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Optimization of Flotation Reagents' Specific Consumption by Modeling During Mineral Enrichment

By A. Alouani, A. Arbaoui, K. Benkhouja, A. Khmich, Y. Alouani, K. Sbiaai & B. Nacer

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The purpose of this study is to determine the optimal experimental conditions, in order to study the main effects of the different parameters and the effects of possible interactions between them, which cannot be revealed by conventional methods. The method of factorial design was applied to optimize the specific consumption of flotation reagents[5-7].

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OPTIMIZATIONOFFLOTATIONREAGENTSSPECIFICCONSUMPTIONBYMODELINGDURINGMINERALENRICHMENT

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Optimization of Flotation Reagents' Specific Consumption by Modeling During Mineral Enrichment

A. Alouani [α], A. Arbaoui [σ], K. Benkhouja [ρ], A. Khmich [Ѡ], Y. Alouani [¥], K. Sbiaai [§] & B. Nacer [χ]

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I. Introduction

Flotation is a process of separating precious minerals from the gangue, based on the differences in the surface properties of the particles, using reagents added in the presence of air bubbles. The consumption of flotation reagents represents a very important part in the mineral enrichment cost. In this study of optimizing the mineral flotation reagents consumption, we have empirically modeled the concentrate contents according to the influence of elements, based on the experimental designs theory[1-4].

The purpose of this study is to determine the optimal experimental conditions, in order to study the main effects of the different parameters and the effects of possible interactions between them, which cannot be revealed by conventional methods. The method of factorial design was applied to optimize the specific consumption of flotation reagents[5-7].

The important parameters which affect the concentrate y (%) are the flotation reagentsR_1 (g/t), R_2 (g/t) and R_3 (g/t)[8]. the other parameters are assumed to be constant by working on the same ore quality with laboratory tests. These parameters were respectively coded x_1, x_2 and x_3, and were studied between two levels -1 (low level) and +1 (high level).

The flotation tests are based on the fixation of the specific concentration of two reagents and changing the third, in order to identify the test that leads to maximum percentage of concentrate y (useful product) and minimum undesirable products (impurities).

II. The Experimental Designtheory

The experimental design methodology is also an effective experimental strategy for determining optimal conditions. This method is a set of statistical and mathematical techniques, used for the development, improvement and optimization of some processes, in which a response of interest is affected by several process variables, whose objective is to optimize this response. To quantify the effects of influential factors and their interactions on the studied response, we identify the form of this influence by developing a mathematical equation that allows describing the studied response according to influential factors, in order to obtain a significant empirical model[9].

Several possible mathematical models are assigned to the experimental designs. The aim is to build a model that uses the action of all factors.

Let X_1, X_2, … X_k be the k factors and Y the response. The model is written in the following form:

$$\boldsymbol{Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{\substack{i=1 \\ j=1 \\ i \neq j}}^{k} \beta_{ij} X_i X_j + \cdots +} \varepsilon$$

$\boldsymbol{\beta_0}$: Constant Term $\boldsymbol{\beta_i}$: Linear Term $\boldsymbol{\beta_{ii}}$: Squarish Term $\boldsymbol{\beta_{ij}}$ Right-angled Termε :Error Term

The problem is to determine the values of the coefficients β_0,β_i, β_{ii} …and β_{ij} of the model. Thus, it is necessary to carry out more than k experiments.

It is then possible to calculate only an estimation of the coefficients β, denoted b, calculated by the method of the least squares. The estimated model equation is then written:

$$\boldsymbol{y = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{\substack{i=1 \\ j=1 \\ i \neq j}}^{k} b_{ij} x_i x_j + \cdots +} \varepsilon$$

y: is called predicted or estimated response.

The latter general equation can be simplified by eliminating non-significant terms. This depends on the choice of the experimenter, according to the level of confidence in regards to the model, which allows obtaining a reduced equation.

III. Software Used

The statistical and graphical analysis software used in this study to interpret the results of the experimental design is Design-expert 7 version 7.0.0.

