CORRELATION AND REGRESSION ANALYSIS IN THE X-RAY FLUORESCENCE SORTING OF A LOW GRADE COPPER ORE

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ABSTRACT

The benefits of pre-concentration using sensor-based sorting have been widely reported with the greatest potential impacts on low grade and high tonnage operations such those mining copper porphyry deposits. Due to the non-selective nature of bulk surface mining methods, significant quantities of waste misreport to the concentrator reducing the feed grade, consuming energy during comminution and increasing water usage. In addition, significant metal misreports to the waste dump that represents a production loss and contributes to the metal content and therefore liability of the waste dump. The two main barriers to broader application of sorting are limitations in processing rates and the inability of sensors to accurately discriminate ore from waste. The present study is focussed on the latter and demonstrates the development of a more intelligent and more accurate sensing system. The X-ray fluorescence (XRF) technology was examined to explore its potential to pre-concentrate a low-grade copper ore through discarding barren particles. Simple linear correlation between the copper grades estimated using XRF and the copper grades obtained through chemical analysis did not meet the sorting requirement. Improved linear correlation and multiple linear correlation analysis were introduced in the study and better sorting results were obtained due to stronger correlations.

KEYWORDS

Sensor-based sorting, x-ray fluorescence, copper ore, pre-concentration, correlation coefficient, regression analysis

INTRODUCTION

Advances in Ore Sorting

Numerous studies have demonstrated the technical and economic benefits of sensor based sorting to preconcentrate ores (Bamber, 2008; Bamber, Klein, Pakalnis, & Scoble, 2008; Kleine & Wotruba, 2010; Knapp, Neubert, Schropp, & Wotruba, 2014; Kobzev, 2014; Lessard, de Bakker, & McHugh, 2014; Robben, Wotruba, Robben, von Ketelhodt, & Kowalzcyk, 2013). For large scale copper porphyry operations the application of sensor-based sorting to discard barren rock results in improved grade control (i.e. higher grades to concentrator), decreased energy consumption for comminution and reduced water usage on a volume per weight of metal basis (Bamber et al., 2008, Gunson, Klein, Veiga, & Dunbar, 2012). Sorting not only diverts barren rock away from the concentrator, it also recovers metal bearing that would otherwise be lost to the waste dump resulting in improved resource utilization. A recent study on waste dumps from two copper porphyry mines showed that 25% of the waste rock was of sufficient grade to report to the concentrator (Mazhary & Klein, 2015).

Despite its potential benefits, sorting is not widely applied and has found only niche applications. Barriers to broader application relate to:

1) The low throughput capacity of available industrial machines, and
2) The limited ability of sensors to discriminate between barren rock and valuable rock.

Innovations aimed at increasing the capacity relate to improving the understanding of ore heterogeneity as the basis for developing semi-bulk or bulk sorting systems by incorporating the sensors in the material handling equipment (MineSense Technologies Ltd, 2015). Advances in sensing systems relate to the improved accuracy and speed of sensor response as well as the development of intelligent methods of analyzing the sensor responses to generate discrimination algorithms for sorting machines.

The present paper focuses on the development of more intelligent sensing systems by using correlation and regression analysis of XRF sensor responses. Sensor-based sorting technologies, which take advantage of the electromagnetic spectrum, include radiometric, x-ray transmission, x-ray fluorescence (XRF), near infrared, photometric, inductive, microwave heating and so on. The physical principle of XRF is based on the excitation of atoms on the ore particle surface. The generated XRF spectrum can be used to sort base metals, ferrous metals, precious metals, industrial minerals and rare earths (Knapp et al., 2014). Mineral association and the grade variation are critical for successful XRF sorting process (Fickling, 2011). For the application of XRF to sorting manganese, the sensor response, referred to as the H-value, was used in linear regression analysis. The H-value is determined by both the number of impulses registered in the manganese and iron x-ray emission spectrum area and the number of impulses registered in the diffused emission spectrum area (Equation 1). A strong linear correlation between the sorter value and the grade of the ore was achieved, indicating the high sorting accuracy (Mohanan, Saxena, Kumar, Naik, & Kumar, 2013).

$$H = \frac{N_{Mn}}{N_S + \left(k \times \frac{N_{Fe}}{N_{Mn}} \times N_{Fe}\right)} \tag{1}$$

As suggested by Mohanan et al., (2013), once the linear correlation between the assay grade of the ore particles and the sorter values met the operational requirement, a simple linear regression equation was used to calibrate the sensor values and transfer them into a metal grade. The predicted grade was then used as the basis for accepting or rejecting the particle as ore or waste, respectively. The accuracy of the XRF measurement is greatly influenced by the heterogeneity of the ore particles (Jenkins, 1999). The correlation and regression relationship between the sensor values and the assay results require further study for successful sorting of ores with complex mineralogy.

