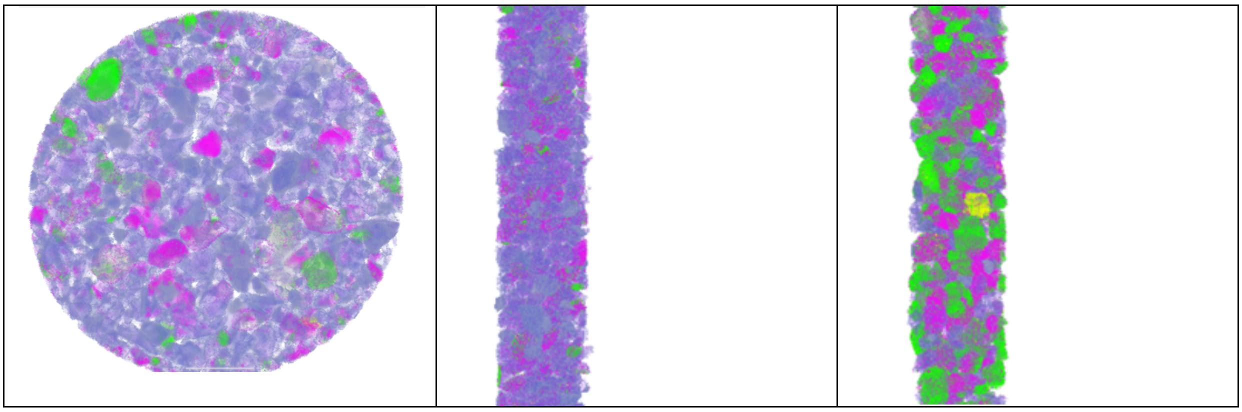

Figure 9. False colour rendered images of crushed sorter feed (left) reject materials (centre) and concentrate (right); each tube represents approximately 25 cm of scanned particles.

This approach makes it possible to explore the impact on mass flows and metal recovery over wide ranges of operating parameters. In addition to predicting unit performance, the approach can inform sampling programme design and reduce the number of samples that are required to design and optimise the sorting circuit.

Initial Results

Applying the approach to a strata-bound sedimentary deposit found that the distribution of sample grades could be constrained by geometrical selection, or domaining, in the zone containing mineralisation. Application of a spatial wireframe to all blocks that were to be mined was then separated into blocks that were *a* - clearly waste, *b* - obvious ore and *c* - in an economic envelope for uncertain extraction and treatment. By flagging blocks that fell within the ultimate pit and were in the intermediate grade range, it was possible to identify the set of blocks that would be selected for sorting and then evaluate their potential mass and metal yields using the sorting algorithm. Using the domain-based method for the prediction of grade distribution, the proportion of blocks that would become economic was determined. For example, in Figure 10, we can see that 29% of the blocks will be economical to mine in rock type one if 25% of the material from these blocks is rejected at the time of mining. Comparing this to the rock type 2 zone, we see that 45% of the blocks will become economical to treat if 25% of their mass is discarded.