Author α σ ρ: Univ Chouaib Doukkali, Laboratory LCMP, Faculty of science, El Jadida, Morocco
Author Ѡ ¥ §: Univ Hassan 1, Laboratory LS3M, Polydisciplinary Faculty of Khouribga, 26000 Settat, Morocco
Author χ: Univ Cadi Ayyad, Group GEMO, Faculty of Sciences and Technology Gueliz, 40000 Marrakech, Morocco
e-mail: a.alouani@ocpgroup.ma

This software was used to analyze the regression of the data obtained and to estimate the coefficients of the regression equation[10].

IV. Experimental Design

To find the optimum conditions for the y concentrate (%), the experiments were designed using the experimental design methodology. For our tests, the three independent variables chosen for this study are: R_1(g/t), R_2 (g/t) and R_3 (g/t). The ranges and levels of these parameters are represented in coded and natural values (xi, Xi) in table 1, therefore, it would take two levels for each factor. This makes a total of 8 necessary experiments, for a polynomial model of individual effects and interactions between the three factors. The matrix defining the conditions of the three-variable experiments is presented in table 1.

Table 1: Coded and natural levels of independent parameters used

Parameters	Coded and natural levels	
	-1	+1
X_1 : R_1(g/t)	300	600
X_2 : R_2 (g/t)	200	400
X_3 : R_3 (g/t)	60	120

The general equation of the model for the response Y (concentrate) in percentage is in the form:

$$y = b_0 + \sum_{i=1}^{3} b_i x_i + \sum_{i=1}^{2} \sum_{j=i+1}^{3} b_{ij} x_i x_j + \varepsilon$$

Where y is the observed response, b_0, b_i and b_{ij} represent respectively the constant term, the coefficients of the linear terms and the terms representing the interactions between variables and **ε** that represents the residual error.

This complete polynomial model is obtained by the multiple regression technique for three factors. Most of the time, the regression method is based on the least squares optimization criterion. We obtain the most probable estimates of the coefficients we denote by:

$$\hat{a} = (X^t X)^{-1} X^t Y$$

Where X is the experiment matrix, X^t the transpose of X and $(X^t X)^{-1}$ is the inverse of the matrix $(X^t X)$.

The values of the coded variables according to natural variables are defined as follows:

$$x_i = \frac{X_i - X_{i0}}{X_i}$$

Where x_i is the coded value of the independent variable i, X_i the natural value of the independent variable i, and X_{io} the natural value of the ith independent variable at the central point.

In order to test the validity of the model, the variance analysis (ANOVA) was used to examine the significance and adequacy of the model. This latter makes it possible to plot the response surfacesand to estimate the interaction between the different factors and their influence on the concentrate.

V. Experimental Design Results

The results of the factorial design experiments are represented in table 2 which shows the statistical combinations of independent variables x_1 (R_1 (g/t)), x_2 (R_2 (g/t)) and x_3 (R_3 (g/t)).

Table 2: Experimental and calculated results of the concentrate(%) factorial design

N° Exp.	Coded Values			Natural Values			Concentrate(%)		Residuals (%)
	x_1	x_2	x_3	X_1 (g/t)	X_2 (g/t)	X_3 (g/t)	$y_{Experimental}$	$y_{calculated}$	
1	-1	-1	-1	300	200	60	62.3	62.35	-0.05
2	+1	-1	-1	600	200	60	62.9	62.78	0.12
3	-1	+1	-1	300	400	60	65.2	65.15	0.05
4	+1	+1	-1	600	400	60	67.7	67.83	-0.13
5	-1	-1	+1	300	200	120	64.5	64.45	0.05
6	+1	-1	+1	600	200	120	66.4	66.53	-0.13
7	-1	+1	+1	300	400	120	67.2	67.25	-0.05
8	+1	+1	+1	600	400	120	71.7	71.58	0.13

VI. Determining The Model Significant Terms

Design-Expert classifies the absolute values of effects from the bottom up and builds a plot of half-normal probability. Significant effects fall to the right on this plot. To the right, select the most important effects. Look for a final gap between the guardians and the many trivial effects near zero. On the other hand, if the effects are negative, a reduction in response occurs at a high level of the same factor[11], and a positive value indicates a synergistic effect that promotes optimization[12].

From figure 1 we notice that the significant effects are A, B, C, AB and AC, which are respectively R_1, R_2, R_3, the interaction R_1-R_2 and the interaction R_1-R_3. These parameters are the only ones that affect the response of the concentrate (%), so the empirical model is a function of the factors' individual effects and the previous interactions.