The results obtained by XRF scanning can be presented in the form of count rates, ratios of counts, and intensities of elements. Attempts were made to calibrate element intensities measured by XRF to element concentrations by conventional chemical analysis. Linear correlation was not applicable in many cases due to the following reasons: heterogeneous of the specimens, low element concentrations, and the interactions of element of interest and/or the other elements present in the sample (Jan Weltje & Tjallingii, 2008). The ideal specimen for XRF analysis is one in which the analyzed volume of the specimen is representative of the total specimen. For XRF sorting of rocks, the ore particle size, particle size homogeneity, and ore composition heterogeneity constrain the ideal circumstance (Jenkins, 2000).

Recent XRF sorting tests on a low grade copper ores were carried out at MineSense Technologies Ltd.. The element grades of interest were reported by XRF and the correlation between the XRF data and the assay results was analyzed. Simple linear correlation and regression equations may not meet the requirements for sorting. It is therefore necessary to develop new methods to analyze the sensor data. The analysis starts from the simplest relationships namely linear correlation and linear regression analyses.

The main objective of this investigation was to study the correlation between the copper grades estimated by XRF and the copper grades through chemical analysis. This included determining the Pearson correlation coefficient and the Spearman rank correlation coefficient in order to understand how the correlations could be improved through applying statistical method to information about the ore particles allowing calibration of copper grades from XRF sensor responses.

EXPERIMENTAL

Ore Sample and Test Procedure

A low-grade copper ore sample was obtained from the Spence copper mine in Chile. A bench scale XRF sorting test procedure as shown in Figure 1 was followed. The sample was weighed and screened into size fractions for testing. About 500 ore particles in the -75+25 mm size fraction were selected for the XRF sorting tests from which 85 particles were selected for assaying. The assay results were used for the correlation and regression analysis. The results of the correlation and regression analyses were used to generate discrimination algorithms, which were applied to the rocks to classify as either ore or waste.

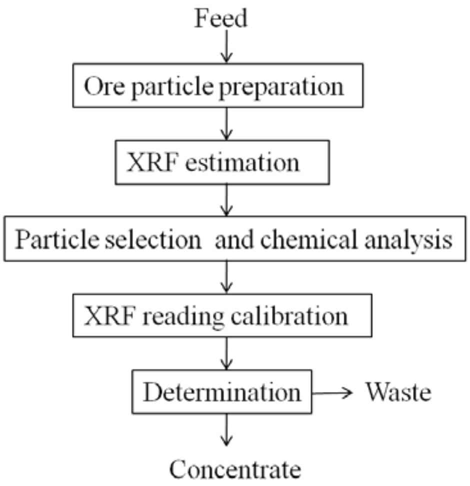

Figure 1 – Bench scale XRF sorting test procedure

Copper Grade Measurements

<u>Copper Grade Estimated by X-Ray Fluorescence</u>

High-energy radiation from the XRF unit causes the atoms on the ore particle surface to ionize to generate X-ray fluorescence. The X-ray detector generates a counting rate (R) from an interested element by converting the collected photons. Equation 2 shows the number of counts (N) generated by the X-ray detector for a given time t. The relationship between the frequency (energy) and the atomic number forms the X-ray spectrum (Jenkins, 1999). Then, the counts of the XRF for a wide range of elements can be utilized to quantify the chemical composition of the particles. Equation 3 shows the factors that can influence the concentration measurement, where C is the concentration of the measured element; K is a calibration constant determined by instrumental factors; M is the matrix effect; S is the specimen effect. Individual ore particles with size range from 1 to 3 inches were tested by the XRF sensor to estimate the copper grade. The specimen effect has great impact on the copper grade measurement of the ores particles.

$$N = R \times t \tag{2}$$

$$C = K \times R \times M \times S \tag{3}$$

Correlation Analysis

Pearson's Correlation

The copper grades measured by both XRF and the assay methods were analyzed by Pearson's correlation. In the analysis, the two sets of copper grades are represented by X, Y, respectively. The correlation coefficient was calculated using Equation 4, where, x_i is the sorting response of each particle, i.e. the copper grade from XRF; $\bar{x}$ is the mean of copper grade of all the particles; y_i is the copper grade of each particle obtained through assay; $\bar{y}$ is the mean of the copper grade of all the particles measured by assay (Bewick, Cheek, & Ball, 2003).

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{4}$$

When the Pearson's correlation method is used, the following assumptions are made. The copper grades should be continuous and there are no significant outliers. There is a linear relationship between the copper grades. The copper grades should be approximately normally distributed. The correlation coefficient ranges from -1 to 1, which can be categorised as positive correlation, negative correlation, and no correlation. In this study, it assumes that when the copper grade obtained by assay increases, the copper grade estimated by XRF also increases, so, only the correlation in the range from 0 to 1 is considered.

Spearman's Correlation

The Pearson's correlation coefficient can be misleading when the relationships between the copper grades is not linear (Hauke & Kossowki, 2011). Spearman's coefficient, Equation 5, assesses how well a function can describe the relationships between two variables. Where, d_i is the difference between ranks; n is the size of the sample.

