Journal of Minerals and Materials Characterization and Engineering, 2025, 13(4), 196-216
https://www.scirp.org/journal/jmmce
ISSN Online: 2327-4085
ISSN Print: 2327-4077

Improvement of Copper Recovery of Low-Grade Deposit Using Optimization of Flotation Process Parameters with Hydrofroth as a Frother

Benedict Ogalabyoshi Ndagano[1], Paulin Kabanga Tshota[2], Jewette Hichikoko Masinja[3], Alphonse Wikedzi[4], Kaniki Tumba[1,5], Alex Kalonji-Kabambi[1]*

[1]School of Mines, Université Officielle de Bukavu, Bukavu, Democratic Republic of the Congo
[2]Ivanhoe, Kamoa Copper SA, Kolwezi, Democratic Republic of the Congo
[3]School of Mines, University of Zambia, Lusaka, Zambia
[4]Department of Mining and Mineral Processing Engineering, School of Mines and Geosciences, University of Dar es Salam, Dar es Salam, Tanzania
[5]School of Chemical and Mineral Engineering, North-West University (Potchefstroom Campus), Potchefstroom, South Africa
Email: *alexkalonjikab@gmail.com, *alexkalonjikab@uob.ac.cd

How to cite this paper: Ogalabyoshi Ndagano, B., Kabanga Tshota, P., Masinja, J.H., Wikedzi, A., Kaniki, T. and Kalonji-Kabambi, A. (2025) Improvement of Copper Recovery of Low-Grade Deposit Using Optimization of Flotation Process Parameters with Hydrofroth as a Frother. *Journal of Minerals and Materials Characterization and Engineering*, **13**, 196-216.
https://doi.org/10.4236/jmmce.2025.134012

Received: May 25, 2025
Accepted: July 20, 2025
Published: July 23, 2025

Abstract

The study uses flotation process optimization to explore how to improve copper recovery from the Kakula deposit. Given the variability in ore grade, achieving high recovery rates and maintaining an optimal copper grade is critical. This research employs the Taguchi experimental design and multi-objective optimization to determine the most effective flotation parameters. Key factors investigated include solid mass percentage, air flow rate, particle size, frother dosage (HYDOFROTH), collector dosage (SIBX), and secondary collector dosage (AERO). The Taguchi method determined optimal conditions for maximum copper recovery at 96.4%, with 14.2% copper content in concentrate. The multi-objective approach provided a more balanced result: 95.4% copper recovery, 48.0% mass pull, 12.2% copper content. Comparing the results obtained by these two methods, it is noted that the multi-objective approach contributes more to the minimisation of silica, 24% versus 35.4%. ANOVA analysis revealed that collector dosage (SIBX) was the most significant factor influencing copper recovery. At the same time, solid mass percentage had the most significant impact on copper content, mass pull, and silica yield. The findings provide practical insights for improving the flotation performance of the Kakula deposit, ensuring higher efficiency and better concentrate quality.

Keywords

Copper Recovery, Flotation, Taguchi Orthogonal Array, ANOVA, Process Optimization, Low-Grade Deposit

1. Introduction

The need to use complex or low-grade ores, whose average particle size is too small for efficient separation, and the high demand for metals are forcing us to resort to new technologies to process rock masses. Flotation is the main process for these rock masses [1]-[3]. According to [2] and [4]-[7], it is an essential physico-chemical process for particle separation, based on differences in surface properties of minerals. The behavior of the flotation technique is linked to the intrinsic characteristics of the ore, which evolve throughout the exploitation of the deposit [3] [8] [9]. In this context, optimizing flotation parameters and conducting a new ore characterization are paramount to continuously maintaining or improving concentrator performance [10]-[12]. However, the Kakula deposit contains indicated and inferred mineral resources with respective cut-off grades of 3% and 1% [13]. After a thorough study and careful analysis, the target grade for feeding the Kakula concentrator was 5%. Nevertheless, there are occasions when the mine feeds the concentrator with grades lower than this target value, impacting the operational performance of the concentrator. Consequently, it has become imperative to investigate the flotation behavior of ore feed at grades below the target grade. The Taguchi and multi-objective methods have proven effective for guiding research, considering the numerous study parameters and the desire to obtain valid and reliable conclusions efficiently and cost-effectively [14] [15]. The Taguchi approach shed light on experimental designs, which previously held less interest among industrial professionals due to a lack of pragmatism [16]. It clarified and simplified experimental designs by solving the problem of excessive trial numbers that scientists would have executed then, risking waiting even a year for results [17] [18]. This approach has been widely adopted in product design and optimization, quality engineering, and experimental methods. The principle of minimizing product or process variability through experimental planning and optimization forms the foundation for this method [19] [20]. The approach described will be applied in this study to establish a cause-and-effect relationship between specific parameters (referred to as factors) assumed to influence the phenomenon's behavior, and others (referred to as responses) characterizing the outcome of this phenomenon. In reviewing the literature, the authors [21]-[25] worked on the flotation of copper sulfide minerals. Among the study parameters, the air flow rate as the study parameter was not considered in their experiments. The authors applied the Taguchi methodology for optimizing control variables; however, this method optimizes control variables and responses separately. Therefore, including the air flow rate parameter in our research and applying multi-objective optimization for all responses distinguishes our work as a unique case compared to recent studies in copper sulfide mineral flotation. Multi-objective optimization deals with problems with multiple objective functions to maximize or minimize [22].

The overall objective of this study is to improve the recovery of copper through froth flotation of ores from the Kakula deposit, while setting optimal parameters that lead to improved copper recovery efficiency and satisfactory copper grade.

Specifically, it will be necessary to characterize the ores from the Kakula deposit, study their grindability, determine the influence of specific parameters on recovery yield and grade, and predict the optimal parameters of the model leading to optimal copper recovery yield and grade.

2. Materials and Methods

2.1. Materials

Flotation tests were conducted on a copper sulfide ore sample from the low-grade ore storage area at the Kakula mine in the southeastern part of the Democratic Republic of Congo (DRC). During the flotation tests, Sodium Isobutyl Xanthate (SIBX) was used as the collector (product of Axis House), Hydrofroth (HDF) was employed as a frother, and AERO (promoter) served as the secondary collector. The water used in our experiments originated from the Kakula wastewater treatment plant. The chemical characterization of the sample was carried out for various metals using the X-ray Fluorescence Spectroscopy (Niton™ XL5 Plus Handheld, Japan).

2.2. Methods

The study began with developing the Taguchi experimental design, followed by sample collection at the Kakula mine. The experiments were conducted in the Kakula concentrator laboratory. The research was concluded by statistical analysis of results using Minitab 21.4.0 software.