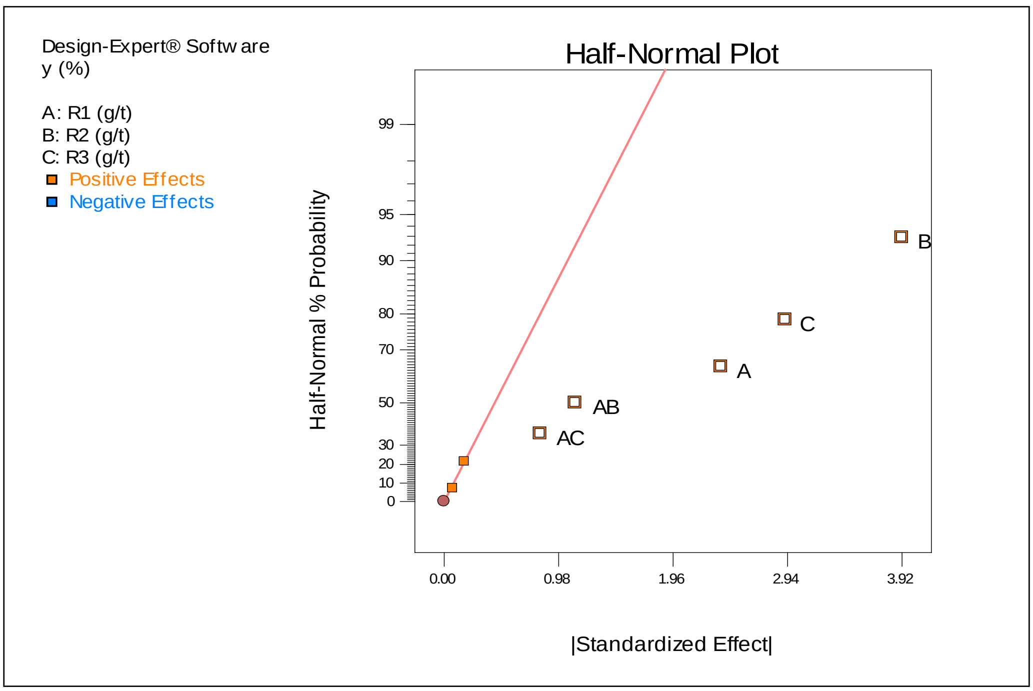

Figure 1: Significant Effects

The polynomial general equation is as follows:

- According to coded factors

$$y = 65.99 + 1.19\,A + 1.96\,B + 1.46\,C + 0.56\,AB + 0.41\,AC$$

- According to natural factors

$$y = 60.925 - 0.011583\,R_1 + 2.7510^{-3}R_2 + 7.510^{-3}R_3 + 3.7510^{-5}R_1R_2 + 9.16667\;10^{-5}\,R_1R_3$$

VII. Evaluation of The Model Quality

a) Residuals Analysis

The actual values of the response y_{exp} are compared to the calculated values y_{cal} by the model and their differences are called residuals. These residuals allow verifying the model quality. They are shown in figure 2.The correlations between the theoretical and experimental responses we obtained are satisfactory[13]. The determination coefficient (0,9989) is close to the unit (statistical tests).

The differences between the experimental and calculated responses (residuals) do not exceed 0.13%, which is due to experimental results variability because of manipulation. These residuals are distributed equally in space[14]. The model was accepted. Moreover, this illustrates that this polynomial model describes well the studied phenomenon and shows a good adjustment of the experimental results.

In Figure 3, the plot of the experimental response is given as a function of the calculated one, in which we notice a strong correlation between the calculated response and that estimated by the model.