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{5}$$

Regression Analysis

Linear Regression Analysis

The copper grades obtained by XRF and chemical assay are believed to be related to each other such that the relationship can be found by regression analysis. The process of linear regression fits estimated responses to measured responses by adjusting coefficient values to minimize the sum of the squared errors and was previously used for XRF sorting studies to calibrate the XRF sorter values (Fickling, 2011; Mohanan et al., 2013). Equation 6 represents the simple linear regression, where, β_0 is a constant, β_1 is the slope, and ε_i is the statistical error for i^{th} data point (Shi & Conrad, 2009). Coefficient of determination (R^2), is a measure of goodness-of-fit for linear regression (Bewick et al., 2003).

$$Y_i = \beta_0 + \beta_1 X_{i1} + \varepsilon_i \tag{6}$$

$$Y_i = \beta_0 + \beta_1 X_{i1} + \cdots \beta_p X_{ip} + \varepsilon_i \tag{7}$$

Multiple Linear Regression Analysis

The XRF determines not only the Cu grade but also the grades of several other elements. Multiple linear regression analysis can be used to describe the relationship between the Cu assay grade and other elements determined by XRF sorting. Equation 7 shows the equation for p variables and $p + 1$ parameters (Shi & Conrad, 2009). Stepwise regression is a method used to determine which of the independent variables are significant, which simplifies the resulting regression expression by eliminating those that are not significant (Cevik, 2007).

RESULTS AND DISCUSSION

Sample Evaluation

Copper values measured by both XRF estimation and chemical analysis on the selected 85 ore particles were analyzed and the results are shown in Table 1. Both the maximum copper grade and the minimum copper grade were reported. The median is the central copper grade when all the 85 particles are sorted in order. The mode is the most commonly occurring copper grade in the sample. For the XRF data, 20% of the particles contained copper grades of 0.1% and 0.2%. Therefore, the mode was set to 0.15% (Figure 2). The normal probabilities of the two data sets are 0.86 and 0.81 for the XRF and the assays respectively, indicating that the copper grade has a normal distribution.

Table 1 – Comparison of the XRF estimation and the assay results on 85 ore particles

Method	XRF	Assay
Maximum Cu%	1.96	2.71
Minimum Cu%	0.03	0.02
Median Cu%	0.25	0.47
Mean, Cu%	0.45	0.57
Mode, Cu%	0.15	0.20

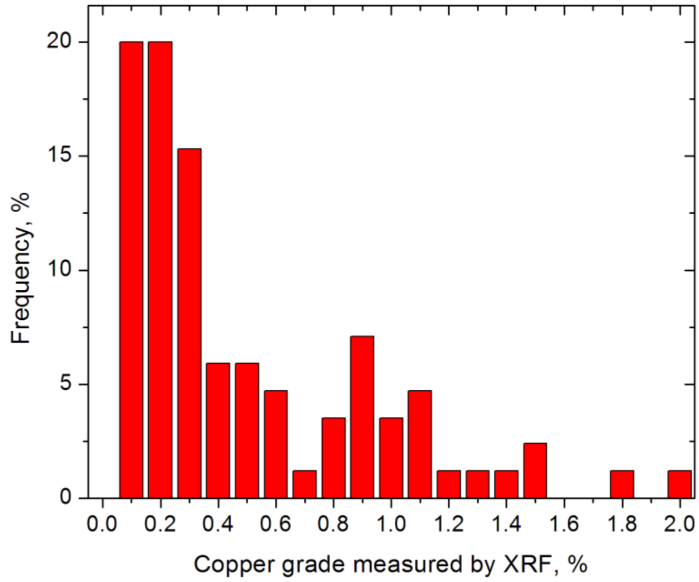

Figure 2 – Copper distribution in the selected 85 ore particles

Correlation Analysis

<u>Theoretical Relationship</u>

Figure 3 presents the correlation concept for Cu grades determined by XRF and chemical assay. Pure mineral refers to chalcopyrite, $CuFeS_2$. The test limit in Figure 3 is a concept line of the maximum copper grade of the ore sample used in the study. The cut-off copper grade is 0.2%. Ideally, the copper grade measured by XRF equals to the copper grade obtained by chemical assay. Due to its mineralogy, the copper grade discussed in the XRF sorting test is limited to a very small range (up to a few percent Cu). The sorting process needs to be more accurate when the grade of the ore particle is close to the cut-off grade. So, a stronger correlation is necessary for the data close to the cut-off grade.

As shown in Figure 4, the mineral particles can be grouped based on the assay and the XRF relationships, e.g. the ratio of the copper grades measured by assay versus the copper grade by XRF. When the ratio equals to 1, it means that the copper distribution inside the ore particle equals to the copper distribution on the particle surface. When the ratio is less than 1, it means that there is more copper on the ore particle surface. When the ratio is greater than 1, it means that more copper is distributed inside the ore particle. For statistics analysis, extremely large or extremely small ratios can be considered outliers in the Pearson's correlation coefficient study. Figure 4 indicates that the mineralogy is critical for a successful sorting process. Simple linear regression analysis requires the data located in a region close to the ideal value.