2.2.1. Experimental Setup

The tests were conducted using an Altso flotation machine with a parallelepiped cell capacity of 2.8 liters. The unit features a variable digital display of shaft rpm (revolutions per minute), allowing for precise agitator speed control, which is crucial for mastering aeration and agitation intensity. It also includes air pressure, flow control, and a digital timer for accurate test duration. The cell agitator's rotation speed was set at 600 rpm. Various materials were employed to facilitate our experiments on the flotation machine, starting from sample collection to chemical analysis of the samples. A scoop and a bag were used for sample collection from the low-grade ore storage area at the mine. A laboratory jaw crusher and a RockLab were utilized for particle size reduction from + 8 mm to 2 mm. A rotary sample divider ensured sample representativeness. A series of sieves (25, 38, 53, 75, 106, 150 μm) was also used for particle size analysis and grindability studies. A laboratory rod mill was used for mineral grinding. A vacuum pump, filter paper, pans, an oven, and a plate, as well as a balance, pipettes (2 μl - 20 μl; 50 μl - 200 μl), and syringes (3, 5, 10 ml), were used respectively for filtering the rough and waste materials, containing the samples, drying the samples, weighing the samples, cleaning the mill, adding water to the cell, extracting the quantity of reagents, preparing the reagents, taking water to put in the mill, and holding the pulp.

2.2.2. Origin of Sample

To successfully conduct the tests, a sample of 100 kg of low-grade ore was collected from the low-grade ore storage area on the Kakula underground mine. Fifteen sample points were randomly targeted on the low-grade ore storage area to ensure representativeness of the sample.

2.2.3. Mineralogy of Kakula Deposit

Based on the previous study on the mineralogy of the Kakula deposit conducted by XPS Expert Process Solutions, the Kakula ore is rich in chalcocite. Other major mineral phases are bornite and chalcopyrite. Gangue minerals are quartz, feldspar, micas, and chlorite. Fe oxides and carbonates are minor phases [13]. This work assumes that the ore sample contains the same mineral phase.

2.2.4. Experimental Procedure for the Grindability Study

The sample, as received, consisted of coarse particles larger than 8 mm. Initially, it underwent primary crushing using a laboratory jaw crusher and secondary crushing in the rock lab. Subsequently, the ore was subjected to wet grinding at various intervals to determine the correlation between particle size and grinding time. The mill was wet fed with 0.835 kg, 1.035 kg, and 1.295 kg, respectively, corresponding to 25%, 30%, and 35% solid percentages. Grinding time was determined for the 15%, 20%, and 25% rejection range on the 53 µm sieve, following variations in solid percentage.

2.2.5. Experimental Flotation Plan

Based on previous studies and literature, the air flow rate is not considered as a parameter. This study chose the percentage solids, air flow rate, oversize at 53µm, collector dosage, frother dosage, and secondary collector dosage as the six main parameters to be investigated. According to the Taguchi design methodology, three levels were chosen for each parameter as illustrated in **Table 1**. Considering the six parameters and the relevant three levels, a Taguchi orthogonal array (L27) was established to execute the experiment. The Kakula Concentrator's operational Conditions inspired the selection of three levels for each factor. Twenty-seven experiments were therefore conducted as shown in **Table 2**. Numbers one (1) to three (3) in **Table 2** are the relative levels of the parameters indicated in **Table 1**. In this study, interactions between parameters were not taken into consideration.

Table 1. Controllable factors and their levels.

Parameter	Code	Unit	Levels		
			I	II	III
Solid mass percentage	A	%	25	30	35
Oversize at 53 µm	B	µm	15	20	25
Air flow rate	C	l/min[a]	6	8	10
SIBX dosage	D	g/t[b]	206	256	306
Hydrofroth dosage	E	g/t	103	133	163
AERO dosage	F	g/t	10	30	50

Note: [a]Litter per min, [b]gram per ton.

In experiments based on the Taguchi design, signal-to-noise (SN) ratios are recommended for optimizing process parameters [20] [26]. The term Signal-to-Noise Ratio (SN) establishes a relationship between the average of the response (signal) and the dispersion of the response concerning the noise (background noise) [15]. The SN ratios can then be calculated based on the required response characteristics, *i.e.*, "larger is better", "smaller is better", and "nominal is better". In this study, the aim is to increase recovery yield and copper content. Therefore, SN ratios for "larger is better" and smaller is better were selected and calculated using response values. The SN ratio for this scenario was determined using Equations (1) and (2) [22]:

$$V_i = \log\left(\frac{1}{n}\sum_{j=1}^{n} Y_{ij}^2\right) \tag{1}$$

$$V_i = \log\left(\frac{1}{n}\sum_{j=1}^{n} \frac{1}{Y_{ij}^2}\right) \tag{2}$$

Where n is the number of repetitions of experiments, and Y_i is the response value (recovery) of the i-th experiment, and j successively takes the values $1, 2, \cdots, n$.

Table 2. Taguchi Orthogonal array (L27) for influencing factors and their levels coded with actual values in brackets.

Row	Controllable factors					
	A	B	C	D	E	F
1	1 (25)	1 (15)	1 (6)	1 (206)	1 (103)	1 (10)
2	1 (25)	1 (15)	1 (6)	1 (206)	2 (133)	2 (30)
3	1 (25)	1 (15)	1 (6)	1 (206)	3 (163)	3 (50)
4	1 (25)	2 (20)	2 (8)	2 (256)	1 (103)	1 (10)
5	1 (25)	2 (20)	2 (8)	2 (256)	2 (133)	2 (30)
6	1 (25)	2 (20)	2 (8)	2 (256)	3 (163)	3 (50)
7	1 (25)	3 (25)	3 (10)	3 (306)	1 (103)	1 (10)
8	1 (25)	3 (25)	3 (10)	3 (306)	2 (133)	2 (30)
9	1 (25)	3 (25)	3 (10)	3 (306)	3 (163)	3 (50)
10	2 (30)	1 (15)	2 (8)	3 (306)	1 (103)	2 (30)
11	2 (30)	1 (15)	2 (8)	3 (306)	2 (133)	3 (50)
12	2 (30)	1 (15)	2 (8)	3 (306)	3 (163)	1 (10)
13	2 (30)	2 (20)	3 (10)	1 (206)	1 (103)	2 (30)
14	2 (30)	2 (20)	3 (10)	1 (206)	2 (133)	3 (50)
15	2 (30)	2 (20)	3 (10)	1 (206)	3 (163)	1 (10)
16	2 (30)	3 (25)	1 (6)	2 (256)	1 (103)	2 (30)
17	2 (30)	3 (25)	1 (6)	2 (256)	2 (133)	3 (50)

Continued

18	2 (30)	3 (25)	1 (6)	2 (256)	3 (163)	1 (10)
19	3 (35)	1 (15)	3 (10)	2 (256)	1 (103)	3 (50)
20	3 (35)	1 (15)	3 (10)	2 (256)	2 (133)	1 (10)
21	3 (35)	1 (15)	3 (10)	2 (256)	3 (163)	2 (30)
22	3 (35)	2 (20)	1 (6)	3 (306)	1 (103)	3 (50)
23	3 (35)	2 (20)	1 (6)	3 (306)	2 (133)	1 (10)
24	3 (35)	2 (20)	1 (6)	3 (306)	3 (163)	2 (30)
25	3 (35)	3 (25)	2 (8)	1 (206)	1 (103)	3 (50)
26	3 (35)	3 (25)	2 (8)	1 (206)	2 (133)	1 (10)
27	3 (35)	3 (25)	2 (8)	1 (206)	3 (163)	2 (30)

2.2.6. Flotation Test Experimental Procedure

The flotation test was conducted according to the Kamoa standard. The flotation time was 40 minutes, with an additional 14 minutes of conditioning (5 minutes for the first adding reagent, 3 minutes for the second, and 2 minutes for the third until five adding reagent). Before beginning the flotation test, the pH of the pulp was fixed at 8.66. For each trial, five (5) concentrate fractions were removed, along with the tailing fraction. The flotation test process carried out during the study can be summarized in Figure 1. The method of obtaining pulp with a well-defined solid percentage was first carried out through wet grinding. Next, a 5-minute conditioning step was performed by adding 60% SIBX, 57% Hydrofroth, and 100% AERO. The reagents, such as SIBX, Hydrofroth, and AERO, were prepared at 1%, 97%, and 50%, respectively.

