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Identifying Separation Potency and Relationship of Grade and Density of Copper Ore for Gravity-Based Early Coarse Gangue Rejection using Statistical Method

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Abstract. The mineral processing industry faces a pressing challenge of declining productivity, particularly in metal minerals production, driven by soaring operational costs, with crushing and grinding operations accounting for a substantial portion of the energy consumption. To mitigate these challenges, early gangue rejection or preconcentration is proposed as an effective solution. This approach involves the removal of non-valuable materials and the concentration of valuable minerals at the initial processing stages, leading to increased efficiency, higher ore feed grades, cost savings, and reduced environmental impact. Various methods for gangue rejection exist, with gravity-based separation and ore sorting being the predominant options. Gravity-based separation stands out for its simplicity and versatility, making it the preferred choice in many scenarios. This study introduces a novel approach for evaluating gangue rejection potential, optimizing data distribution, and generating theoretical separation potential curves that account for both grade and density criteria. These curves provide insights into material rejection, metal losses, and optimal separation points, offering valuable guidance for mineral processing operations. Additionally, the study investigates the correlation between raw ore grade and density data, highlighting a strong relationship across different size fractions. This finding suggests that gravity-based separation can effectively rely on both grade and density parameters, resolving previous disparities observed in distribution models. By shedding light on advanced gangue rejection strategies, this research contributes to improved productivity and informed decision-making in the mineral processing industry.

1 Introduction

Productivity is a crucial factor in the mineral processing industry. Unfortunately, this sector has experienced a notable decline in productivity in recent years, primarily due to increased operational costs in comminution processes, especially in the production of metal minerals, where the substantial energy demand poses a significant challenge [3, 6]. From four gold mines and three iron mines, it was found that the average energy consumption for the entire mineral processing plant stands at approximately 21,000 kWh/kt [3, 10, 14]. Notably, 53% of this energy is attributed to size reduction activities, with crushing accounting for 18% and grinding for 35% [3].

To address the energy consumption issue, early gangue rejection or preconcentration is regarded as the optimal solution. Since many gangue materials are already rejected, and valuable minerals are preconcentrated in the initial stages of the process, there are fewer valuable materials to process subsequently. This enhances process efficiency, resulting in increased ore feed grade, reduced cost per metal production, lower water and reagent consumption, and minimized chemical-contaminated waste/tailings [2, 4, 8, 9, 11, 13].

Several methods can be employed for early gangue rejection or preconcentration, including screening, ore sorting, gravity separation, and magnetic separation. However, ore sorting and gravity-based separation are the predominant choices in this context. A comparison between these methods reveals that gravity-based separation is preferred due to its simplicity, reduced complexity, and applicability to different ore types [5, 7, 15, 16]. Conversely, sensor-based sorting, despite offering higher-grade materials, is less favored due to sensor sensitivity in extreme mining conditions, as well as higher capital and maintenance costs [13].

In the implementation of early coarse gangue rejection, one of the challenges lies in handling large

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particle sizes, leading to labor-intensive tasks during sampling, ore characterization, and sample pretreatment. Therefore, a proposed rapid assessment aims to gauge the potential for gangue rejection [16]. It was demonstrated that a group of 3000 particles exhibits a similar grade distribution to that of a group of 66 or even 33 particles, all following a statistical lognormal model [16]. This rationale justifies the use of 100 particles in this study for grade and density measurements.

It was further illustrated that through rapid grade assessment, leveraging theoretical sorting curves can identify the percentage of mass rejected, optimal metal grade, and the most effective sorting grade [16]. Remarkably, these curves can be generated from raw grade data collected. Nevertheless, the prior research emphasizes the potential of rejection in sensor-based sorting. Given the less promising nature of sensor-based sorting compared to gravity-based separation, this study's first objective is to employ the previously developed theoretical curve to comprehend material rejection in the context of gravity separation.

Another study highlights a significant disparity between grade and density distribution trends when incorporating the lognormal model for gravity-based gangue rejection [1]. Consequently, the second aim of this study is to employ statistical correlation analysis to assess the degree of correlation between raw ore grade and density data. Therefore, this study aims to make a substantial contribution by shedding light on the potential for separation, not solely based on grade but also on density and material size. This research indirectly aims to assist metallurgists in interpreting ore data, facilitating informed decisions regarding further ore processing.