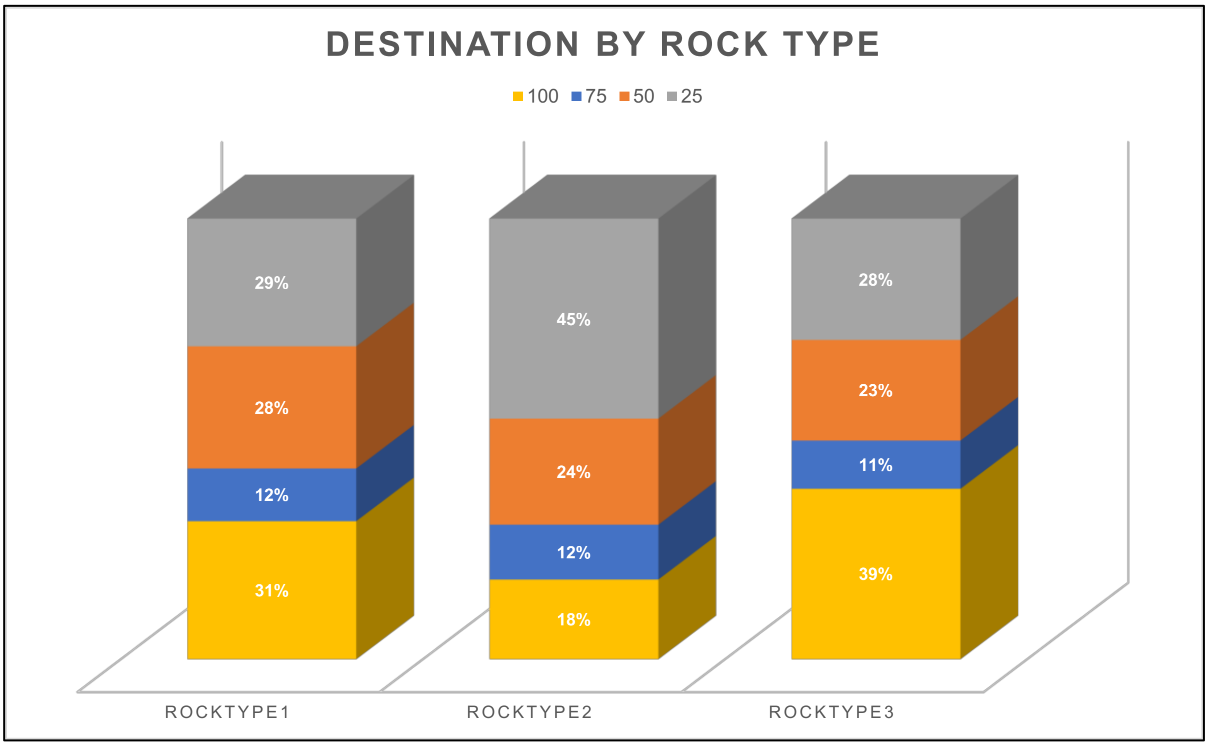

Figure 10. Percentage of blocks above cut-off for a given proportion of material selected from the block.

These results can readily be used to determine the impact of sorting and selection in each of these zones to investigate the economics of sorting across each of these domains. To evaluate at a higher resolution within each of the domains, the downhole variability can be applied to the same set of blocks. Additionally, this can be used to predict the economic viability and impact of particle sorting technology on the project. For the material delivered to particle sorting, it is possible to evaluate the possible yields of metal and mass achieved for various sorting device settings. In Figure 11 curves have been plotted for the expected mass and metal recovery for a variety of feed sizes. In this figure, for instance if sorting was conducted on 5 cm particles, and the eject threshold was set to 1.108 aluminium equivalents, of the order of 80% of the metal will be recovered whilst rejecting 50% of the mass.