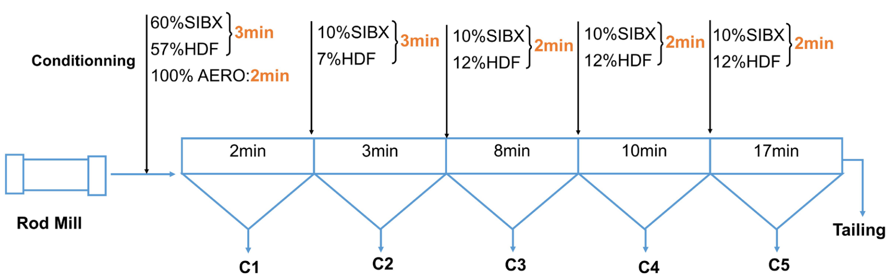

Figure 1. Flotation test experimental procedure.

The amount of metal copper recovered was calculated using Equation (3), which is based on assays alone of the feed (f), tailings (t), and concentrate (c) [9]:

$$\text{Recovery} = 100\left(\frac{c}{f}\right)\left(\frac{f-t}{c-t}\right) \quad (3)$$

2.2.7. Analysis of Variance

The theory of analysis of variance (ANOVA) aims to analyze a situation where the effect of one or more factors on a variable is investigated. In other words, it is a method for studying the variability of a product based on a set of production factors that can be systematically controlled [22] It uses statistical tests to evaluate the variation between groups (intergroup variance) compared to the variation within groups (intragroup variance). More formulas used in ANOVA can be shown in **Table 3**.

Table 3. Formulas in analysis of variance [22].

Parameters	Formulas	Equation
Total sum of squared deviations	$SS_T = \sum_{i=1}^{N} (Y_i)^2 - \frac{\left(\sum_{i=1}^{N} Y_i\right)^2}{N}$	(4)
Sum of squared deviations	$SS_P = \sum_{i=1}^{N_K} \frac{(Y_j)^2}{N_K} - \frac{\left(\sum_{i=1}^{N} Y_i\right)^2}{N}$	(5)
Sum of squared error	$SS_E = SS_T - \Sigma SS_P$	(6)
Variance	$V_P = \frac{SS_P}{(N_K - 1)}$	(7)
Total degrees of freedom of the result	$DF = f_T - \Sigma f_P$	(8)
Variance ratio	$F_{calc} = \frac{V_P}{V_E}$	(9)
Pure sum of squares of each factor	$PSS_P = SS_P - f_i V_E$	(10)
Contribution of each parameter to the response	$\%PC = \frac{PSS_P}{SS_T}$	(11)

In Equations (4) and (5), N is the total number of observations or experiments, Y_i is the metal recovery for the i[tch] experiment. In Equations (6) and (7), p is one of the experiment's parameters, and j is the level number of this p parameter. NK is the number of levels for each parameter (3 in this case), and $N_{k-1} = f_p$ is the degrees of freedom for the p parameter. In Equation (8), (f_T) is the total degrees of freedom of the result and is equal to the total number of experiments (27 in this case) minus one. In Equation (9), V_E is the error's mean square (variance). This is used to evaluate the significance of the parameters on the response. Minitab breaks down the SS Regression or SS treatments component into the amount of variation explained by each term using both the sequential sum of squares (*Seq SS*) and adjusted sum of squares (*Adj SS*) after Minitab defines the mean square Adjusted (*MS Adj*) to determine the F-Value as presented in Equations (10) and (11).

2.2.8. Performance Prediction by Taguchi Method

The Taguchi methodology operates on the principle that the trial corresponding to the optimal conditions found may or may not be conducted during the experimentation phase, but the prediction of the performance value of the experiment can be made based on the prediction function represented by Equation (12) [8].

$$Y_{opt} = \frac{T}{n} + \left(A_j - \frac{T}{n}\right) + \left(B_j - \frac{T}{n}\right) + \cdots \quad (12)$$

With T representing the sum of all trial responses, n the total number of trials, and $A_j, B_j, \cdots$ the average responses at level i, j, etc.

2.2.9. Performance Prediction by Multi-Objective Method

To optimize all outcomes simultaneously, a compromise is necessary. Based on [22], the desirability function is the most effective way to achieve this. Minitab Software was used to calculate composite desirability as the weighted geometric mean of the individual desirability for each response. This mathematical approach ensures that if any individual's desirability is zero (implying that one response is unacceptable), the composite desirability will also be zero, thereby highlighting a critical failure point. The formula for composite desirability is given by (Equation (13)):

$$D = \prod_{i=1}^{n} \left(d_i^{w_i}\right)^{\frac{1}{\sum_{i=1}^{n} w_i}} \quad (13)$$

d_i represents the individual desirability score for the i-th response. w_i denotes the importance value assigned explicitly to the i-th response, reflecting its relative priority. n is the total number of responses included in the optimization. We fixed w_i at 10, 10, 5, 5 for the recovery, silica yield, mass pull, and copper content responses.

A quadratic model was established for each response as a function of the control variables. This was done to determine the relationship between the technological performance factors (copper recovery, mass pull, copper content, and silica yield) and the control parameters. Several models were tested before considering the models presented in **Table 17**.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i=1}^{k} \sum_{j=1}^{k} \beta_{ij} x_i x_j + \varepsilon \quad (14)$$

Where $x_1, x_2, \cdots, x_k$ are input factors that influence the responses y; $\beta_o, \beta_{ii}\left(i = 1, 2, \cdots, k\right), \beta_{ij} \quad \left(i = 1, 2, \cdots, k\right)$ are constant parameters of the model, and ε is the random error. Furthermore, cross-factors and variables were applied to the models to ensure fit. Statistical parameters such as R^2 and S (a parameter accounting for residuals) were a guide for good model fit.

3. Results and Discussion

This section summarizes the findings regarding copper flotation performance in the supplied sulfide ores. It is also dedicated to data analysis and identifying the optimal levels for all control parameters.

3.1. Chemical and Sieve Assay Analysis of the Sample

Table 4 details the chemical analysis of the sample examined in this study. The analysis revealed a copper concentration of 4.29%, alongside a significant silica presence of 55.81%, which poses a considerable challenge for the process. Figure 2 visualizes the results of the particle size chemical analysis conducted on the ore sample. This figure shows that a significant proportion of copper is below 53 µm. These findings corroborate the metallurgical test results reported recently during feasibility studies related to the Kakula deposit [13].

