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A Methodology to Determine the Potential for Particulate Ore Sorting Based on Intrinsic Particle Properties

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Abstract: Sensor-based particulate ore sorting is a pre-concentration technique that sorts particles based on measurable physical properties, resulting in reduced energy consumption by removing waste prior to grinding. This study presents an integrated methodology to determine the potential for ore sorting based on intrinsic particle properties. The methodology first considers the intrinsic sortability based on perfect separation. Only intrinsically sortable ore is further assessed by determining the sensor-based sortability. The methodology is demonstrated using a case study based on a typical copper porphyry comminution circuit. The sorting duty identified for the case study was the removal of low-grade waste material from the pebble crusher stream at a suitable Cu cut-off grade. It was found that the ore had the potential to be sorted based on the intrinsic and ideal laboratory sensor sortability results but showed no potential to be sorted using industrial-scale sensors. The ideal laboratory XRF sensor results showed that around 40% of mass could be rejected as waste at copper recoveries above 80%. An economic analysis of the sortability tests showed that, at optimum separation conditions, the intrinsic, ideal sensor and industrial sensor sortability would result in an additional annual profit of ~$30 million, $21 million and $−7 million (loss), respectively.

Keywords: ore sorting; ore characterisation; sortability

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1. Introduction

Sensor-based ore sorting is a pre-concentration technique that uses electronic sensors to differentiate ore particles based on measurable physical properties that are intrinsic to the ore, i.e., naturally occurring properties (grade, texture, mineralogy, density, colour etc.). Pre-concentration of ore by waste rejection prior to fine grinding can have a positive impact on an operation by decreasing energy consumption whilst improving the efficiencies of downstream processes [1–5].

Although particulate ore sorting has long been recognised as having the potential to impact mining operations positively, ore sorting technologies have not been widely implemented on an industrial scale in base and precious metal projects. There has, however, been increasing interest in the use of this technology in recent years due to the significant processing, economic and environmental benefits [6].

There are a number of reasons why ore sorting has not seen implementation across a wider range of commodities. One of the reasons is that standard methodologies, similar to those used in other branches of mineral processing (e.g., sink-float analysis), to determine ore sortability using sensor-based ore sorting technologies are not well established. This is the focus of this study.

Previous studies related to this area of research include a methodology to determine ore sortability at a pilot-scale [3], at a laboratory scale [4], a model to determine ore sortability for bulk ore sorting [6] and a method for optimal sensor selection based on mineralogy data [7]. This paper presents an integrated methodology to determine the sorting potential of an ore based on intrinsic (natural ore properties) and measured particle properties using a case study from a copper porphyry deposit in South America. It should be noted that the purpose of this paper is to demonstrate the application of the methodology to a case study for illustrative purposes and not to provide a specific technological solution to the sorting of the ore used in the case study, i.e., the methodology is demonstrated by way of the case study.

2. Methodology

The methodology consists of six stages, as presented in Figure 1. The first stage of the methodology is to identify a potential sorting duty based on processing information and ore mineralogy. Potential sorting duties can be divided into three categories depending on the desired result, including upgrading of value elements (e.g., increasing Cu grade by removing waste rock), removing penalty elements (e.g., removing phosphorus-rich particles from an iron ore stream) or splitting material into two or more processing streams (e.g., splitting an ore into hard and soft components for separate treatment). Once a sorting duty has been identified, a representative sample of the material is then collected. The individual particles of the representative sample are mineralogically and chemically characterised in the next stage. The intrinsic sortability is then calculated based on the particle characterisation data, with these results representing the theoretical sortability. Ore that is intrinsically sortable is further assessed by establishing the amenability of various sensors to sort the ore based on differences in particle properties. Sensors that are amenable to sorting are then assessed by conducting ideal laboratory-scale sensor sortability tests and if the potential exists, industrial-scale sortability tests.

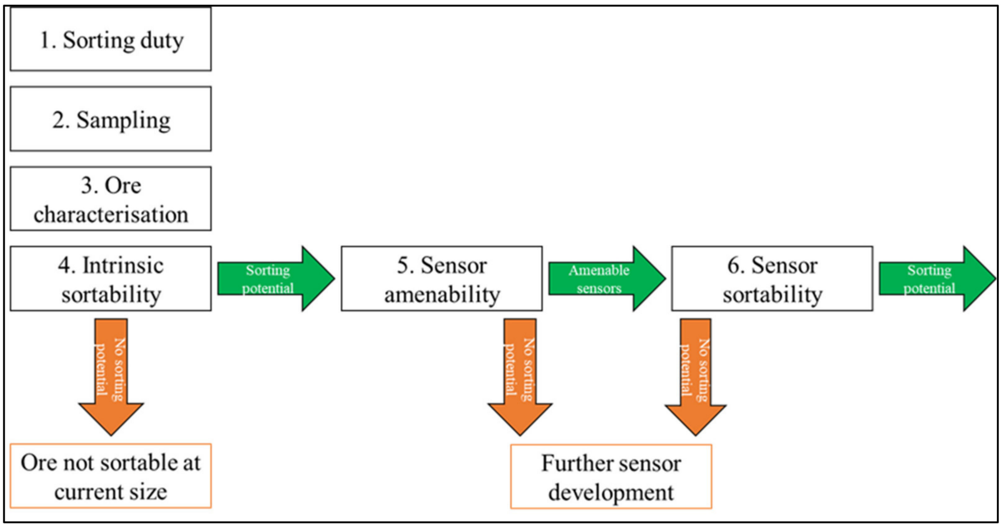

Figure 1. Flow diagram of the six stages in the methodology.

For the intrinsic and sensor sortability tests in the methodology, the grade-recovery relationship is established using a method presented by Tong [4]. The method uses a series of simulated separation tests based on cut-off grades for the intrinsic sortability and sensor response thresholds for the sensor sortability. To quantify the sortability, the grade-recovery results are used to estimate the overall economic impact of implementing ore sorting on an operation based on plant throughput data and operational costs using a method developed by Lessard [5]. In the methodology, an additional positive profit would indicate that there is the *potential* to sort the ore; these results are used for prospective purposes. This information can then be used to motivate further test work to establish the actual ore sorting potential. Examples of the application of the methodology as applied to a case study on a copper ore are given in Section 3.