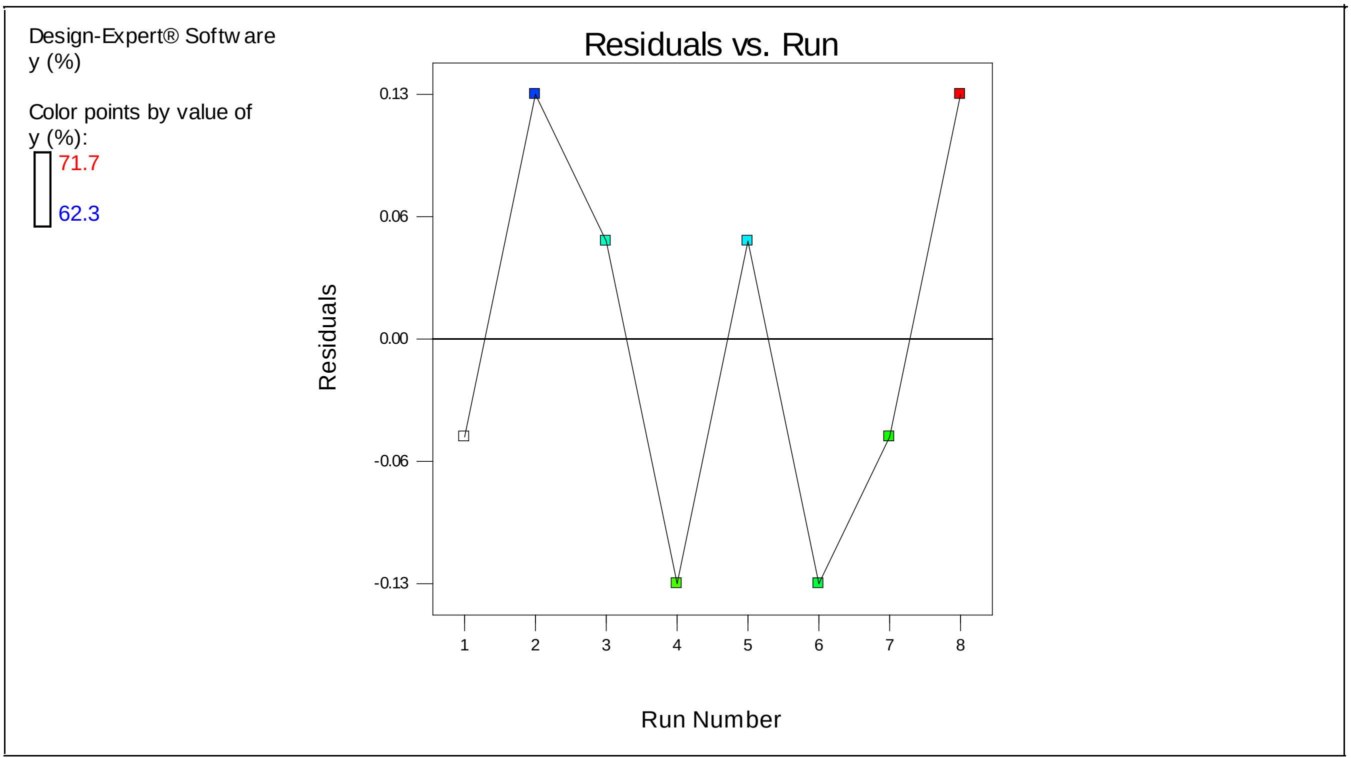

Figure 2: Diagram of response residuals (%) based on number of experiments

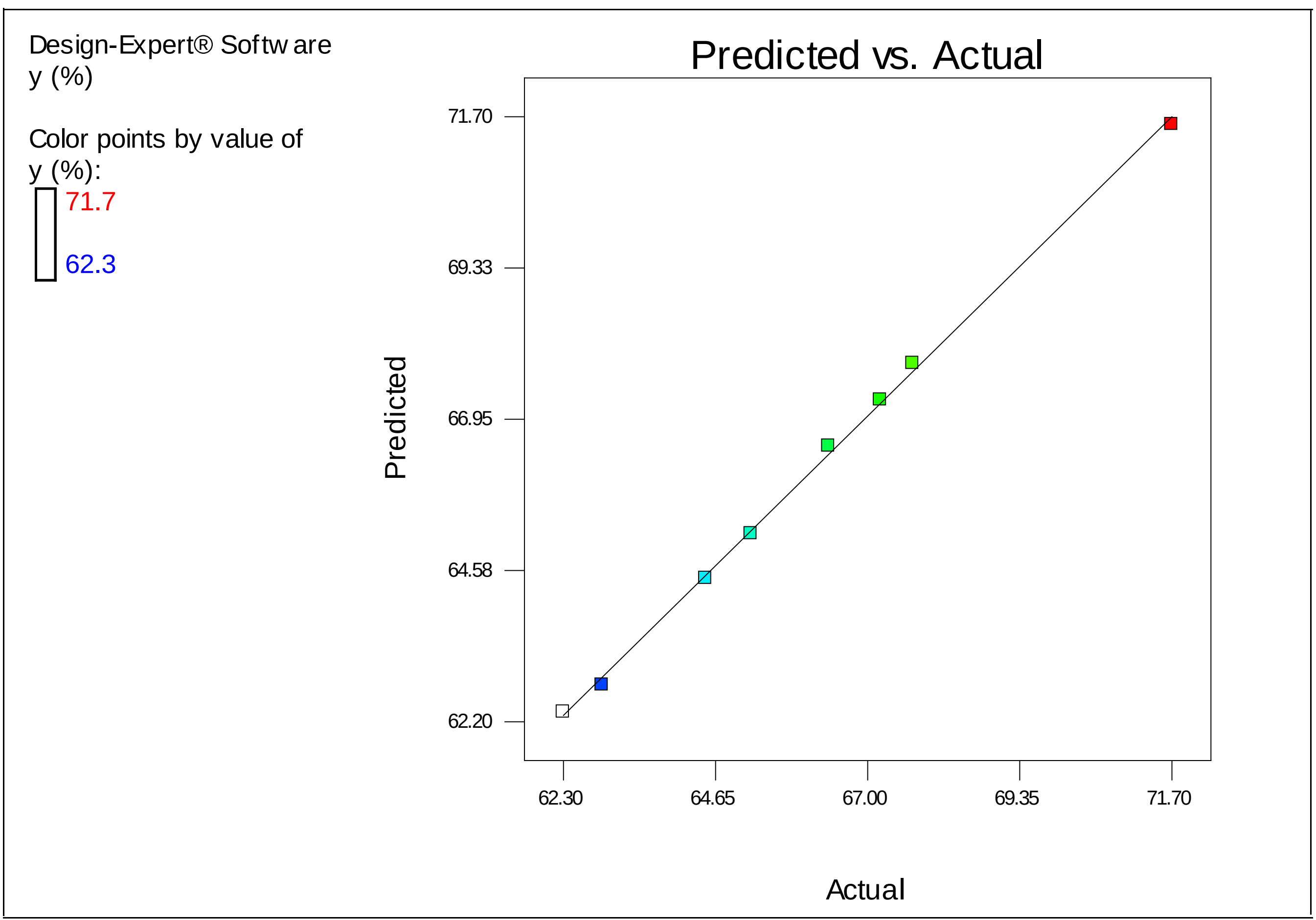

Figure 3: Comparison between calculated and experimental values of the concentrate y(%)

b) Residuals normal probability

The normality of the data can be verified by plotting a plot of residuals normal probability. If the data points on the ground fall close enough to the straight line, the data is normally distributed[15].

The residuals normal probability graph is given in figure 4. We find that in the response in concentrate function y (%), the data points are close enough to the straight line and this indicates that the experiments arise from a normally distributed population.