Table 4. The chemical composition of the ore sample from the Kakula mine.

Component %	Cu	SiO_2	MgO	Ca	Fe
	4.29	55.81	4.37	0.67	5.01

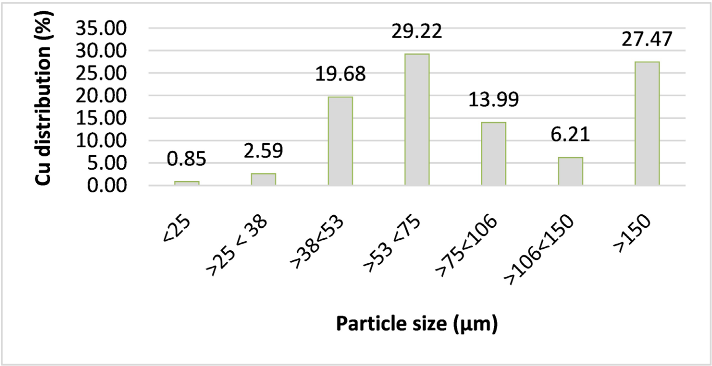

Figure 2. Sieve assay analysis results for Cu from the Kakula mine ore.

Based on the grindability study results presented with the equations of the curves below (Figure 3), the times required were determined (see Table 5) to achieve 15%, 20%, and 25% oversize at 53 µm sieve.

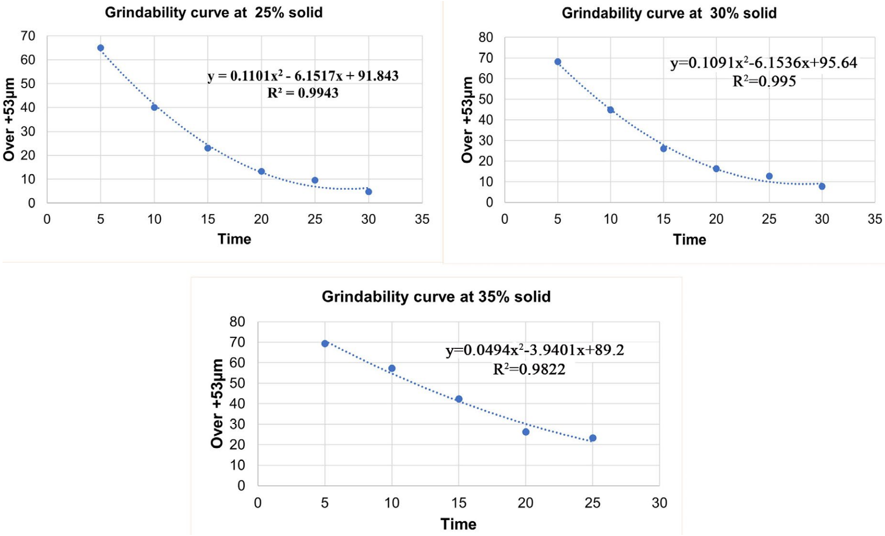

Figure 3. Grindability curves: Each equation determined the grind time at 15.20, and 25% oversize at +53 µm. y represents the oversize at +53 µm, and x represents the grind time(min).

Table 5. Grinding results at various times.

Sample Types	Oversize at 53 µm (%)	Grinding time (min)
Sample (25% solid)	15	18.9
	20	16.6
	25	14.8
Sample (30% solid)	15	20.7
	20	18.1
	25	16
Sample (35% solid)	15	30.5
	20	26.1
	25	22.8

3.2. Results of Copper Metal Recovery

The average recovery of copper by flotation and the copper content for the various combinations of process parameters and levels are shown in Table 6. The highest recovery of copper of 95,45% into the concentrate occurred in the 24th experiment run (% solids = 35; oversize at 53 µm = 20%; air flow rate = 6l/min; SIBX dosage = 306 g/t; HDF dosage = 163g/t; AERO dosage = 30 g/t) and the lowest (86.88%) was recorded in the 27th experiment run ((% solids = 35; oversize at 53 µm = 25%; air flow rate = 8l/min; SIBX dosage = 206g/t; HDF dosage = 163g/t; AERO dosage = 30g/t). The highest copper content of 12.30% of the concentrate, occurred in the 18th experiment run.

Table 6. Experimental results for Cu metal.

Row	A	B	C	D	E	F	R_Cu	%Cu	Mass pull	Silica yield
1	25	15	6	206	103	10	91.90	11.98	43.42	39.93
2	25	15	6	206	133	30	92.70	12.02	44.19	40.71
3	25	15	6	206	163	50	94.62	6.76	54.30	51.19
4	25	20	8	256	103	10	93.85	7.33	49.98	44.33
5	25	20	8	256	133	30	94.33	7.09	51.59	47.27
6	25	20	8	256	163	50	94.92	6.81	55.25	52.36
7	25	25	10	306	103	10	94.34	7.42	51.58	49.44
8	25	25	10	306	133	30	94.78	7.08	52.98	49.02
9	25	25	10	306	163	50	94.29	7.60	48.94	46.16
10	30	15	8	306	103	30	94.29	12.02	48.65	45.28
11	30	15	8	306	133	50	94.48	11.64	49.62	45.80
12	30	15	8	306	163	10	92.62	10.07	48.31	45.19

Continued

13	30	20	10	206	103	30	94.31	11.66	50.95	47.91
14	30	20	10	206	133	50	94.30	11.10	51.76	48.30
15	30	20	10	206	163	10	93.85	11.95	49.58	18.35
16	30	25	6	256	103	30	92.76	9.76	48.94	45.46
17	30	25	6	256	133	50	93.88	11.96	49.37	45.84
18	30	25	6	256	163	10	93.98	12.30	49.10	45.66
19	35	15	10	256	103	50	93.73	11.06	55.69	52.80
20	35	15	10	256	133	10	94.89	9.38	57.76	55.09
21	35	15	10	256	163	30	95.10	10.01	61.67	59.26
22	35	20	6	306	103	50	92.74	11.64	51.83	51.79
23	35	20	6	306	133	10	93.51	10.61	58.27	53.96
24	35	20	6	306	163	30	95.45	7.62	57.96	55.42
25	35	25	8	206	103	50	93.50	7.89	45.96	43.08
26	35	25	8	206	133	10	92.91	10.01	52.11	50.48
27	35	25	8	206	163	30	86.88	7.62	60.56	57.76

3.3. Effect of Different Parameters on Responses

To determine the effect that each parameter has on the responses (copper recovery, copper content, mass pull, and Silica yield), the signal-to-noise ratio (SN) was calculated for each experiment. The SN ratio is based on "larger is better" (Equation (1)) or "smaller is better" (Equation (2)). The average SN ratios of each level of the six parameters for the flotation of copper were calculated and listed in **Tables 7-10**. Delta values, which show the relative significance of the factors, were also calculated as the difference between the maximum and minimum average values. Based on this, the collector SIBX dosage was the most influential factor affecting the copper recovery response. The Hydrofroth dosage had the least influence on copper recovery response. Furthermore, Solid mass percentage is the most influential factor affecting the copper content, Mass pull, and Silica yield responses.