2 Methodology

In this study, we utilized chalcopyrite ore ($CuFeS_2$) as the ore mineral. The ore data were organized into eight size categories ranging from 45.00 mm to 0.50 mm. These sizes were further divided into two main groups: four coarse size fractions (- 45.00 + 31.5; - 31.50 + 19.00; - 19.00 + 9.50; and - 9.50 + 4.75 mm) and four fine size fractions (- 4.75 + 3.35; - 3.35 + 2.00; - 2.00 + 1.00; and - 1.00 + 0.50 mm).

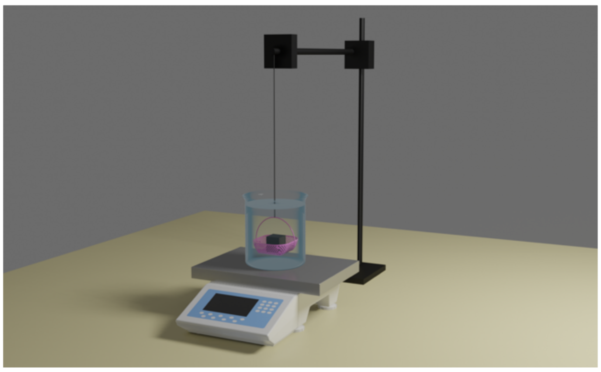

Fig. 1. Density Measurement using Archimedes Principle.

Each of these size fractions comprised 100 individual particles. We determined the grade of each particle using Inductively Coupled Plasma-Optical Emission Spectrometry (ICP-OES) and Acid Digest analysis. For the coarse size fractions, we measured the density of each particle using the Archimedes principle, as depicted in Fig 1. Meanwhile, the density of the particles in the fine size fractions was determined using Quantitative Evaluation of Minerals by Scanning Electron Microscopy (QEMSCAN). The simplified methodology for this study is outlined in Fig 2.

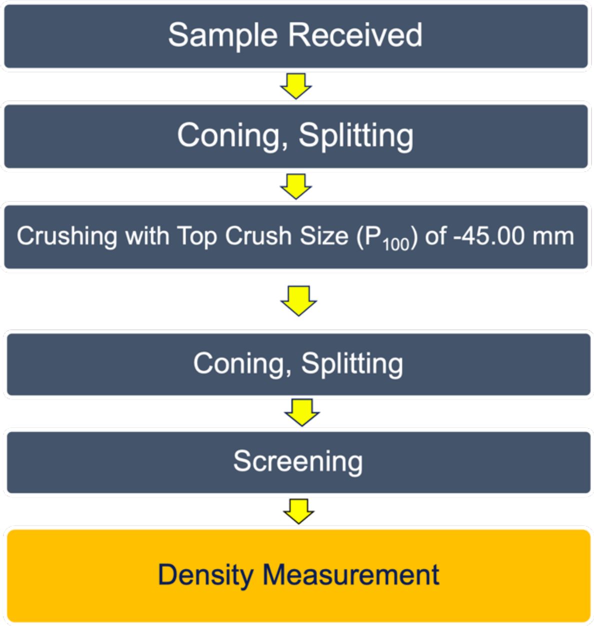

Fig. 2. Simplified methdology.

3 Result and Discussion

3.1 Theoretical Separation Potential (TSP) Analysis

In this study, the theoretical sorting potential analysis previously developed was utilized [16]. However, since the focus is on gravity separation involving both grade and density data, in contrast to sensor-based sorting, which relies solely on grade data, the term "theoretical separation" instead has been opted.

To enhance our previous findings, an optimization process for the distribution was conducted. For each size fraction, all 100 data for each grade and density group were categorized using specific bin width values, determined based on the data's maximum and minimum values (as presented in Table 1). The calculation of the bin width values was rooted in the square root of the total data for each size fraction of the grade or density group. Across all size fractions, a total of ten different classes using various bin width values was created.

Table 1 provides details on the calculation of grade-based bin width, including the method to derive the cumulative percentage of material mass and metal rejection from the system. Utilizing the information from Table 1, theoretical separation potential curve was generated, as depicted in Fig. 3. Fig. 3 illustrates the plot of cumulative mass percentages of rejected material, along with the cumulative mass of metal contained within the rejected materials.

As elucidated, "rejection" is defined by insignificance, which in this context is represented by the highest percentage of mass being rejected but the lowest percentage of metal within a certain mass of rejected material [16]. Hence, in Fig. 3, the most significant gap between the curves indicates the optimal point for rejection (at a specific grade percentage) with a particular average grade of the rejected material. Similar tables and curves were also then generated for density-based separation.