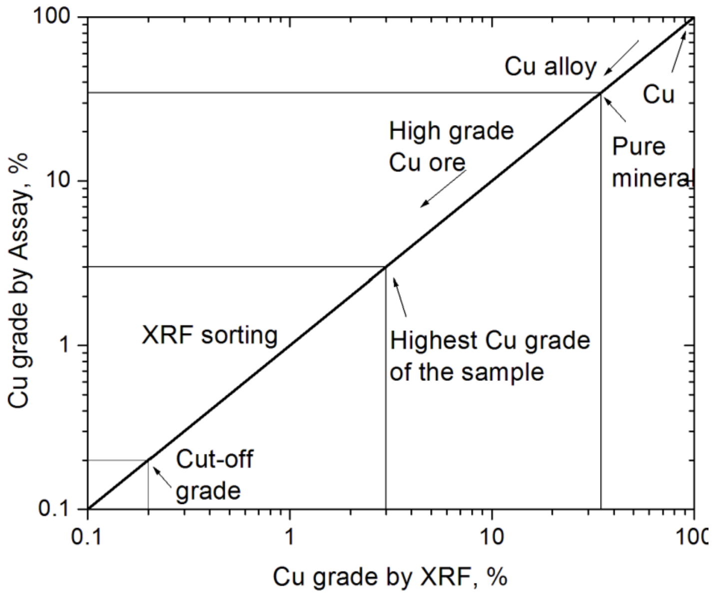

Figure 3 – Variation of copper grades in the XRF measurement

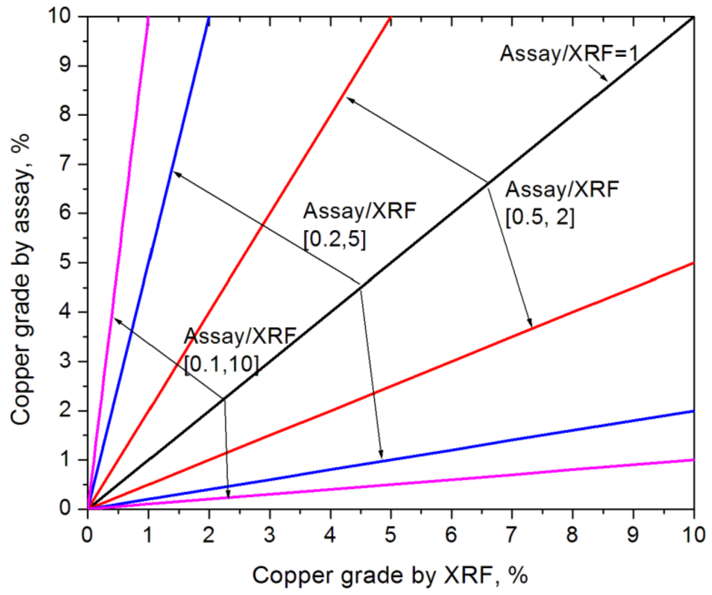

Figure 4 – Effect of copper distribution on the XRF estimation and chemical analysis

For a sorting operation, the efficiency is determined by the accuracy of the XRF measurement on each ore particle, which is determined by the count rate, measurement time, and heterogeneity of the copper distribution in the particle. A high count rate, long measurement time, and homogeneous particles are positive for sorting. Sorting at the cut-off grade requires that the sorting element has a high count number. Wide ranges of the copper grade ratio between the assay data and the XRF readings limit the usage of the sorting operation.

Figure 3 indicates that the copper ore sorting efficiency is also determined by the copper distribution in the sample. The sorting process is easy when the sample contains only copper rich and barren particles. The constitutional heterogeneity (CH) refers to the heterogeneity dependence on the copper grade/weight differences between the individual ore particles. A large CH value indicates greater heterogeneity making the ore easy to sort.

Linear Correlation

The copper grades of the selected 85 particles measured by XRF and chemical analysis are shown in Figure 5. As shown in Table 2, the Pearson's correlation coefficient is 0.47, which indicates a weak linear correlation between the two sets of data. The effect of outliers on the correlation was assessed and there was no significant improvement to the correlation when the outliers were removed.