Table 7. Average SN values for copper recovery at three levels of parameters and delta statics.

Code	Flotation parameter	Level 1	Level 2	Level 3	Delta (max-min)	Rank
A	Solid mass percentage	39.46	39.45	39.38	0.07	4
B	Oversize at 53 μm	39.44	39.48	39.37	0.10	3
C	Air flow rate	39.42	39.37	39.50	0.12	2
D	SIBX dosage	39.35	39.48	39.47	0.13	1
E	Hydrofroth dosage	39.42	39.46	39.42	0.04	6
F	Aero dosage	39.42	39.40	39.47	0.06	5

Table 8. Average SN values for copper content at three levels of parameters and delta statics.

Code	Flotation parameter	Level 1	Level 2	Level 3	Delta (max-min)	Rank
A	Solid mass percentage	18.09	21.10	19.49	3.02	1
B	Oversize at 53 µm	20.34	19.36	18.97	1.37	3
C	Air flow rate	20.26	18.84	19.57	1.43	2
D	SIBX dosage	19.90	19.38	19.39	0.52	6
E	Hydrofroth dosage	19.90	19.93	18.84	1.09	4
F	Aero dosage	19.96	19.29	19.42	0.67	5

Table 9. Average SN values for mass pull at three levels of parameters and delta statics.

Code	Flotation parameter	Level 1	Level 2	Level 3	Delta (max-min)	Rank
A	Solid mass percentage	34.00	33.91	34.89	0.99	1
B	Oversize at 53 µm	34.18	34.47	34.14	0.34	5
C	Air flow rate	34.08	34.18	34.53	0.46	4
D	SIBX dosage	33.99	34.50	34.30	0.51	3
E	Hydrofroth dosage	33.90	34.29	34.61	0.70	2
F	Aero dosage	34.14	34.45	34.21	0.31	6

Table 10. Average SN values for silica yield at three levels of parameters and delta statics.

Code	Flotation parameter	Level 1	Level 2	Level 3	Delta (max-min)	Rank
A	Solid mass percentage	−33.50	−32.40	−34.50	2.10	1
B	Oversize at 53 µm	−33.62	−33.02	−33.61	0.60	4
C	Air flow rate	−33.53	−33.58	−33.14	0.44	6
D	SIBX dosage	−32.55	−33.90	−33.80	1.35	2
E	Hydrofroth dosage	−33.35	−33.68	−33.22	0.46	5
F	Aero dosage	−32.66	−33.88	−33.71	1.22	3

The level of a parameter with the highest average SN ratio corresponds to a better performance and gives the best combination level. Therefore, the optimal levels of flotation parameters have the most significant average SN ratio. The optimum levels of parameters for recovery of copper are solid mass percentage, 25% (Level 1); oversize at 53 µm, 20% (Level 2); air flow rate, 10 l/min (Level 3); SIBX dosage, 256 g/t (Level 2); Hydrofroth dosage, 133 g/t (Level 2); and AERO dosage, 50 g/t (Level 3). As far as, the optimum levels of parameters for copper content response are solid mass percentage, 30% (Level 2); oversize at 53 μm, 15% (Level 1); air flow rate, 6 l/min (Level 1); SIBX dosage, 206g/t (Level 1); Hydrofroth dosage,133 g/t (Level 2); and AERO dosage, 10 g/t (Level 1). The optimum levels of parameters for mass pull response are solid mass percentage, 35% (Level 3); oversize at 53 μm, 20% (Level 2); air flow rate, 10 l/min (Level 3); SIBX dosage,256 g/t (Level 2); Hydrofroth dosage,163 g/t (Level 3); and AERO dosage, 30 g/t (Level 2). The optimum levels of parameters for silica yield response are solid mass percentage, 30% (Level 2); oversize at 53 μm, 20% (Level 2); air flow rate, 10 l/min (Level 3); SIBX dosage,206g/t (Level 1); Hydrofroth dosage, 163 g/t (Level 3); and AERO dosage, 10 g/t (Level 1). A plot of the graph of the parameter against its response on each level is referred to as the main effect, and it indicates the general trend of influence of each parameter (**Figure 4**).

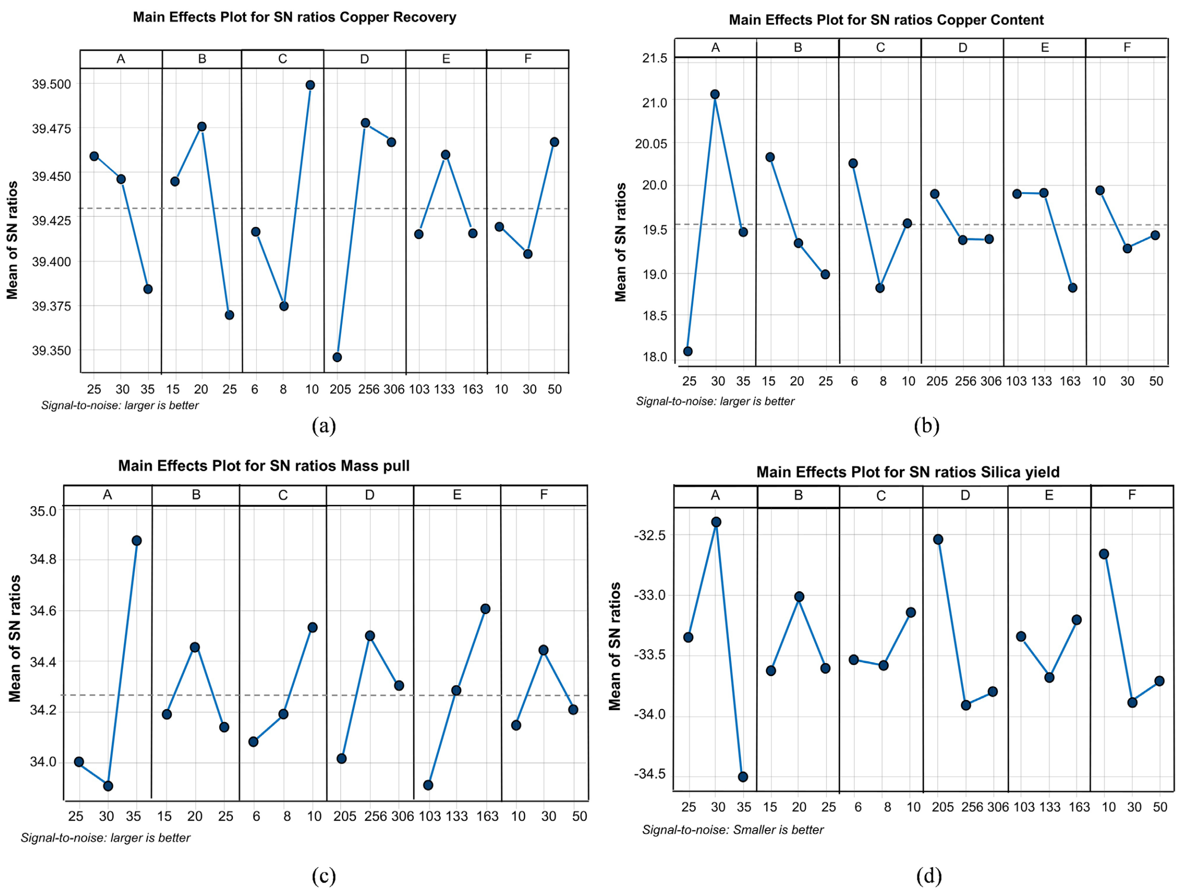

Figure 4. The main effects of the process parameter on copper recovery, copper content, mass pull, and silica yield, respectively.