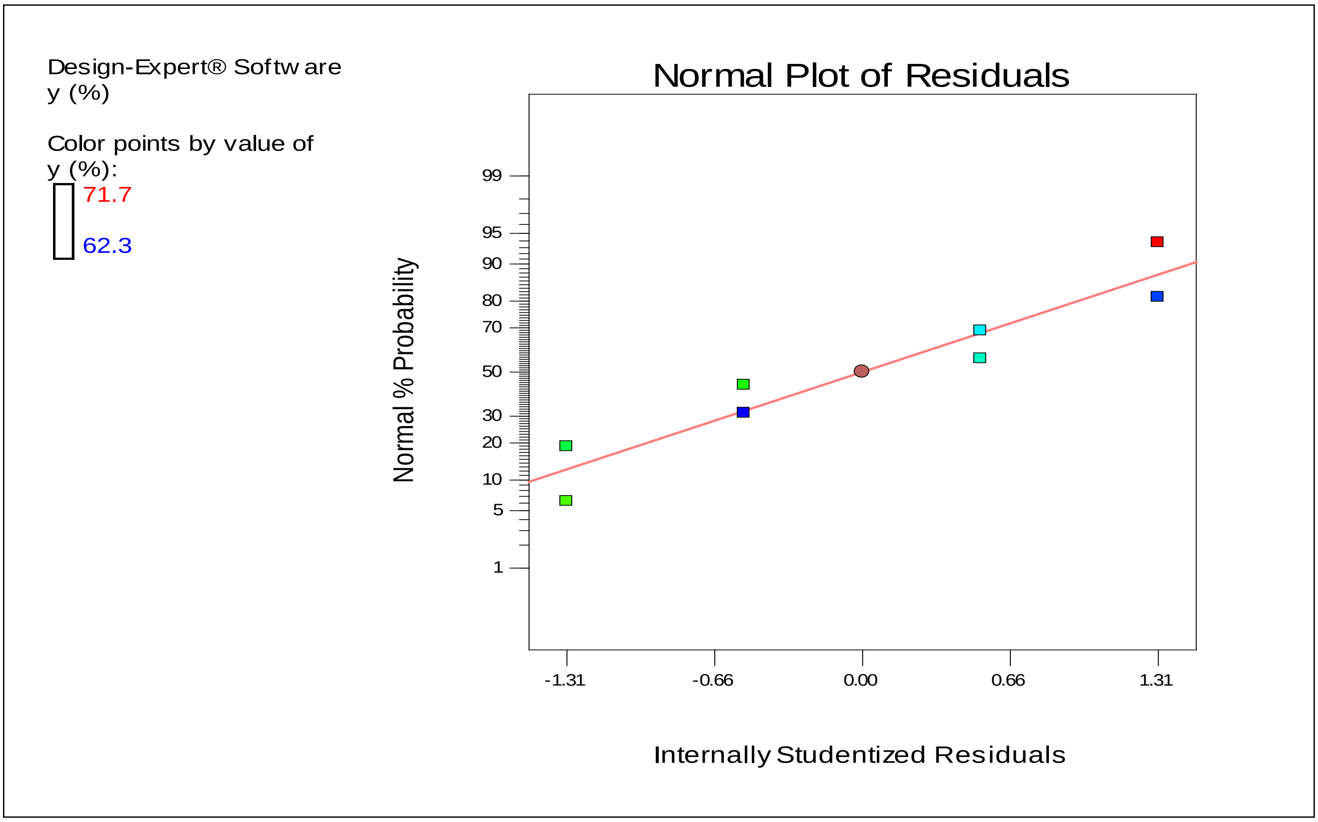

Figure 4: Residuals Probability

The results of the concentrate y (%) variance analysis are given in Table 3:

Table 3: Concentrate y (%) variance analysis

Source	Freedom degree	Mean squares	F-value	p-value Prob>F	Signification
Model	5	12.62	348.12	0.0029	Significant
A- R_1	1	11.28	311.21	0.0032	Significant term
B- R_2	1	30.81	849.97	0.0012	Significant term
C- R_3	1	17.11	472.03	0.0021	Significant term
AB	1	2.53	69.83	0.0140	Significant term
AC	1	1.36	37.55	0.0256	Significant term

It appears from these results that:

- The Model F-value of 348.12 implies the model is significant. There is only a 0.29% chance that a "Model F-Value" this large could occur due to noise;
- Values of "Prob > F" less than 0.0500 indicate model terms are significant[16];
- In this case A, B, C, AB, AC are significant model terms. Values greater than 0.1000 indicate the model terms are not significant;
- The "Pred R-Squared" of 0.9816 is in reasonable agreement with the "Adj R-Squared" of 0.9960;
- "Adeq Precision" measures the signal to noise ratio. A ratio greater than 4 is desirable[17]. Your ratio of

55.948 indicates an adequate signal. This model can be used to navigate the design space.

VIII. Comparison Between the Empirical Model Responses and Experimental Ones

Based on the experimental responses found in the laboratory and the responses calculated by the empirical model and their differences, i.e. the residuals (table 2), we can plot thefigure 5 that illustrates the comparison between these responses (experimental and model) for the 8 tests.