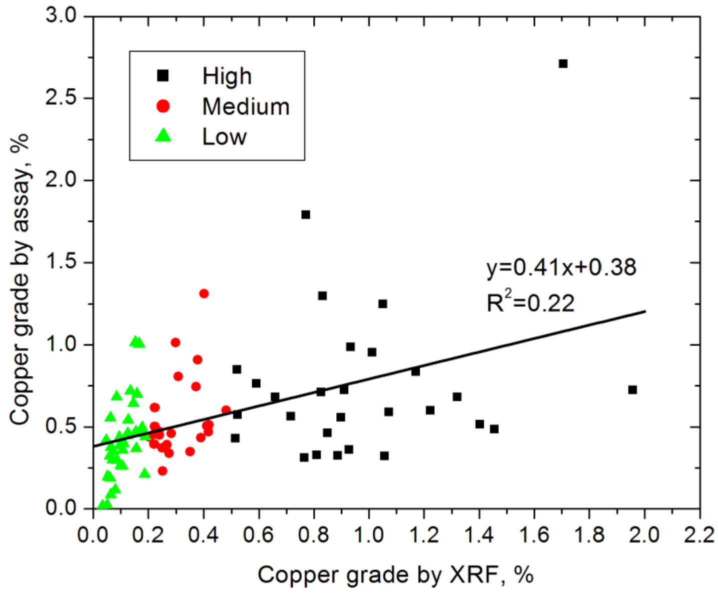

Figure 5 – Copper grades measured by assay versus results measured by XRF

<u>Piecewise Linear Correlation</u>

The Spearman rank correlation coefficient, presented in Table 2, is higher than the Pearson correlation coefficient which means that a non-linear equation can better describe the copper grade relationship for the 85 ore particles. Linear correlation analysis has to consider both the copper grade and the sorting requirement. Based on the copper grade determined by XRF, the 85 particles were sorted into three groups referred to as "high", "medium", and "low" grade. The Pearson's correlation coefficient was calculated for each group of data (Table 2). The correlation of the "low" copper grade group is the highest, which is positive for indentifying the low grade particles.

Copper values measured by both XRF and chemical assay on the three groups of particles were analyzed and the results are shown in Table 3. The mean Cu grade suggests that the XRF sorter values increase with the assayed Cu grade. Generally, the XRF values are smaller than the assayed grades for the low and medium groups while the XRF value is larger than the assayed Cu grade for the high grade particles. When the XRF reading is higher than 0.2%, the assayed Cu grade is higher than the cut-off grade. Therefore both the high and medium grade groups can be recovered as concentrate and the efficiency of Cu sorting is dependent on the ability to sort the low grade particles.

Table 2 – List of correlation coefficients between the XRF and the chemical analysis results

Range of Cu grade, % Measured by XRF	Pearson's grade correlation	Pearson's weight correlation	Spearman's grade correlation	Spearman's weight correlation
Overall	0.48	0.52	0.53	0.65
High	0.28	0.57	0.12	0.72
Medium	0.36	0.87	0.38	0.86
Low	0.55	0.86	0.58	0.91

Table 3 –Cu grade of three groups of ore particles based on XRF estimation

Group	Low XRF	Low Assay	Medium XRF	Medium Assay	High XRF	High Assay
Ore particle number	34	34	23	23	28	28
Maximum Cu%	0.19	1.02	0.48	1.31	1.96	2.71
Minimum Cu%	0.03	0.02	0.2	0.23	0.52	0.31
Median Cu%	0.10	0.41	0.28	0.47	0.9	0.64
Mean, Cu%	0.11	0.39	0.31	0.56	0.98	0.76
Mode, Cu%	0.15	0.5	0.3	0.5	0.9	0.6

Multiple Linear Correlation Analysis

Correlation analysis was carried out between the assayed Cu grade and the elemental content estimated by XRF. The correlation coefficient of up to 0.6 was achieved indicating that the improvement of copper ore sorting can be achieved by considering several elements as well as their interaction effects. As shown in Table 4, a strong correlation was achieved between the copper grade and the 12 elemental contents and their interaction effects as estimated by XRF. It is important to recognize that the elements reflect on the mineralogical composition of the ore such that may be positively or negatively correlated to the copper grade. For example, chalcopyrite contains Fe which should be positively correlated to Cu grade. Conversely, elements such as Al, may represent the gangue alumina-silicate minerals and would be negatively correlated. Interaction affects must also be considered as they can relate to a specific mineral such as Fe and Cu in chalcopyrite. Therefore multiple linear correlation analysis is recommended for the low grade ore sorting data analysis.

Table 4 – List of correlation coefficients between the copper grade (assay) and the various elements estimated by XRF: 85 ore particles

Elements estimated by XRF	Multiple linear regression analysis without interaction	Multiple linear regression analysis with interaction
Al, Si, S, Ti, V, Fe, Cu	0.53	0.60
Al, Si, S, Ti, V, Fe, Cu, Zn, Mo, Sn, Zr, Sb	0.61	0.94

Regression Analysis

Linear Regression Analysis

The purpose of the regression analysis is to find an equation to convert the sorter values to the copper grade. The linear regression method was used for the regression analysis. As shown in Figure 6, the ideal curve was drawn based on the assayed Cu grade. Similar curves were drawn based on XRF sorting, calibrated data based on a single linear equation, and calibrated data based on a stepwise linear equation. In Figure 6, when the XRF readings on Cu were calibrated based on single linear equation, there was no improvement on the sorting results due to the weak correlation.