3.4. Analysis of Variance (ANOVA) Results

The parameters that significantly affected responses were investigated using the analysis of variance (ANOVA). The analysis of variance for copper recovery shows that at a confidence level of $\alpha = 0.95$, the calculated F-values for parameters

A (F = 0.62), B (F = 1.12), C (F = 1.54), D (F = 2.05), E (F = 0.26), and F (F = 0.42) not exceed the critical F-value read from Fisher tables (F (2,14) = 3.739) (Table 11). None of these factors significantly affects the recovery of copper at the tested confidence level of 95%. Regarding importance, the critical probabilities or p-values for A, B, C, D, E, and F parameters are 0.553, 0.354, 0.249, 0.165, 0.776, and 0.667, respectively. This allows us to judge the D parameter as the most significant, as it has the least critical probability.

Table 11. ANOVA table for copper recovery (at 95% confidence interval).

Source	DF	Seq SS	Adj SS	Adj MS	F-Value	P-Value
A	2	0.02895	0.02895	0.014477	0.62	0.553
B	2	0.05244	0.05244	0.026218	1.12	0.354
C	2	0.07213	0.07213	0.036064	1.54	0.249
D	2	0.09607	0.09607	0.048036	2.05	0.165
E	2	0.01208	0.01208	0.006039	0.26	0.776
F	2	0.01956	0.01956	0.009778	0.42	0.667
Residual Error	14	0.32777	0.32777	0.023412		0.553
Total	26	0.60900				

Analysis of variance for copper content in concentrate shows that at a confidence level of $\alpha = 0.95$, the calculated F-values for parameters A (F = 12.7) exceed the critical F-value read from Fisher tables (F (2,14) = 3.739) (Table 12). This parameter is therefore statistically significant for copper content. Regarding importance, A's critical probabilities or p-value is 0.001 (<5%). This allows us to judge the A parameter as the most significant. Furthermore, the A parameter is statistically significant for mass pull and silica yield (Table 13 and Table 14).

Table 12. ANOVA table for copper content (at 95% confidence interval).

Source	DF	Seq SS	Adj SS	Adj MS	F-Value	P-Value
A	2	40.982	40.982	20.4910	12.17	0.001
B	2	8.957	8.957	4.4784	2.66	0.105
C	2	9.155	9.155	4.5775	2.72	0.101
D	2	1.624	1.624	0.8119	0.48	0.627
E	2	6.938	6.938	3.4692	2.06	0.164
F	2	2.273	2.273	1.1366	0.68	0.525
Residual Error	14	23.565	23.565	1.6832		
Total	26	93.494				

Table 13. ANOVA table for mass pull (at 95% confidence interval).

Source	DF	Seq SS	Adj SS	Adj MS	F-Value	P-Value
A	2	5.3760	5.3760	2.6880	8.73	0.003
B	2	0.6004	0.6004	0.3002	0.98	0.401
C	2	1.0259	1.0259	0.5130	1.67	0.224
D	2	1.1913	1.1913	0.5956	1.93	0.181
E	2	2.2399	2.2399	1.1200	3.64	0.053
F	2	0.4692	0.4692	0.2346	0.76	0.485
Residual Error	14	4.3100	4.3100	0.3079		
Total	26	15.2128				

Table 14. ANOVA table for Silica Yield (at 95% confidence interval).

Source	DF	Seq SS	Adj SS	Adj MS	F-Value	P-Value
A	2	5.3760	5.3760	2.6880	8.73	0.003
B	2	0.6004	0.6004	0.3002	0.98	0.401
C	2	1.0259	1.0259	0.5130	1.67	0.224
D	2	1.1913	1.1913	0.5956	1.93	0.181
E	2	2.2399	2.2399	1.1200	3.64	0.053
F	2	0.4692	0.4692	0.2346	0.76	0.485
Residual Error	14	4.3100	4.3100	0.3079		
Total	26	15.2128				

3.5. Prediction Results of the Optimum Performance by Taguchi Method

Table 15. Predicted SN and responses at optimum conditions.

Target	A	B	C	D	E	F	Predicted value	
							SN	Response (%)
Copper recovery (max)	25	20	10	256	133	50	39.69	96.4
Copper content (max)	30	15	6	206	133	10	23.71	14.2
Mass pull	35	20	10	256	163	30	34.58	56.3
Silica yield	30	20	10	206	163	10	-29.89	35.4

The established optimal conditions, defined by specific levels of factors A to F, enabled the maximization of the signal-to-noise ratio (SN) for copper recovery and content, as well as for mass pull (M_Pull), while minimizing silica yield (S_Y) (**Table 15**). This optimization suggests improved process stability in the face of operational parameter fluctuations. Although copper recovery reaches a high level

(96.4%) under these ideal conditions, a trade-off is evident with the silica yield (35.4%). To overcome this imbalance, a multi-objective approach would prove essential to simultaneously improve copper recovery and minimize silica entrainment in the concentrate.

3.6. Prediction Results of the Optimum Performance Using Multi-Objective Method

The Taguchi method identified the best values for each outcome. However, a multi-objective approach was necessary for this study to prove essential to obtain optimal parameters that can improve copper recovery and minimize silica yield. **Table 16** provides statistical parameters such as R^2 and S (a parameter accounting for residuals). A quadratic model was established for each response as a function of the control variables (**Table 17**).

Table 16. Summary of models.

Reponses	Statistical parameters	
	S	R^2
R_Cu	1.71638	69.42%
M_pull	2.23661	93.65%
%_Cu	1.29,73	89.01%
S_Y	6.45793	80.70%

Table 17. Mathematical models obtained.

Terms	Coefficients			
	R_Cu[a]	%Cu	M_pull[b]	S_Y[c]
A	62.8	−33.3	59.1	204
B	0.87	6.35	−9.41	−19.28
C	1.61	−1.291	3.42	−1.06
D	−2.56	−6.51	−0.03	8.2
E	0.065	−0.100	0.673	0.882
F	−0.026	0.058	−0.189	−0.54
A*A	0.381	−0.097	0.666	1.08
B*B	−0.0100	−0.1000	0.1366	0.277
C*C	−0.0286	0.0110	−0.0693	0.064
D*D	0.216	0.291	0.198	−0.095
E*E	−0.000298	0.000118	−0.000838	−0.00125
F*F	−0.000257	−0.001035	0.00144	0.00200
A*E	0.00070	0.00046	−0.00076	−0.00059
A*F	−0.00152	−0.00327	0.01977	0.0387
B*E	−0.00474	0.00721	−0.0288	−0.0600

Continued

B*F	−0.00235	0.00670	−0.00627	−0.0149
C*E	−0.00763	−0.00628	0.0048	0.0151
C*F	−0.0017	0.01373	−0.0251	−0.0702
D*E	−0.0152	−0.0058	0.0287	0.0863
	0.000754	0.000253	−0.001707	−0.00144

Note: [a]Copper Recovery, [b]Mass pull, [c]Silica yield.