2.1. Stage 1—Sorting Duty

Stage 1 of the methodology identifies a sorting duty, i.e., the end case as to why the ore should be separated. A potential sorting duty for porphyry copper ores is the removal of barren or low-grade rock prior to milling. This would increase the grade of material reporting to the concentrator resulting in improved processing performance, increased revenues and reduced environmental impact [8].

2.2. Stage 2—Ore Sampling

Stage 2 in the methodology in determining the required sample size for a representative sample of the ore to be tested. Methodologies for sampling are well established in the literature and are mostly based on Gy's Theory of Sampling (TOS). The theory describes the method of collecting a representative sample by reducing or eliminating the intrinsic/physical errors associated with sampling. Petersen [9] provides a comprehensive review of the theoretical and practical aspects of TOS. Gy's sampling equation (Equation (1)) is used to determine the minimum sample mass based on the variance of the fundamental error (σ_{FE}^2). The components of σ_{FE}^2 are the sampling constant *(K)*, the nominal top size *(d_N)* with exponent (α) and the sample mass *(M_s)*.

$$\sigma_{FE}^2 = \frac{Kd_N^\alpha}{M_s} \tag{1}$$

K and α must be calibrated for different ore types. The sampling tree method is one of the techniques used to determine the components of Gy's equation, as described in Minnit [10]. A portion of the ore under investigation is collected (~30 kg) and crushed into progressively finer portions to produce 4 nominal top sizes. Each nominal top size is split into 32 sub-samples. These sub-samples are chemically analysed for the elements of interest and the relative variance for each of the 4 series is calculated. Equation (1) is linearised and used to determine K and α from a plot of $\mathrm{Ln}(\sigma^2 M_S)$ and $\mathrm{Ln}(d_N)$ for the 4 series.

Ideally, one should use TOS to determine the minimum sample mass required for a sample to be representative with a known error. However, depending on the ore type, analysing the minimum sample mass, as determined using TOS, may be impractical. Other sampling techniques, such as the binomial distribution method described by Fitzpatrick [3], can be used to collect a sample representing the ratio of the various components within the ore without taking the variability of particle size and composition into account. The binomial distribution determines the minimum sample mass required to collect sufficient particles of the least abundant component.

The sampling method employed is dependent on which stage a project is in (prefeasibility, feasibility etc.). There may be an insufficient mass of material produced from exploration drilling to produce a representative sample in cases where ore sorting is considered in the initial plant design. Here, the method developed by Fitzpatrick [3] (or similar sampling techniques) may be useful. In operations where ore sorting is being retrofitted into an existing circuit, bulk samples can easily be acquired. TOS should ideally be used in these cases.

2.3. Stage 3—Particle Characterisation

The third stage in the methodology is the characterisation of the ore particles to establish the size, mass, density and mineralogical/chemical composition of individual particles in the sample collected in Stage 2. The particle size, mass and density can be determined using various routine analytical methods. The particle size can also be determined from the volume using the equivalent spherical diameter. Particles are screened into appropriate size fractions for analysis. The top to bottom size ratio for each size fraction should not exceed 3:1 for particles less than 40 mm and 2:1 for particles coarser than 40 mm.

The next step is to characterise the surface composition of each particle if possible. The data is used to establish whether there is a correlation between the surface and volumetric composition. Such a correlation between value or proxy minerals/elements is necessary if ore sorting sensors that only measure a particle's surface are to be investigated in the laboratory-scale sensor sortability tests. Examples of surface characterisation techniques include XRF [4], hyperspectral imaging [11,12], and thermal infra-red reflectance [13].

Ideally, the volumetric composition is determined using non-destructive analytical techniques, such as X-ray computed tomography [14]. If only destructive techniques are viable, then an additional sample will need to be collected for subsequent stages in the protocol. Destructive techniques include well-established mineralogical and chemical assay techniques. Commonly used automated mineralogical techniques include systems such as the Mineral Liberation Analyser (MLA) and QEMSCAN technique [7,15–17]. Chemical assay techniques such as ICP-OES/MS and XRF are commonly used techniques to determine the elemental composition. The XRF technique may be adequate for analysis of both intact as well as crushed particles, depending on the matrix of the material.

To validate the ore characterisation results, a statistical method based on bootstrap resampling can be applied to the data [18]. This will also establish whether the minimum sample mass determined from Equation (1) is sufficient. The particle composition data for the mineral/element of interest (or proxy mineral/element) for each particle is collected and the population is randomly resampled to produce M random subsets of N particles. The process is repeated for different values of N. The relative standard deviation (RSD) between the M random subsets at differing N values is determined. The RSD values are plotted and a regression curve is fitted to the data. The regression curve determines whether the population comprises enough particles at a sufficiently low RSD. If the RSD is not sufficiently low, the slope of the curve can be used to predict how many additional particles are required for the data set to be representative.

The particle characterisation results can be used to establish whether any proxies correlate with the composition of the value mineral/element. The size, density and mineral/element compositions are compared with the value mineral/element composition to determine if there are any correlations. Proxies may allow additional ore sorting sensors to be assessed, e.g., if a correlation exists between density and grade, then an XRT sensor would be considered. Ores that show a correlation between surface and volume composition can be sorted using sensors that measure the surface of particles (e.g., XRF, NIR, SWIR).

2.4. Stage 4—Intrinsic Sortability

The fourth stage in the methodology is determining the intrinsic sortability of the ore from the particle composition based on theoretical separation, i.e., perfect separation at the composition of interest (e.g., Cu grade). The particle characterisation data assesses the intrinsic sortability on a size-by-size basis to determine if the sorting potential varies with size. The intrinsic grade-recovery relationship is calculated using a method developed by Tong [4] using the intrinsic properties from the particle characterisation section to determine the sortability. The particle composition data for each size fraction are grouped into appropriate composition categories (x_1, x_2, x_3 … etc.). These composition categories are used as the separation criteria in a simulated theoretical separation process, as shown in Figure 2. All of the particles from the feed to Test x_1 that are higher than the composition category for Test x_1 are removed to form Concentrate x_1. The remaining particles then form the feed to Test x_2. The process is repeated for all of the selected composition categories. Cumulative grade-recovery relationships are calculated on an overall and size-by-size basis using the data generated from the simulated theoretical separation process.