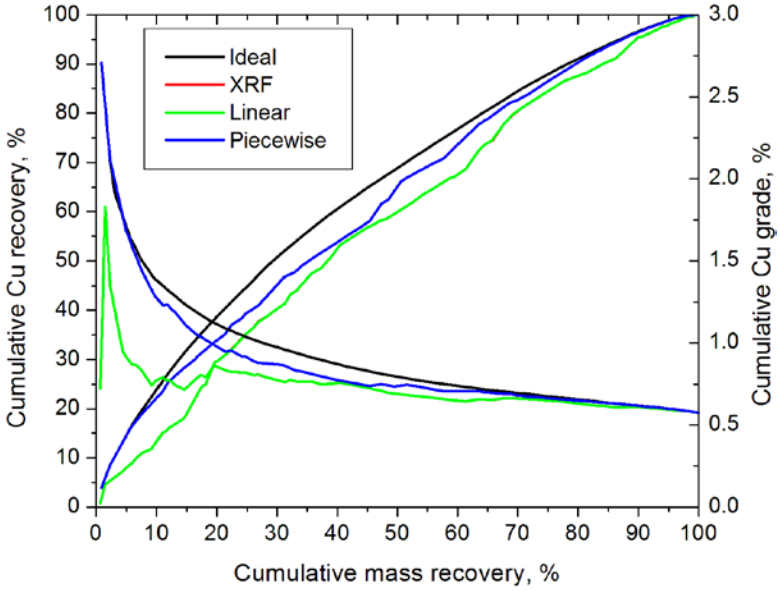

Figure 6 – Grade/recovery relationships of the overall sample

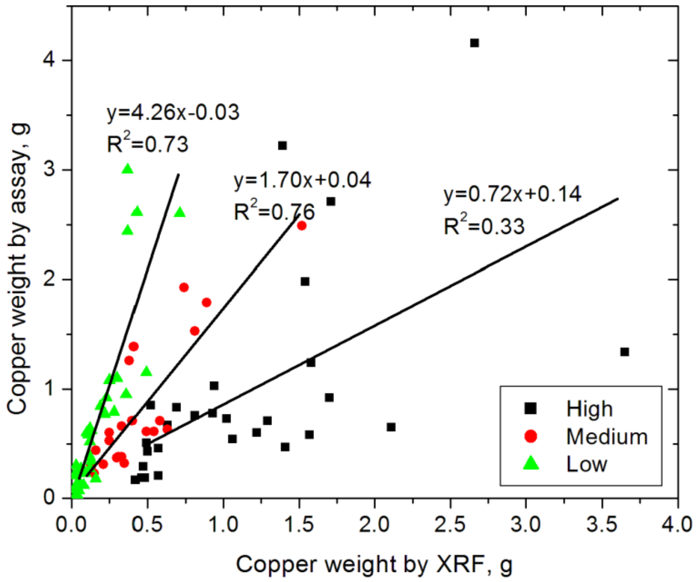

Figure 7 – Copper weights measured by assay versus data measured by XRF

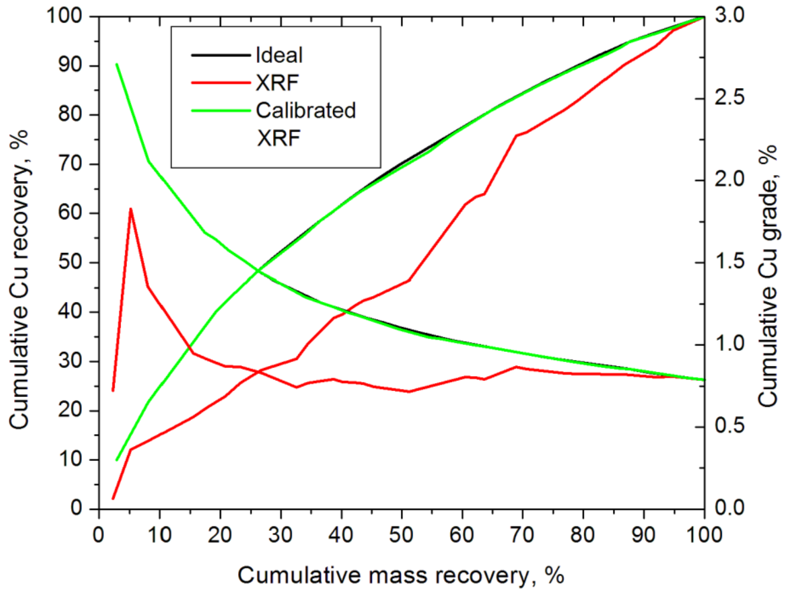

Figure 8 – Grade/recovery relationships of the ore particles: high grade group

<u>Piecewise Linear Regression Analysis</u>

The piecewise linear relationship of the low, medium, and high grade groups of ore particles were shown in Figure 7. As shown in the Figure, a simple linear equation was suggested for each group of ore particles and the equations can be used to convert the XRF values to Cu grade. The improvement of the piecewise regression on the Cu grade/recovery is shown in Figure 6. When piecewise regression was used in the sorting process, more Cu was recovered as concentrate with a higher Cu grade.