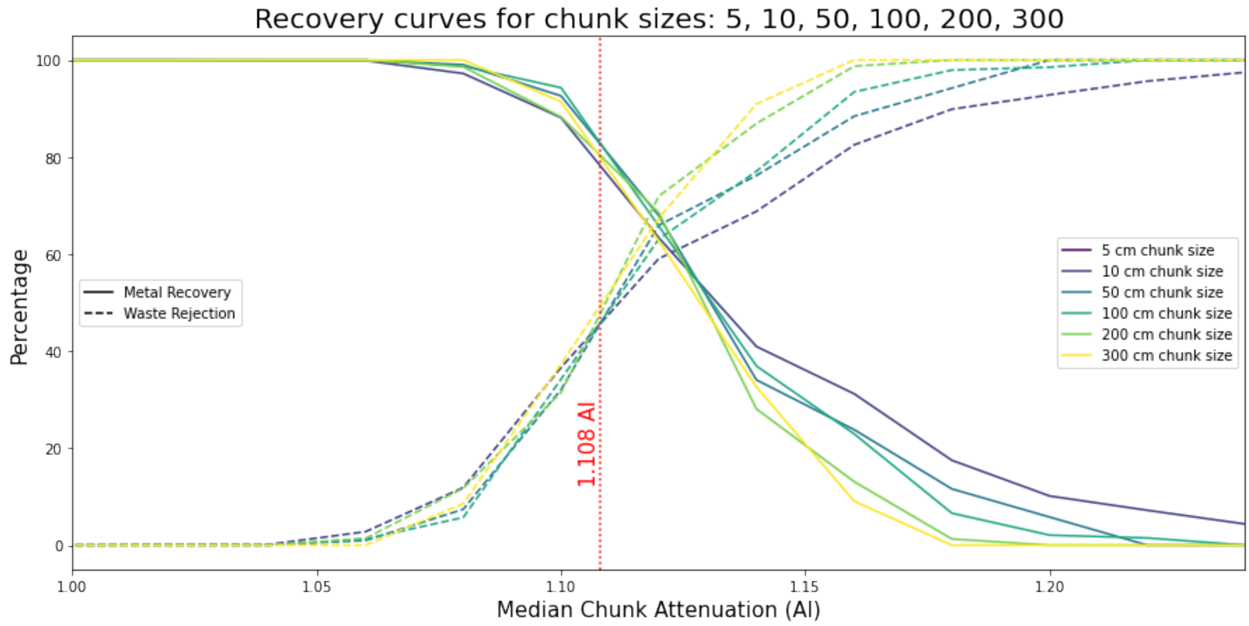

Figure 11. Mass and metal yields for distinct size selection.

As the attenuation threshold has increased the size of the chunk considered begins to have a much higher influence on the difference between mass rejection and metal recovery.

CONCLUSION

To exploit emerging technologies that facilitate the selection and segregation of ore body materials requires advanced quantification at multiple scales of material characteristics in ore bodies. This can be achieved using a number of technologies, including bulk sensed methods such as regional seismic surveys, in-hole scanning and core digitisation using continuous through-the-rock scanning. Non-destructive sensed data presents opportunities to collect multiscale and co-located continuous data. Once the orebody has been sampled, the collection of data sets can be used to create multiple realisations of the orebody. With mining and processing simulation, it is possible to predict how the material will present at face scale, through loading and to transportation. The correct characterisation of this material can also facilitate the prediction of how well particle sorting devices will perform. The information derived from simulations of the process can be used to assess a limited number of selected processing designs and operating strategies and evaluate their sensitivity to changes in ore body knowledge. This approach, however, requires an integrated approach to measuring, modelling and simulation of both the orebody characteristics and the process responses. The data can now be collected with a variety of sensors and scanners that have previously been limited by both the sensors and data management capabilities. Emergent scanning data present an opportunity to readily assess the value presented by more precise selection and segregation of rocks for treatment. Some challenges remain, however, including the use of the data to generate stochastic realisations of the orebody and link these to realistic and stochastic simulations of unit performance. This will enable an understanding of the benefits of selection that may be unrecognised when using interpolated models and average machine performance models. Embracing the emerging paradigm of designing mines to harness the benefits of rock selection and segregation technologies will liberate most value when they are integrated with more traditional historical approaches to dealing with variability and uncertainty in ore body and process performance, such as extensive use of stockpiling and blending. In this way, mines can be designed and operated to provide the highest probability that each block of rock will be treated in a way that is suited to the economics of the operation and prevailing market conditions and result in improved performance of the greater mineral resources industry.

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A seasoned mining professional with a passion for improving performance of the mining industry by driving integration, in many forms ranging from multidisciplinary collaboration to integrated systems modelling and anaylitics.

His presentation today addresses some of the challenges that are faces when looking to adopt sorting and selection technologies in new projects and existing operations.