The economic impact of ore sorting can be used at each stage in the methodology to quantify the ore sorting potential. There are various financial models in the literature that can be used to determine the economic impact of implementing process changes. An example of how to determine the economic impact of implementing ore sorting on an operation is presented by Lessard [5]. The feasibility of moving to the next stage in the methodology is determined based on the financial analysis.

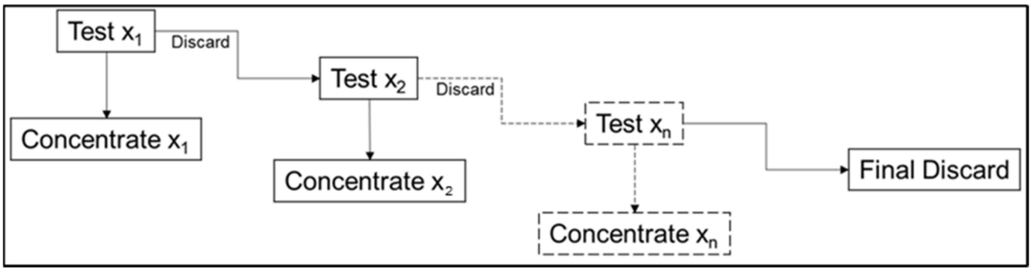

Figure 2. Simulated theoretical intrinsic sortability test.

2.5. Stage 5—Sensor Amenability Tests

The fifth stage in the methodology is identifying sensors which have the potential to differentiate between particles of varying composition based on the measurable physical properties of the ore type under investigation. Table 1 presents a selection of sensing technologies, the physical properties that they measure as well as applications where these sensors have been successful. The selection of appropriate sensors can be achieved based on quantitative mineralogical and textural data, i.e., the intrinsic properties of the ore [7].

Table 1. Ore sorting sensor technologies, physical properties detected and applications [4].

Sensing Technologies	Physical Properties	Applications
Radiometric	Natural Gamma Radiation	Uranium, Precious Metals
X-ray Transmission (XRT)	Atomic Density	Base & Precious Metals, Diamonds
X-ray Fluorescence (XRF)	Fluorescence	Diamonds
X-ray Fluorescence Spectroscopy	Elemental Composition	Base & Precious Metals
Near Infra-Red (NIR)	Reflection, Absorption	Base Metals, Industrial Minerals
Colour (CCD)	Colour, Reflection, Brightness, Transparency	Base & Precious Metals, Industrial Minerals, Gemstones
Photometric (EM)	Monochromatic Reflection, Absorption & Transmission	Industrial Minerals, Diamonds
Electromagnetic (EM)	Conductivity, Magnetic Susceptibility	Base Metals

A selection of particles from the representative sample (~10%) that are known to vary quite widely in composition are analysed on a particle-by-particle basis. The sensor response tests are carried out using ideal measurement settings for each sensor, e.g., particles are measured on multiple sides for a long enough period to get accurate readings. The aim is to assess the amenability to sorting without considering the throughput required for industrial-scale ore sorting machines. The sensor responses are compared with the composition of each particle and only sensors that are most responsive are considered for the next stage.

2.6. Stage 6—Sortability Tests

The final stage in the methodology is to conduct sortability tests on all particles in the representative sample using the selected sensors from Stage 5. Firstly, laboratory-scale sensor sortability tests are conducted using ideal measurement settings for each sensor, as discussed in the previous section. If the sortability is poor using ideal sensor responses, then ore sorting will not work on an industrial scale. Sensors that indicate the potential to sort the ore based on ideal sensor responses are then tested at an industrial scale. The cumulative grade, recovery and mass rejection data are plotted for comparison between the intrinsic, ideal laboratory sensor and industrial sensor sorting tests, an example of which is shown in Figure 3. The economic impact is calculated for the ideal laboratory sensor and industrial sensor sortability tests using the approach discussed in Stage 4, with the difference that the results are determined at different sensor response thresholds instead of cut-off grades. If the results are promising, the next stage would be further industrial-scale ore sorting tests exploring factors such as throughput and varying ore characteristics. Depending on the type of mining undertaken (bulk vs. selective mining), it may be necessary to test the different ore types for sorting potential.

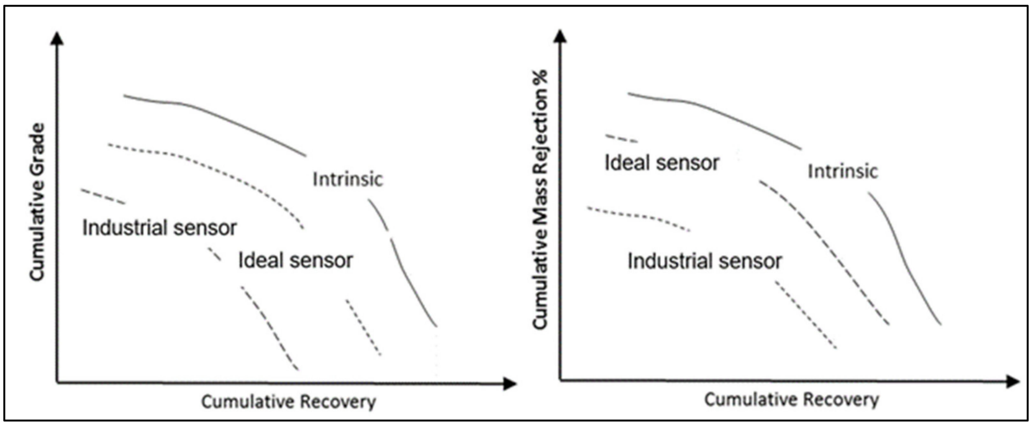

Figure 3. Examples of cumulative grade, recovery and mass rejection curves comparing the intrinsic, ideal sensor and industrial sensor sortability tests.