Following the creation of all these tables and curves, a recapitulation for all size fractions of grade and density groups, focusing on identifying where the largest gaps were found, was conducted. Tables 2 and 3 present the separation grade and density (cut-off), respectively. These tables also provide information on the cumulative mass of feed being rejected and the associated metal loss due to rejection. Additionally, they specify the average grade of the rejected material.

Tabel 1. Calculation of Grade-Based Bin Width and Percentage of Mass and Metal Rejection.

Increment/ Bin Size	**Data Count**	**Max**	**Min**	**Bin Width**				
10	100	34.48	0.00	3.45				
Number of Size Class/Bins	**Mass (g)**	**Mass (%)**	**Cum. Mass (%)**	**Average Grade (%)**	**Cum. Average Grade (%)**	**Metal (g)**	**Metal (%)**	**Cum. Metal (%)**
0.00	0.00000	0.00	0.00	0.00	0.00	0.00000	0.00	0.00
3.45	3.73524	80.15	80.15	0.58	0.58	0.02069	14.17	14.17
6.90	0.19703	4.23	84.38	0.00	0.58	0.00951	6.52	20.69
10.34	0.20447	4.39	88.76	9.16	9.74	0.01804	12.36	33.04
13.79	0.16100	3.45	92.22	12.15	21.89	0.01966	13.47	46.51
17.24	0.21764	4.67	96.89	0.00	21.89	0.03278	22.46	68.97
20.69	0.02099	0.45	97.34	0.00	21.89	0.00420	2.88	71.85
24.13	0.00000	0.00	97.34	0.00	21.89	0.00000	0.00	71.85
27.58	0.00251	0.05	97.39	25.74	47.63	0.00067	0.46	72.31
31.03	0.00006	0.00	97.39	30.73	78.36	0.00002	0.01	72.32
34.48	0.12149	2.61	100.00	33.26	111.62	0.04041	27.68	100.00
	4.66044					0.14597		

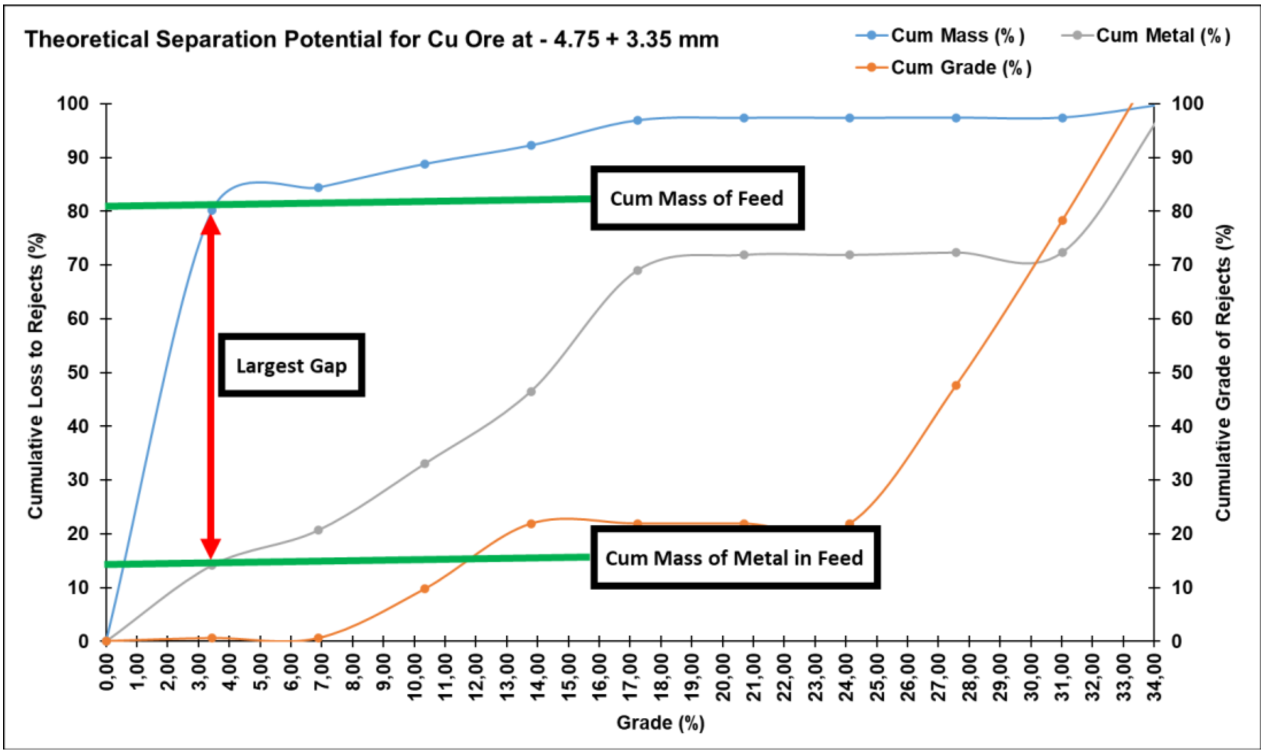

Fig. 3. Theoretical Separation Potential Curve Based on Grade for – 4.75 + 3.35 mm Size Fraction.