The obtained models were applied to the multi-objective method's algorithm using Minitab 21.4.0 software. Thus, the optimized results are visualized in **Figure 5**. It can be seen that to achieve the best overall results (95.4% copper recovery, 48.0% mass pull, 12.2% copper content, and 24.8% silica yield), the following control variables should be used: 28.53% mass solid percentage, 21.1% oversize at 53 μm sieve, 10 l/min air flow rate, 249.4 g/t of SIBX, 163.0 g/t of Hydrofroth, and 10 g/t of AERO.

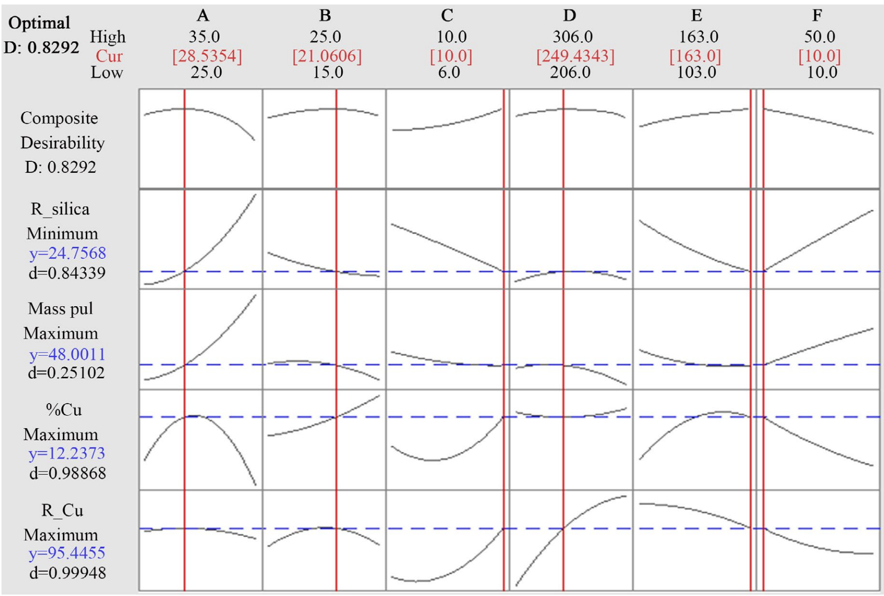

Figure 5. Optimization plot for all responses using Minitab 21.4.0 software.

Comparing the results obtained by the Taguchi and multi-objective methods, the multi-objective approach contributes more to minimizing silica, 24% versus 35%. This means a small percentage of silica would be carried into the concentrate.

4. Conclusions

Given the variability in ore grade, achieving high recovery rates and maintaining an optimal copper grade was critical. The current study explored improving copper recovery from the Kakula low-grade deposit using flotation process optimisation. This research employed the Taguchi experimental design and multi-objective optimisation to determine the most effective flotation parameters. Key factors investigated included solid mass percentage, air flow rate, particle size, frother dosage (HYDOFROTH), collector dosage (SIBX), and secondary collector dosage (AERO). The main conclusion of this study within the levels of process parameters selected is:

1) For Taguchi method, the optimum conditions for maximum copper recovery are solid mass percentage, 25%; oversize at 53 μm, 20%; air flow rate, 10 l/min; SIBX dosage, 256 g/t; Hydrofroth dosage, 133 g/t; and AERO dosage, 50 g/t collector dosage, 80 g/t. For maximum copper content in concentrate, the optimum conditions are solid mass percentage, 30%**;** oversize at 53 μm**,** 15%; air flow rate, 6 l/min; SIBX dosage, 206 g/t; Hydrofroth dosage, 133 g/t; and AERO dosage, 10 g/t. For maximum mass pull response, the optimum condition are solid mass percentage, 35% (Level 3); oversize at 53 μm**,** 20% (Level 2); air flow rate, 10 l/min (Level 3); SIBX dosage, 256 g/t (Level 2); Hydrofroth dosage**,** 163 g/t (Level 3); and AERO dosage, 30 g/t (Level 2). The optimum levels of parameters for silica yield response are solid mass percentage, 30% (Level 2); oversize at 53 μm, 20% (Level 2); air flow rate, 10 l/min (Level 3); SIBX dosage, 206 g/t (Level 1); Hydrofroth dosage, 163 g/t (Level 3); and AERO dosage, 10 g/t (Level 1). The predicted values for copper recovery, copper content, mass pull, and silica yield at the optimum conditions are: 96.38%, 14,18%, 56.3%, and 35.4%, respectively. For the Taguchi method, despite having better Copper recovery, a potential entrainment of silica into the concentrate is noted. Working with the operating conditions proposed by this method requires additional cleaning steps to eliminate entrained silica in the concentrate.

2) The best overall results for the multi-objective method are 95.4% copper recovery, 48.0% mass pull, 12.2% copper content, and 24.8% silica yield. The following control variables should be used: 28.53% mass solid percentage, 21.1% oversize at 53 μm sieve, 10 l/min air flow rate, 249.4 g/t of SIBX, 163.0 g/t of Hydrofroth, and 10 g/t of AERO. The multi-objective approach contributes more to minimizing silica, 24% versus 35%.

3) The relative significance of flotation parameters (based on the difference between max and min. average values) was that the collector SIBX dosage was the most influential factor affecting the copper recovery response. The Hydrofroth dosage had the least influence on copper recovery response. Furthermore, solid mass percentage is the most influential factor affecting the copper content, mass pull, and silica yield responses.

4) Based on ANOVA and at a 95% confidence level, the collector dosage SIBX parameter is the most significant, as it has the lowest critical probability. Solid mass percentage is statistically significant for copper content in concentrate, mass pull, and silica yield.

5) The finding in this study constitutes a basis for the comprehension of the flotation of Kakula ores. Still, it would be necessary to carry out pilot-scale tests

for these findings and consider the economic approach of the proposed processes, energy consumption, and water consumption for future research.

Acknowledgements

The authors gratefully acknowledge Kamoa Copper SA for permitting experiments in their metallurgical laboratories. Special thanks are also extended to SGS SA for their invaluable assistance in characterizing the ore sample.

Author Contributions

Conceptualization and methodology, B.O.-N, K.-T, and P.K.-T; formal analysis and investigation, B.O.-N; writing—original draft preparation, B.O.-N; writing—review and editing, B.O.-N, A.K.-K, K.-T, J.H.-M, and A.W; Supervision, K.-T and A.K.-K. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Drzymata, J. (2014) Mineral Processing, Foundations of Theory and Practice of Minerallurgy. University of Technology.