3. Results & Discussion

This section presents and discusses the application of the methodology to the Cu ore case study.

3.1. Stage 1—Sorting Duty

The case study is based on a typical copper porphyry comminution circuit consisting of various crushing stages followed by autogenous/semi-autogenous milling (AG/SAG milling). The AG/SAG milling stage often comprises a recirculating pebble circuit where pebbles are crushed. The sorting duty identified for the case study was the removal of low-grade waste material from the pebble crusher stream at a suitable Cu cut-off grade. The flotation feed stream in the case study has a cut-off grade of 0.4% Cu, which is typical for Cu-porphyry ore; removing any particles that are below this cut-off grade would enable the concentrator throughput to be maximised, thus increasing production. The methodology does not consider whether it is viable to increase throughput in an operation for reasons such as processing constraints but aims merely to demonstrate whether ore sorting has potential.

3.2. Stage 2—Ore Sampling

Ideally, the sampling methods discussed in Section 2.2 should be used to determine the minimum sample mass required. However, for the purposes of this study, a smaller sub-sample of 100 pebbles was used as these had to be analysed non-destructively. Here, the non-destructive method used for characterisation had an excessively long turnaround time. A sample of SAG mill oversize pebbles was screened at 20 mm for the test work. The −20 mm material was discarded as it was considered too fine for efficient ore sorting. The particles were visually inspected, and 100 pebbles were collected for the case study, with varying particle sizes and amounts of mineralisation, i.e., qualitative assessment of mineralogy/texture. The aim was to produce a set of pebbles that was sortable so that each stage of the methodology could be effectively demonstrated. The methodology requires a representative sample to produce accurate sortability results. The sample used in the case study cannot be considered representative but is fit for the purpose of demonstrating the application of the methodology. Methods for determining representative ore samples, such as those discussed in Section 2.2, are routinely used for various purposes in mineral processing. Obtaining a representative sample is a necessary step in the methodology, but the focus of this study is on demonstrating the application of the methodology for determining the ore sorting potential and not this routine procedure.

3.3. Stage 3—Particle Characterisation

The first step in the particle characterisation stage was to establish whether there was a correlation between the surface and volumetric mineralisation. The surface and volumetric mineralisation for a sample of 35 pebbles were determined using XRF and XCT, respectively. A portable XRF was used to analyse multiple points on the surface of each particle to determine Cu content. Bootstrap resampling was used to determine a statistically valid number of spot analyses required on the pebble surface. Here, 30 to 50 surface measurements per particle were required depending on particle size. An Xradia Versa 520 XCT was used to determine the volumetric mineralisation. The resolution achieved by the analysis was >40 µm. The analyses took up to 12 h per pebble, depending on the number of tomographies required. A positive linear correlation was found with an R^2 of 0.82, indicating that the particles can be characterised based on either surface or volumetric composition and that sensors which only measure surface composition can be used. Consequently, it was decided to determine particle composition for all 100 pebbles based on surface characterisation only. Here, the pebbles were divided into +40 mm (n = 48) and −40 + 20 mm (n = 52) size fractions as there were sufficient particles in each size fraction for characterisation. The grade distribution based on individual particle grade and mass in 0.2% Cu categories for the 100 pebbles is presented in Figure 4.

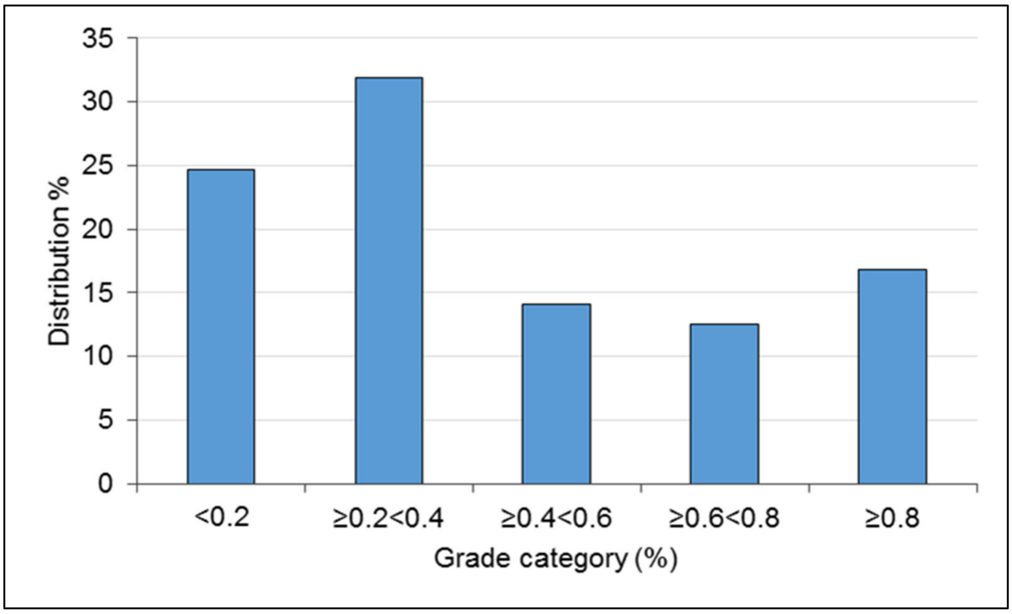

Figure 4. Grade distribution of the pebbles (% Cu).

Figure 4 shows that >55% of the pebbles in the sample are below a fairly low Cu cut-off grade of 0.4%. This suggests that there is potential to remove a volumetrically significant mass of material from the SAG oversize stream by removing low-grade pebbles. The XRF analyses were also used to determine whether any proxy elements correlated with Cu grade, but no correlations were identified.

Bootstrap resampling was again used to determine a statistically significant number of particles for analysis. Figure 5 presents the regression curve showing the relative standard deviation (RSD) of copper grade vs. number of particles resampled based on the results of bootstrap resampling [18]. The target error of <10% RSD on the copper content was achieved when ~40 particles are analysed, indicating that 40 randomly selected particles are sufficiently representative of the 100 particles used in the study.