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Table 2. Summary of Theoretical Separation Potential Curve Based on Grade for Different Size Fractions

Ore	Size Fraction (mm)	Separation Grade (Cut-off) (g/cm³)	Cumulative Mass Feed (%)	Cumulative Mass of Metal in Feed Loss (%)	Gap (%)	Average Grade Metal Rejection (%)
			a	b	a-b	
Coarse	- 45.00 + 31.50	4.21	68.89	17.14	51.75	3.20
	- 31.50 + 19.00	3.61	70.99	17.95	53.05	2.63
	- 19.00 + 9.50	2.91	62.32	9.54	52.78	0.69
	- 9.50 + 4.75	6.28	73.55	29.83	43.72	4.54
Fine	- 4.75 + 3.35	3.45	80.15	14.17	65.98	0.58
	- 3.35 + 2.00	6.39	69.32	15.28	54.04	4.57
	- 2.00 + 1.00	6.87	74.59	9.67	64.92	4.58
	- 1.00 + 0.50	13.82	57.81	10.38	47.44	0.00

Table 3. Summary of Theoretical Separation Potential Curve Based on Density for Different Size Fractions

Ore	Size Fraction (mm)	Separation Density (Cut-off) (g/cm³)	Cumulative Mass Feed (%)	Cumulative Mass of Metal in Feed Loss (%)	Gap (%)	Average Grade Metal Rejection (%)
			a	b	a-b	
Coarse	- 45.00 + 31.50	3.10	73.03	24.20	48.84	1.47
	- 31.50 + 19.00	3.04	71.45	25.67	45.78	1.19
	- 19.00 + 9.50	3.66	68.12	26.31	41.81	2.97
	- 9.50 + 4.75	2.97	61.82	22.21	39.61	2.36
Fine	- 4.75 + 3.35	3.32	78.06	22.41	55.64	3.30
	- 3.35 + 2.00	3.00	48.92	12.56	36.37	1.28
	- 2.00 + 1.00	2.99	67.36	6.42	60.94	2.17
	- 1.00 + 0.50	4.07	60.67	11.88	48.78	8.65

As indicated in Tables 2 and 3, two groups of size fractions were analyzed: the coarser fractions (- 45 + 4.75 mm) and the finer fractions (- 4.75 + 0.50 mm). For the coarser size fractions in terms of grade-based separation, the optimal rejection point is observed at the - 31.50 + 19.00 mm size fraction, marked by the highest gap. At this point, 70.99% of the material can be effectively rejected, with a corresponding loss of 17.95% of metal in the rejection stream. This separation was executed with a cut-off grade of 3.61%. However, it is worth noting that the average metal content in the rejected material remains relatively high at 2.63%, compared to the - 19.00 + 9.50 mm size fraction, where it is only 0.69%.

On the other hand, for the finer size fractions, the most favorable outcome is achieved at the - 4.75 + 3.35 mm size fraction, with 80.15% of material being rejected, a mere 0.58% average grade in the rejected material, and 14.17% metal loss in the rejection stream. It's essential to highlight that the 0.00% average grade in the - 1.00 + 0.50 mm size fractions indicate an exceedingly low metal grade for that specific size fraction.

Similarly, referring to Table 3, within the coarser size fraction group, 73.03% of the material mass can be rejected, which includes 24.20% of metal, with an average metal grade of only 1.47%. This grade percentage corresponds to a cut-off density of 3.10 g/cm³, which is slightly higher compared to when the separation was performed at a cut-off density of 3.04 g/cm³. In contrast, for the finer fractions, 78.06% of the material can be rejected, which contains 22.41% of metal. However, the average metal grade is notably higher at 3.30%, in contrast to the grade of metal in the - 3.35 + 2.00 mm size fraction, where the cut-off density was 3.00 g/cm³.