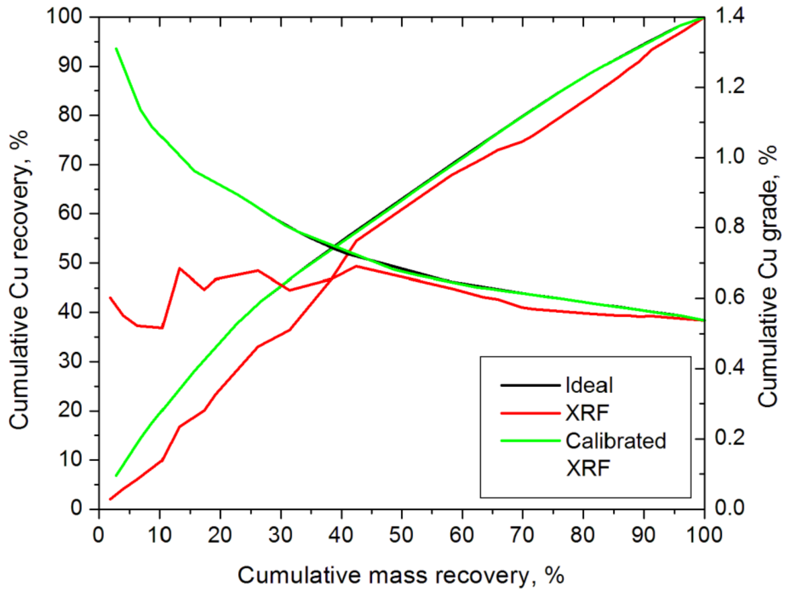

Figure 9 – Grade/recovery relationships of the ore particles: medium grade group

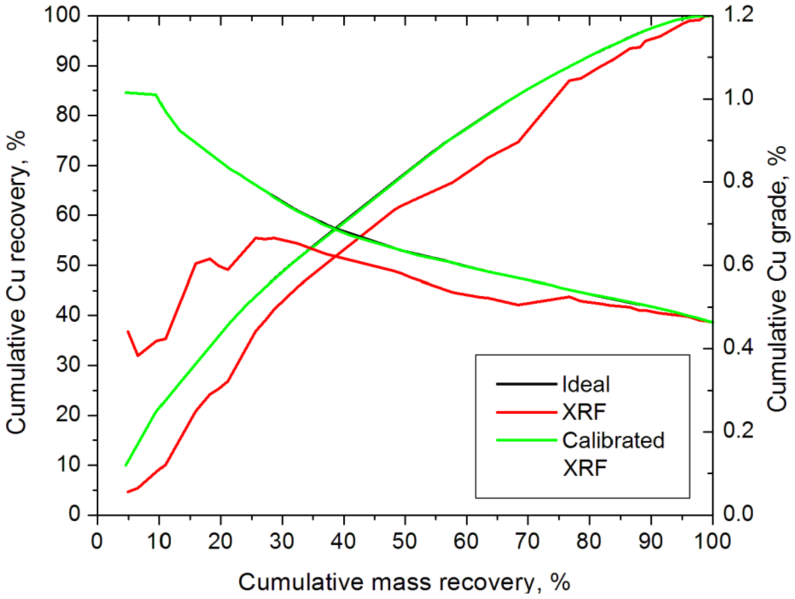

Figure 10 – Grade/recovery relationships of the ore particles: low grade group

The grade/recovery relationships of the three groups of copper ore particles are shown in Figures 8 to 10. The ideal curves were drawn based on the assay data which indicates the sorting potential. If the ore particles are sorted based on the XRF measurement, for the high grade ore particles, the sorting result is poor which is consistent with the weak correlation. For both medium and low grade ore particles, better sorting results were achieved when the mass recovery is roughly higher than 40%. For all of the three groups of data, the sorting results could be excellent after the XRF values were calibrated. Stronger correlation in the low and medium Cu grade region is very useful in the sorting process and better sorting results are achieved at the cut-off grade.