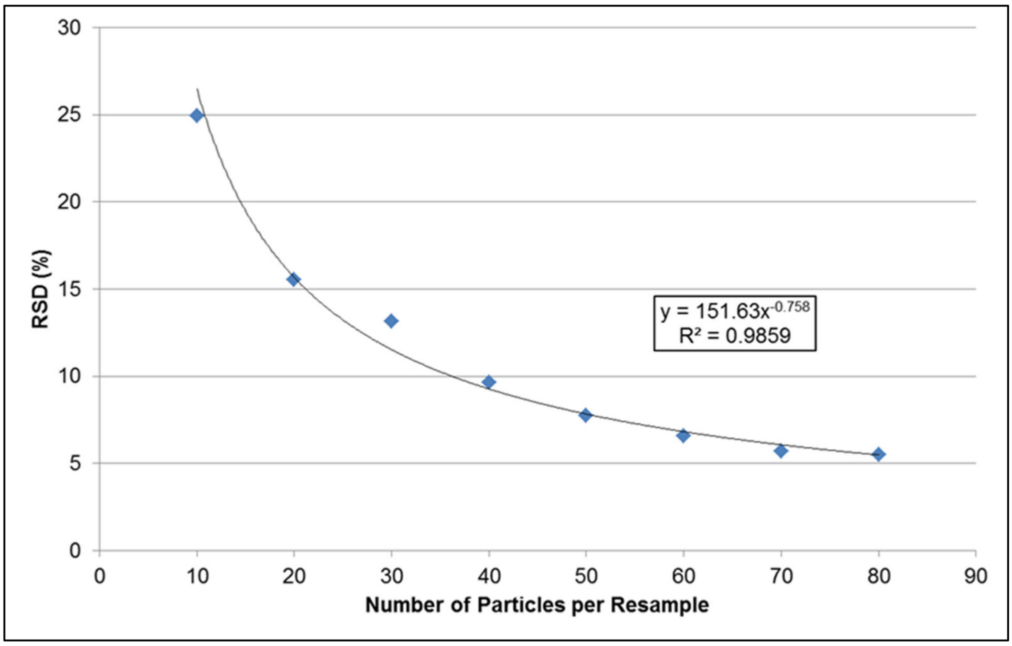

Figure 5. Regression curve for the Cu grade determined using the hand−held XRF.

3.4. Stage 4—Intrinsic Sortability

The overall and size-by-size intrinsic grade-recovery relationship was calculated based on the ore characterisation data using the method described in Section 2.4. Here, simulated separation tests were conducted at 5 different Cu cut-off grades. The intrinsic sortability results calculated for the simulated separation tests are given in Tables 2 and 3, respectively.

Table 2. Overall intrinsic sortability results for the combined +40 mm and −40 mm fractions.

Product	Mass (%)	Cu Grade (%)	Cu Distribution (%)
Test 1 Feed	100	0.44	100
Concentrate 1	8.01	1.44	26.0
Test 2 Feed	92.0	0.36	74.0
Concentrate 2	8.82	0.91	18.1
Test 3 Feed	83.2	0.3	55.9
Concentrate 2	6.86	0.65	10.0
Test 4 Feed	76.3	0.27	45.8
Concentrate 4	19.7	0.53	23.5
Test 5 Feed	56.6	0.17	22.4
Concentrate 5	25.9	0.25	14.8
Discard	30.7	0.11	7.57

Table 3. Cumulative intrinsic sortability results for the combined +40 mm and −40 mm fractions.

Cut-Off Grade (%)	Cu Recovery (%)	Conc Grade (%)	Mass Rejected (%)
1	26.0	1.44	92.0
0.8	44.1	1.16	83.2
0.6	54.2	1.01	76.3
0.4	77.7	0.79	56.6
0.2	92.4	0.59	30.7

The cumulative grade-recovery curves for the overall and size-by-size simulated separation tests are given in Figure 6. From this figure, it is clear that the results for the overall sample and the −40 mm and +40 mm fractions are similar, indicating no preferential grade by size upgrade. Consequently, it was decided to proceed with the methodology considering results for the overall sample only, i.e., no further size-by-size analysis.

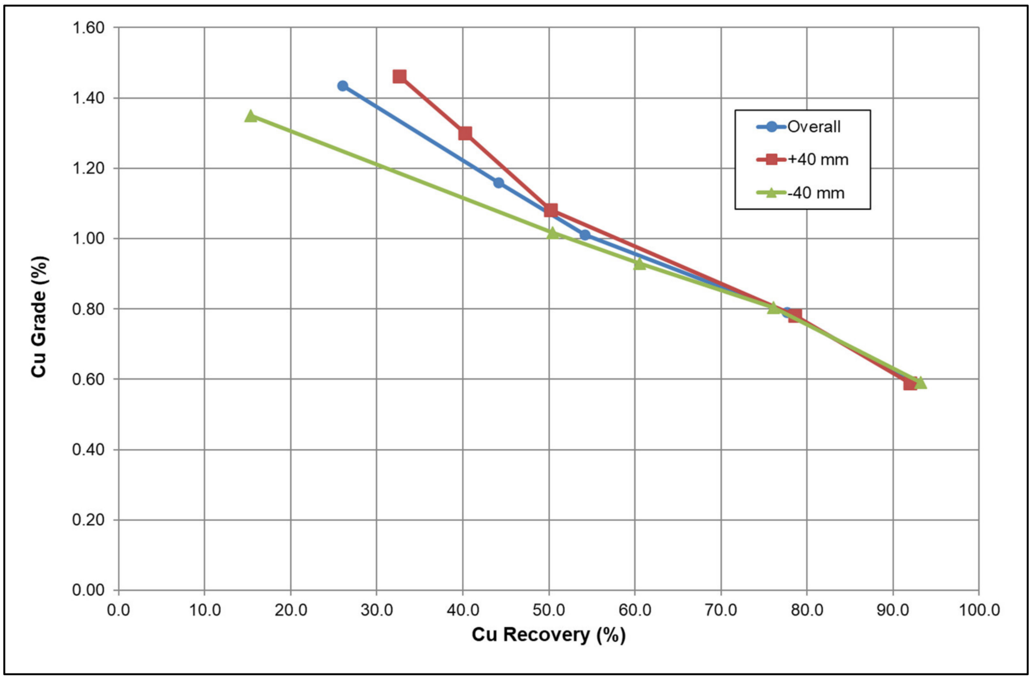

Figure 6. Cumulative grade−recovery curves for the overall sample as well as the +40 mm and −40 mm size fractions.