Nevertheless, despite showcasing different mass percentages of rejected material at various size fractions, it is important to note that the information provided in the grade and density-based tables (Table 2 and Table 3, respectively) cannot be directly compared for grade-based separation versus density-based separation. This discrepancy arises from the classification of different ore particles into grade and density classes, resulting in varying grades of rejected metal. However, the insights from both tables are sufficient for metallurgists and mineral processing plant operators to determine the grade or density cut-off points for effective rejection. In summary, both tables underscore the utility of theoretical separation potential curves not only for grade-based sensor-based sorting but also for grade and density-based rejection using gravity separation.

3.2 Statistical Correlation Test Analysis

Despite the earlier explanation regarding the theoretical separation potential, it remains challenging to establish a direct correlation between grade and density, even though both aspects of separation appear to be well-associated with each other. Therefore, at this juncture, an endeavor was undertaken to investigate the relationship between the grade and density variables.

This investigation encompassed nine distinct size fractions, each consisting of grade and density data for 100 particles.

To assess the strength of this correlation, statistical tool, specifically correlation coefficients, was used. These coefficients were computed using standard statistical measures such as mean, median, variance, standard deviation, and covariance, applied to the raw grade and density data within each size fraction. The summary of these correlation coefficients for all size fractions is presented in Table 4.

Table 4. Grade-Density Correlation

Ore	Size Fraction (mm)	Correlation Coefficient (r)	Descriptor
Coarse	- 45.00 + 31.50	0.89	Very High
	- 31.50 + 19.00	0.77	Very High
	- 19.00 + 9.50	0.64	High
	- 9.50 + 4.75	0.74	Very High
Fine	- 4.75 + 3.35	0.68	High
	- 3.35 + 2.00	0.69	High
	- 2.00 + 1.00	0.78	Very High
	- 1.00 + 0.50	0.68	High

As depicted in Table 4, it is evident that the correlation between grade and density data remains consistently high across all size fractions. The coefficient values are closely aligned with each other, providing compelling evidence of the strong correlation not only within grade and density data but also across different size fractions.

In essence, there is no significant difference between the coarsest size and those smaller than it, considering that the descriptors "high" and "very high" have closely adjacent correlation coefficient values. It is important to note that these descriptors or categories tend to have varying ranges in many papers or books found, especially in the digits one or two places behind the decimal point.

However, upon closer examination of why such differences may occur, the significant contrast in correlation coefficients in the coarse size fraction may be attributed to a larger variation in the distribution of both grade and density within that size range. The presence of particles with diverse grade and density characteristics in the coarse size fraction could lead to higher correlation values. Therefore, in the context of gravity-based separation, the disparity in particle distribution within the coarse size fraction becomes a crucial factor influencing the correlation between grade and density in the separation process.

Generally, the context of gravity separation, this robust correlation also suggests that separation can effectively rely on both grade and density parameters. Furthermore, this finding addresses the issue of incongruent grade and density distribution models identified in the earlier research [1]. It suggests that the disparities observed are more likely attributable to the statistical distribution models applied to grade and density, rather than inherent issues with the grade or density data themselves. Consequently, to achieve compatibility between these models, it may be necessary to explore alternative statistical frameworks.

4 Conclusion

In summary, this study has explored the potential of theoretical separation in the context of mineral processing, with a specific focus on gravity separation incorporating grade and density data. Several key findings have emerged, shedding light on the optimization of separation processes, and addressing disparities in grade and density distribution models.

The study initially introduced the concept of "theoretical separation," differentiating it from sensor-based sorting by emphasizing its reliance on both grade and density data. An optimization process was then employed to refine the distribution of these data across various size fractions, yielding valuable insights into the potential for material rejection.

Theoretical separation potential curves were generated and analyzed, pinpointing optimal rejection points in terms of grade and density for both coarser and finer size fractions. These results showcased the feasibility of effective material rejection with varying degrees of metal loss in the rejection stream.

Notably, the study also examined the correlation between grade and density data across different size fractions. The consistently high correlation coefficients demonstrated a strong relationship between these parameters, reaffirming the potential for gravity separation based on both grade and density criteria. This finding provides a solution to the incongruities observed in previous grade and density distribution models.

In conclusion, this research offers valuable insights into the optimization of mineral processing, highlighting the practicality of theoretical separation and its applicability to various size fractions. It emphasizes the importance of considering both grade and density in separation processes and suggests the exploration of alternative statistical models to improve compatibility between grade and density distribution models. These findings contribute to the advancement of mineral processing practices and offer a foundation for further research in this field.

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