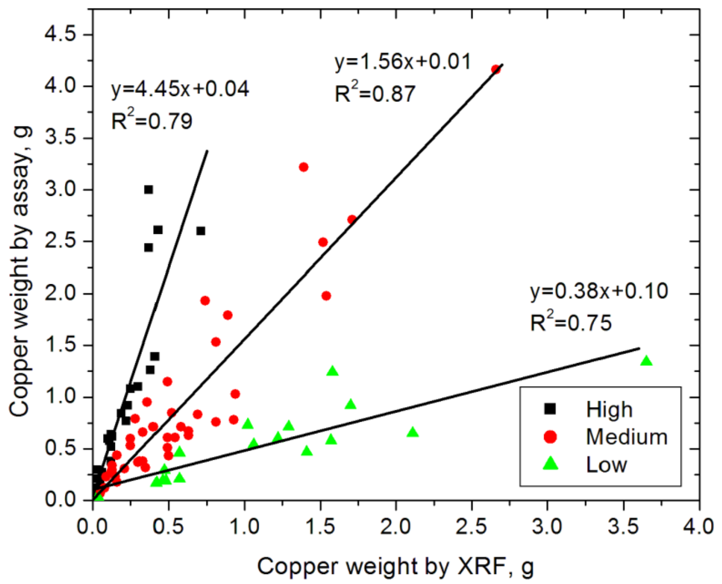

Figure 11 – Effect of copper distribution on copper weight-weight relationships: data separated by the grade ratio (GR) between the assayed Cu grade and the XRF estimation, High (8.9<GR<3.0), Medium (2.8<GR<0.8), Low (0.8<GR<0.3)

Effect of Copper Distribution

The sorting result is greatly influenced by the copper distribution on the ore particle surfaces and the copper values inside the ore particles. An alternate way to separate the 85 ore particles into three groups is based on the grade ratio between the assayed copper grade and the XRF value. As shown in Figure 11, three equations can be used to describe the relationships. We noticed that both the matrix effect and the specimen effect influence the XRF value. The wide range of grade ratios indicates the heterogeneity of the copper values in the selected ore particles, which is the reason why simple linear regression does not work for the sorting process.

Multiple Linear Regression Analysis

As shown in Table 4, strong correlation was achieved between the copper grade (assay) and the 12 elements measured by XRF. The application of the multiple linear regression equation to the sorting results of the 85 particles is shown in Figure 12. The ideal curve was drawn based on the assayed Cu grade. Similar curves were drawn based on the two multiple linear regression equations: with and without interaction effects. Great improvement was achieved for the sorting results due to the strong correlation.

Table 5 – List of the copper grade (%) after sorting through various analytical methods: 85 ore particles, feed grade: 0.58%

Cu recovery: %	10	30	60	90
Assay data	1.91	1.26	0.87	0.66
XRF reading without calibration	0.78	0.77	0.65	0.61
Linear correlation	0.86	0.85	0.69	0.62
Piecewise linear correlation	0.87	0.70	0.74	0.62
Multiple linear correlation with interaction	1.91	1.17	0.85	0.64

A summary of the copper grade/recovery relationships obtained through various analytical methods is shown in Table 5. Sorting by XRF reading without calibration or with simple linear correlation does not meet the requirement due to the weak correlation. The multiple linear correlation analysis is a useful method for developing algorithms for sorting the low grade Cu ore particles.

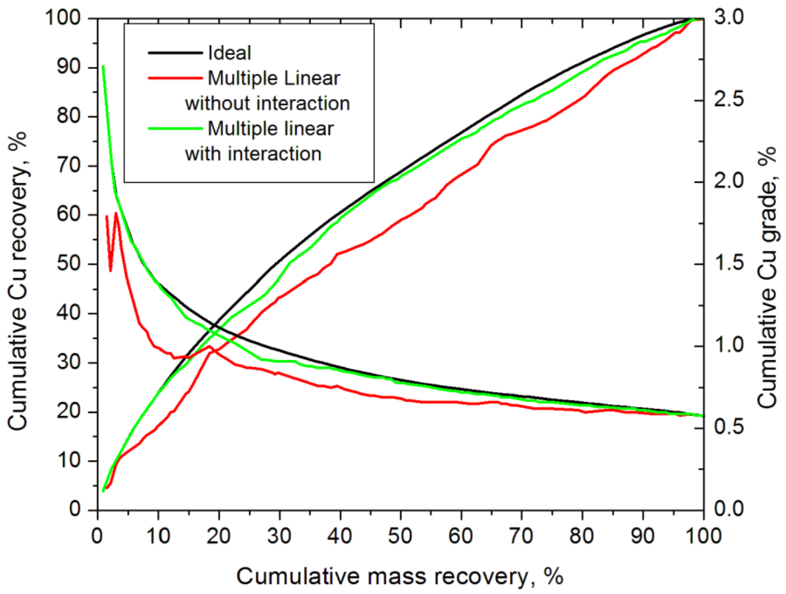

Figure 12 – Grade/recovery relationships of the overall sample: multiple linear regression analysis

CONCLUSIONS

The copper grades of ore particles from the Spence copper mine in Chile were measured by both XRF and assay. Linear and multiple linear correlation and regression methods were used to evaluate the relationships of the copper grades. When the ore particles were separated into different groups based on the copper grade measured by XRF, the 'low' grade group of data shows better correlation than the 'high' grade groups. Based on the regression equation, the XRF values can be converted into copper grades. The multiple linear correlation analysis is a useful method for developing algorithms for sorting the low grade Cu ore particles. The developed method can be used in the similar sorting process.

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