The case study results show that the ore has the potential to be sorted as a large proportion of low-grade pebbles can be rejected from the process without incurring significant copper losses to the waste stream. The intrinsic sortability results were used to conduct an economic analysis at various Cu cut-off grades using the method developed by Lessard [5], as shown in Table 4. The economic analysis indicates that the best-case sorting potential occurs at a Cu cut-off grade in the vicinity of 0.4%. A more accurate "optimum" Cu cut-off grade could be found by conducting the financial analysis over a broader range of grades and determining the peak in the response.

Table 4. Economic analysis of ore sorting based on intrinsic sortability and Cu cut-off grade.

	Baseline	**0.2**	**0.4**	**0.6**	**0.8**	**1.0**
Mill Data						
ROM Feed (tph)	3000	3184	3339	3458	3499	3552
Pebble Feed (tph)	600	416	261	142	101	48
SAG Feed (tph)	3600	3600	3600	3600	3600	3600
Pebble Circuit						
Sorter Feed (tph)		600	600	600	600	600
Rejection (%)		31	57	76	83	92
Waste (tph)		184	339	458	499	552
Pebbles (tph)	600	416	261	142	101	48
Flotation Circuit						
Feed Grade (%)	0.80	0.78	0.80	0.81	0.81	0.82
Recovery (%)	80	80	80	80	80	80
Pebble Grade (%)	0.44	0.59	0.79	1.01	1.16	1.44
Waste Grade (%)		0.11	0.17	0.27	0.30	0.36
Add. Cu Feed (tpd)		35	65	89	98	108
Add. Cu Waste (tpd)		5	14	29	36	47
Add. Cu Rec (tpd)		24	41	48	50	49
Add. Rev. ($/day)		105,720	180,788	212,753	220,249	216,301
Waste Cu ($/day)		17,105	50,526	103,609	126,274	167,256
Operating Costs						
Mining ($/ton)	3	3	3	3	3	3
Mining ($/day		13,272	24,439	32,967	35,932	39,741
Waste Disp. ($/ton)	1	1	1	1	1	1
Waste Disp. ($/day)		4424	8146	10,989	11,977	13,247
Milling ($/ton)	4	4	4	4	4	4
Sorting ($/ton)		2	2	2	2	2
Sorting ($/day)		8848	16,293	21,978	23,954	26,494
Add. Rev. ($/day)		105,720	180,788	212,753	220,249	216,301
Add. Costs ($/day)		26,544	48,879	65,935	71,863	79,482
Add Profit						
Add. Profit ($/day)		62,072	81,384	43,209	22,112	−30,436
Add. Profit ($/year)		22.6 m	29.7 m	15.8 m	8.1 m	−11.1 m

Note: In Table 4, values similar to those observed on typical copper operations and commercial sorters have been used in the calculations.

Here, an additional profit of around $30 million per year could theoretically be achieved by implementing ore sorting for the SAG mill oversize pebbles, which is the theoretical best case. However, this additional profit is based on the assumption of perfect separation and does not include the costs of installing an ore sorting system or whether the additional ROM throughput required is practically feasible. The positive profit merely indicates that the next stage of the methodology should be conducted, i.e., there is the potential for implementing ore sorting as it results in a positive additional cash flow. It should be noted that the analysis was performed at a Cu price of $4400/ton, which was the price at the time the financial information for operating costs was obtained. The additional profit would be significantly higher at current Cu prices, which are over double this.

3.5. Stage 5—Sensor Amenability Tests

Laboratory-scale XRF, XRT, and NIR sensors were selected for the sensor amenability tests as these have been successfully used on base-metal ores. A much broader range of sensors could have been evaluated, but these three were considered sufficient to demonstrate the methodology. Sensors were supplied by Tomra Sorting Solutions. Standard laboratory test measurement conditions were used but are not specified here as this detail is not relevant to demonstrate the methodology. However, for example, the XRF sensor measurement was based on two repeated measurements on two sides of the particle on a ±10 mm diameter spot. The result of the two spot analyses was combined to give a single datum for each pebble for comparison with the corresponding Cu grade determined by hand-held XRF at 30–50 points per particle. A comparison of copper grade and sensor response is presented in Figure 7. Here, the aim was to determine which sensors could discriminate between particles of differing grades based on measured physical properties. A positive correlation was observed between the XRF sensor response and the Cu grade. A weak positive correlation was found for the XRT sensor and no correlation for the NIR sensor. The NIR sensor does not directly detect the Cu-bearing phases but can be used to measure alteration silicate content (e.g., biotite). The results indicate no correlation between Cu grade and alteration. Based on the sensor amenability test results, the XRF and XRT sensors were selected for the next stage of the methodology, although of these, the XRF provided the most promising results.