[2] Alsafasfeh, A. (2020) Modeling and Optimization of Froth Flotation of Low-Grade Phosphate Ores: Experiments and Machine Learning. https://scholarsmine.mst.edu/doctoral_dissertations/2948

[3] Rehman, B.U. (2019) Modelling and Mineral Froth Flotation. *Sustainability* (*Switzerland*), **11**, 1-14. http://scioteca.caf.com/bitstream/handle/123456789/1091/RED2017-Eng-8ene.pdf?sequence=12&isAllowed=y%0Ahttp://dx.doi.org/10.1016/j.regsciurbeco.2008.06.005%0Ahttps://www.researchgate.net/publication/305320484

[4] Pérez-Garibay, R., Ramírez-Aguilera, N., Bouchard, J. and Rubio, J. (2014) Froth Flotation of Sphalerite: Collector Concentration, Gas Dispersion and Particle Size Effects. *Minerals Engineering*, **57**, 72-78. https://doi.org/10.1016/j.mineng.2013.12.020

[5] Fuerstenau, M.C. and Han, K.N. (2003) Principles of Mineral Processing. Society for Mining, Metallurgy, and Exploration. https://books.google.ca/books?id=MDiZQCSBENMC

[6] Crozier, R.D. (1992) Flotation: Theory, Reagents and Ore Testing. In: *Theory*, *Reagents and Ore Testing Series*, Pergamon. https://books.google.ca/books/about/Flotation.html?id=r0R-QgAACAAJ&redir_esc=y

[7] Fuerstenau, M.C., Jameson, G.J. and Yoon, R.H. (2007) Froth Flotation: A Century of Innovation. Society for Mining, Metallurgy, and Exploration. https://books.google.ca/books/about/Froth_Flotation.html?id=8zpjAhBViC0C&redir_esc=y

[8] Sony, P., Tshibangu, O., *et al.* (2021) Comportement à la flottation du minerai oxydé cuprocobaltifère de Kimpe en RD Congo par sulfuration superficielle. *International Journal of Innovation and Applied Studies*, **31**, 498-508.

[9] Bhondayi, C. (2014) A Study of Flotation Froth Phase Behaviour. Doctor of Philosophy in Engineering Thesis, Wits University.

[10] Kalenga, K.K.J. (2018) Valorisation des gisements de cuivre et cobalt par flottation. Éditions Universitaires Européennes.

[11] Wills, B.A. and Finch, J. (2015) Wills' Mineral Processing Technology: An Introduction to the Practical Aspects of Ore Treatment and Mineral Recovery. Butterworth-Heinemann. https://books.google.ca/books?id=uMWcBAAAQBAJ

[12] Temur, H. and Kocaker, M.M. (2009) Determination of the Optimum Conditions of the Dissolution of Chalcopyrite Concentrate in Aqueous Solutions Saturated with Chlorine.

[13] Mines, I. (2016) Ivanhoe Mines Files NI 43-101 Technical Report for the Independent Pre-Feasibility Study for the First Phase of Mine Development at the Kamoa Copper Project in the Democratic Republic of Congo. https://ivanhoemines.com/site/assets/files/2197/2016-03-30_nr.pdf

[14] Semioshkina, N. and Voigt, G. (2006) An Overview on GSF Activities at the Semipalatinsk Test Site, Kazakhstan. *Journal of Radiation Research*, **47**, A95-A100. https://doi.org/10.1269/jrr.47.a95

[15] Roy, R.K. (2010) A Primer on the Taguchi Method. 2nd Edition, Society of Manufacturing Engineers. https://books.google.ca/books/about/A_Primer_on_the_Taguchi_Method_Second_Ed.html?id=k5VBsRZfzQsC&redir_esc=y

[16] Ghani, J.A., Choudhury, I.A. and Hassan, H.H. (2004) Application of Taguchi Method in the Optimization of End Milling Parameters. *Journal of Materials Processing Technology*, **145**, 84-92. https://doi.org/10.1016/s0924-0136(03)00865-3

[17] Bozkurt, Y. and Bilici, M.K. (2013) Application of Taguchi Approach to Optimize of FSSW Parameters on Joint Properties of Dissimilar AA2024-T3 and AA5754-H22 Aluminum Alloys. *Materials & Design*, **51**, 513-521. https://doi.org/10.1016/j.matdes.2013.04.074

[18] Athreya, S. and Venkatesh, Y.D. (2012) Application of Taguchi Method for Optimization of Process Parameters in Improving the Surface Roughness of Lathe Facing Operation. *International Refereed Journal of Engineering and Science*, **1**, 13-19.

[19] Dehnad, K. (1989) Quality Control, Robust Design, and the Taguchi Method. Wadsworth & Brooks/Cole Advanced Books & Software. https://ulaval.on.worldcat.org/oclc/1131371872

[20] Taguchi, G. (1993) Taguchi on Robust Technology Development: Bringing Quality Engineering Upstream. American Society of Mechanical Engineers. https://ulaval.on.worldcat.org/oclc/872149500

[21] Shengo, M.L., Kime, M.-P., Mambwe, M.P. and Nyembo, T.K. (2019) A Review of the Beneficiation of Copper-Cobalt-Bearing Minerals in the Democratic Republic of Congo. *Journal of Sustainable Mining*, **18**, 226-246. https://doi.org/10.1016/j.jsm.2019.08.001

[22] Masiya, T.T. and Nheta, W. (2014) Flotation of Nickel-Copper Sulphide Ore: Optimisation of Process Parameters Using Taguchi Method. *Proceedings of the International Conference on Mining, Material and Metallurgical Engineering*, Prague, 11-12 August 2014, 1-11.

[23] Bilal, M., Park, I., Hornn, V., Ito, M., Hassan, F., Jeon, S., *et al.* (2022) The Challenges and Prospects of Recovering Fine Copper Sulfides from Tailings Using Different Flotation Techniques: A Review. *Minerals*, **12**, Article 586. https://doi.org/10.3390/min12050586

[24] Bulatovic, S.M. (2007) Flotation of Copper Sulfide Ores. In: *Handbook of Flotation Reagents*, Elsevier, 235-293. https://doi.org/10.1016/b978-044453029-5/50021-6

[25] Luo, Y., Ou, L., Sun, W., Han, H., Chen, J. and Peng, J. (2023) A Case Study of Flotation of Chalcopyrite-Molybdenite Ore Using a Mixture of Pyrogallic Acid and O-Isopropyl Ethylthiocarbamate: Insights from Ab Initio Calculations. *Advanced Powder Technology*, **34**, Article 104039. https://doi.org/10.1016/j.apt.2023.104039

[26] Ramarao, M., King, M.F.L., Sivakumar, A., Manikandan, V., Vijayakumar, M. and Subbiah, R. (2022) Optimizing GMAW Parameters to Achieve High Impact Strength of the Dissimilar Weld Joints Using Taguchi Approach. *Materials Today*: *Proceedings*, **50**, 861-866. https://doi.org/10.1016/j.matpr.2021.06.137