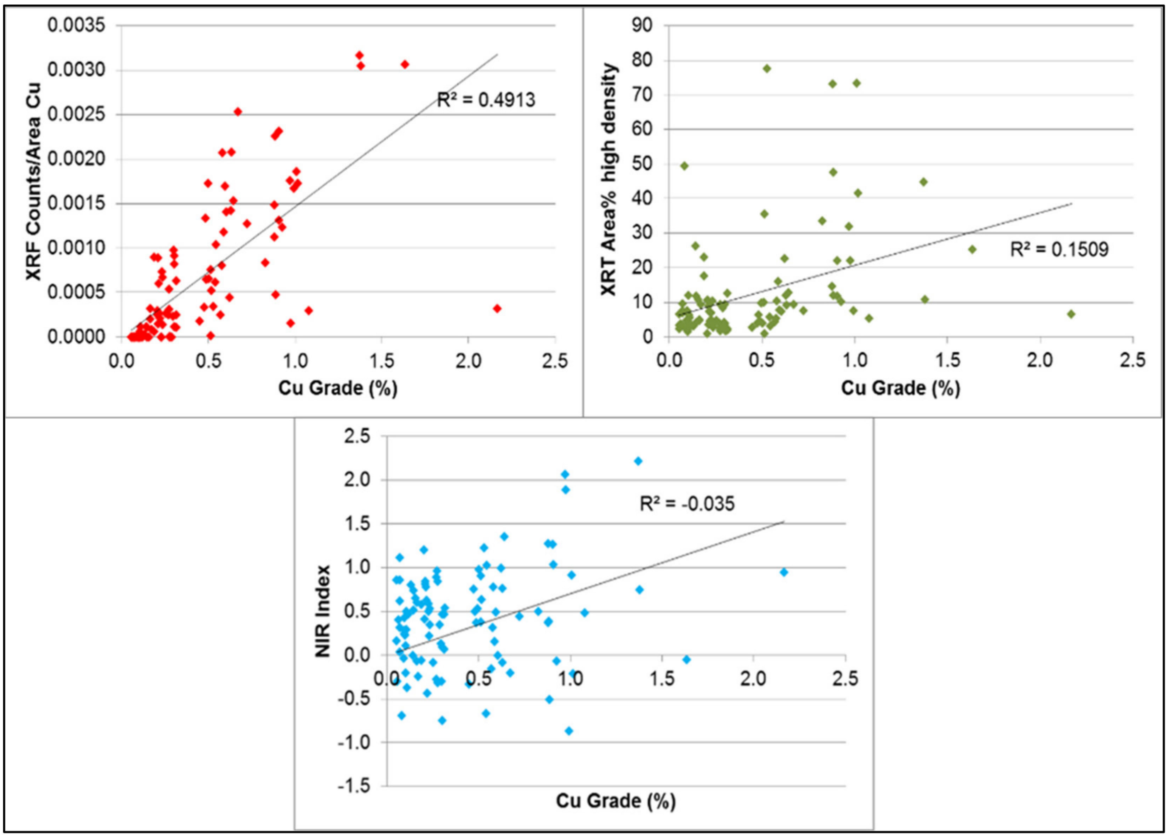

Figure 7. XRF, XRT and NIR sensor response curves.

3.6. Stage 6—Sortability Tests

3.6.1. Ideal Sensor Sortability

The laboratory-scale sensor measurements from the sensor amenability tests discussed in the previous section were used to determine the ideal sensor sortability for the XRF and XRT ore sorting sensors. Here, simulated separation tests were conducted at five different sensor response thresholds applying the same methodology used to determine the intrinsic sortability. The only difference is that the Cu cut-off grade is used to determine the intrinsic sortability, whereas the sensor response threshold is used for the ideal sensor sortability. The cumulative grade-recovery curves for the simulated laboratory (ideal) sensor sortability tests are given in Figure 8.

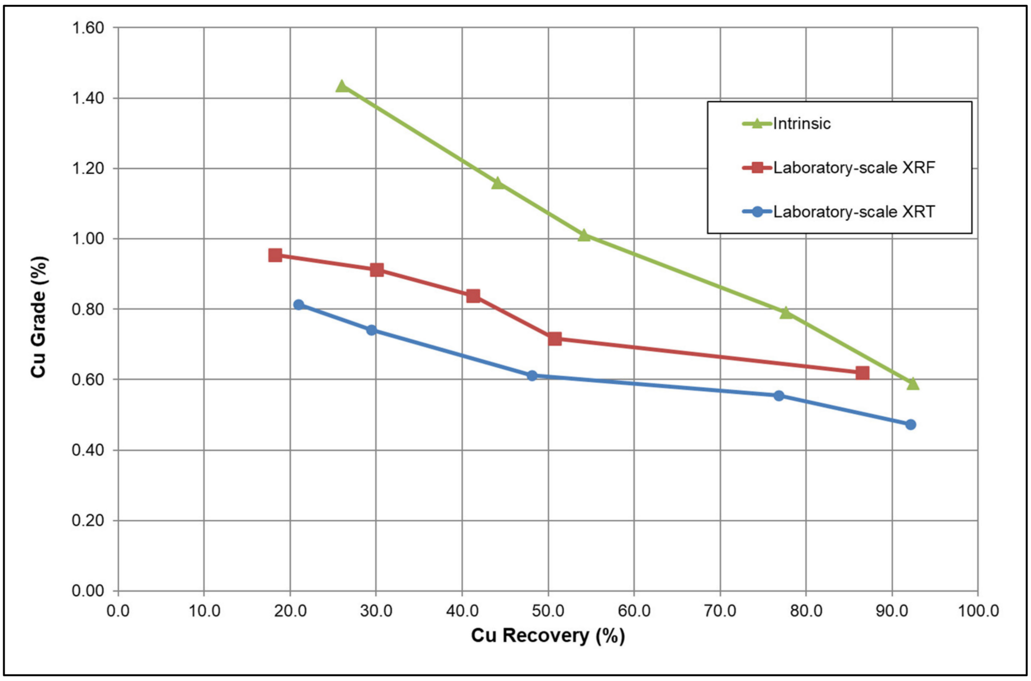

Figure 8. Cumulative grade-recovery curves for the intrinsic and laboratory (ideal) sensor tests.

Here, the intrinsic grade-recovery curve is also shown, representing the limit of the ore's separation efficiency based on mineralogical characteristics, i.e., the maximum theoretical separation. The upgrade ratios for the two sensors are clearly lower than that for the intrinsic sortability. However, the results indicate that there is potential to sort the ore using the selected sensors as ~40% of mass can be rejected as waste at copper recoveries above 80% with a maximum upgrade ratio of 1.4.

The additional profit was calculated using the same method described in Section 3.4. Here, sorting at the optimal sensor response thresholds would add an additional profit of ~$21 million and ~$7 million for the XRF and XRT sensors, respectively. This indicates that there is a potential to implement ore sorting using either sensor. The XRF sensor showed the best grade recovery and was, therefore, selected for further investigation using an industrial-scale sensor.

3.6.2. Industrial-Scale Sensor Sortability

The industrial-scale sensor sortability response was determined by passing the 100 pebbles through an industrial XRF sensor using a vibratory feeder. Here, the analysis time was of the order of 50 milliseconds. Simulated separation tests and profitability were again calculated as described in the previous section. The cumulative grade-recovery curves for the simulated sensor sortability tests are given in Figure 9.

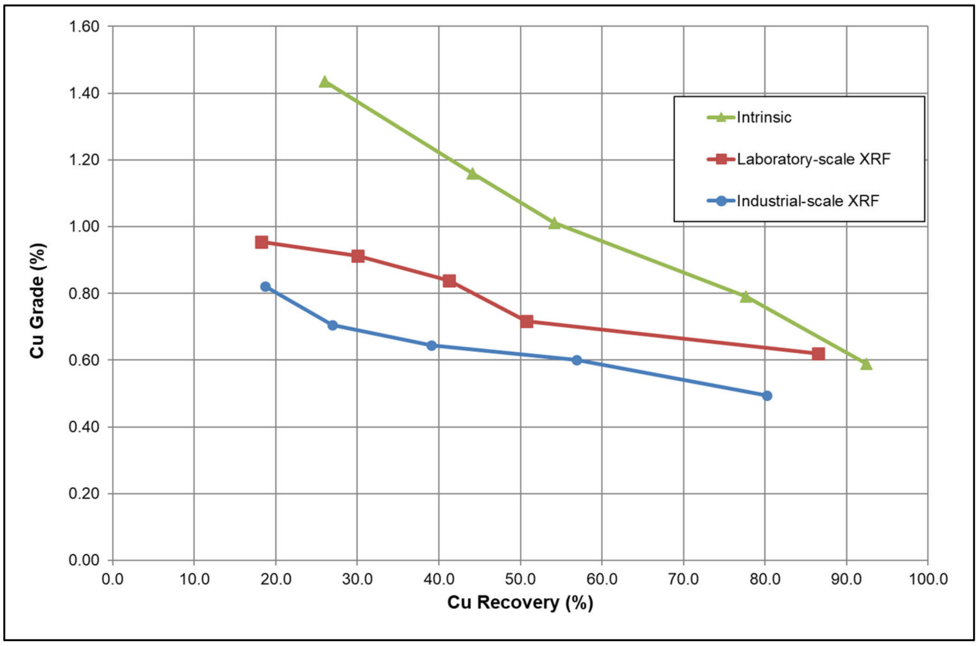

Figure 9. Cumulative grade-recovery and mass rejection curves for the intrinsic, ideal and industrial sensor tests.

The upgrade ratio for the industrial-scale sensor is significantly lower than that for the ideal laboratory sensor. It is common that decreased performance occurs when upscaling from benchtop to piloting through to full production. Here, ~30% of mass can be rejected as waste at copper recoveries above 80% with a maximum upgrade ratio of 1.1. With this separation efficiency, no additional profit could be achieved across the entire range of sensor response thresholds. Therefore, there is no potential for industrial-scale XRF sorting using the sensor in its current configuration.

3.7. Case Study Discussion

A summary of ore sortability results at optimum separation conditions is given in Table 5. Here, the results represent the best case for sorting where additional profit was highest for intrinsic/sensor sortability. As discussed previously, the intrinsic and ideal sensor sortability results show that there is potential for ore sorting based on the physical attributes of the SAG oversize particles. However, the industrial sensor sortability results clearly show that there is no potential to implement ore sorting with the current sensor. This suggests that there is an opportunity to consider improved XRF sensors (better resolution, combining sensors etc.), alternative sensor types or other separation techniques as there is an economic argument for implementing ore sorting. However, it should be noted that this case study was used to demonstrate the application of the methodology and not to make conclusions on implementing ore sorting for general copper operations.

Table 5. Summary of ore sortability results at optimum separation conditions (Cu cut-off grade or sensor response threshold). Cu head grade for the sample was 0.4% Cu. An additional profit is rounded to the nearest million.

Sortability	Property/Sensor	Cu Recovery (%)	Concentrate Grade (%)	Mass Rejected (%)	Upgrade Ratio	Add. Profit ($/Year)
Intrinsic Sortability	Cu (%)	77.7	0.79	56.6	1.8	~30 m
Sensor Sortability	Ideal XRF	86.5	0.62	38.4	1.4	~21 m
	Ideal XRT	76.8	0.56	39.0	1.3	~7 m
	Ind. XRF	80.2	0.49	28.3	1.1	~ −7 m

4. Conclusions

This study presented a methodology to determine the potential for ore sorting based on intrinsic particle properties. The methodology was demonstrated using a case study based on a typical copper porphyry comminution circuit.

The methodology consists of six stages. Stage 1 identifies the potential ore sorting duty. Stage 2 determines the required sample size for a representative sample of the ore. Stage 3 involves the characterisation of particles in the sample in terms of physical, chemical and mineralogical composition. Stage 4 determines the intrinsic sortability of the ore from the particle composition based on theoretical separation. Stage 5 identifies sensors which have the potential to differentiate between particles of varying physical, chemical or mineralogical properties. Stage 6 involves conducting sortability tests on particles in the representative sample, firstly using ideal laboratory sensors and ultimately industrial-scale sensors.

The intrinsic and ideal sensor sortability results showed that there is potential for ore sorting. Here, the ideal XRF sensor results showed that around 40% of mass could be rejected as waste at copper recoveries above 80%, with a maximum upgrade ratio of 1.4. However, the industrial sensor sortability results showed that there is no potential to implement ore sorting with an upgrade ratio of 1.1.

An economic analysis of the sortability tests showed that, at optimum separation conditions, the intrinsic, ideal sensor, and industrial sensor sortability would result in an additional annual profit of $\pm$\$30 million, \$21 million and \$$-$7 million (loss), respectively.

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