According to this curve, we notice that the response of the concentrate y (%) found starting from the empirical model are identical to those found in the laboratory with the same elaboration conditions. In other words, they are similar for most tests. Therefore, we infer that there is a strong correlation between the experimental and empirical models responses.

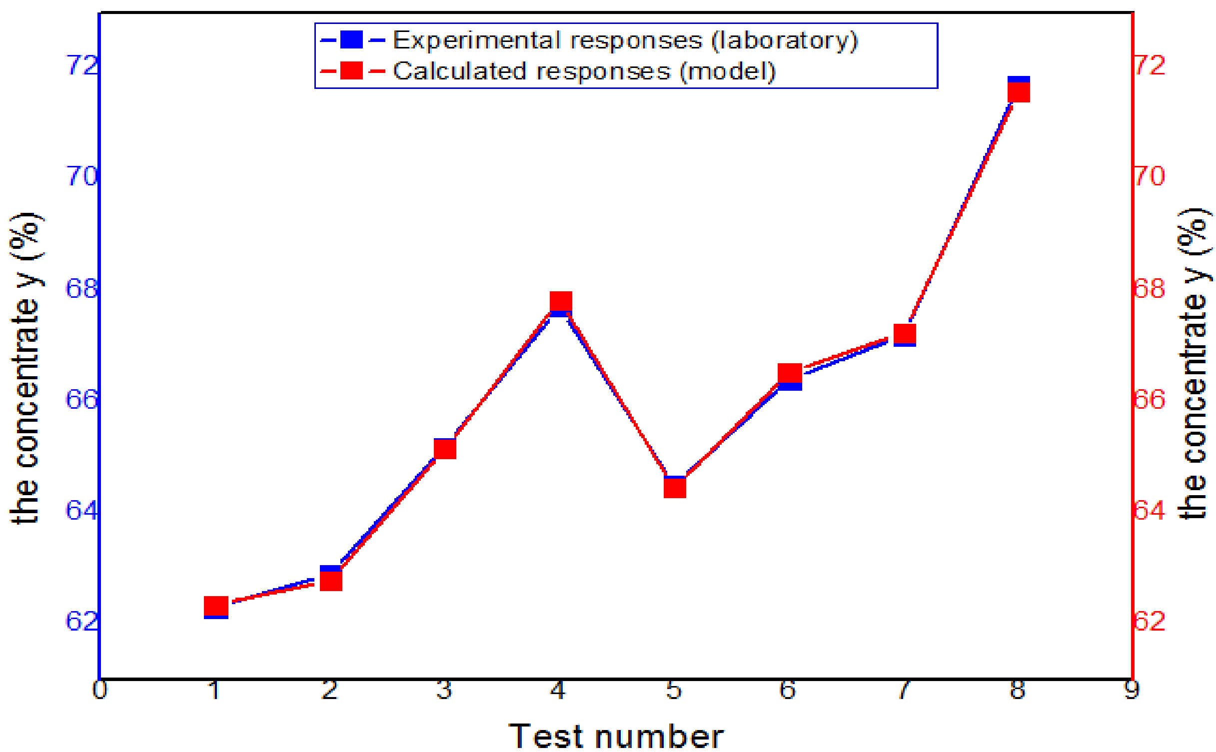

Figure 5: The correlation between experimental and model results

IX. 3D Response Surface and 2D Contour Graph

The 3D response surface is a three-dimensional graphical representation, it was used to determine the individual and cumulative effect of the mutual interaction between the variables[18]. The response surface analyzes the geometric nature of the surface, the maxima and minima of the response. The contour graph plot by this model is a graphical technique to represent a three-dimensional polynomial response surface by plotting z-slices on a two-dimensional format. Lines are plotted to connect the coordinates (x, y) where this z-value occurs[19].

The study of contour graphs provides a simple method of optimizing the rate of treatment, and identifying interactions between variables (Figs. 6-9). Each curve represents, in our case, the combinations between two variables when the third variable is maintained at a constant level. These constant levels are the central levels of each variable.

For the interaction R_1-R_2, the response surface of figure 6 shows that the concentrate y (%) increases progressively with the increase of the values of R_2 and R_1. The contour graph (figure 7) illustrates well these variations.

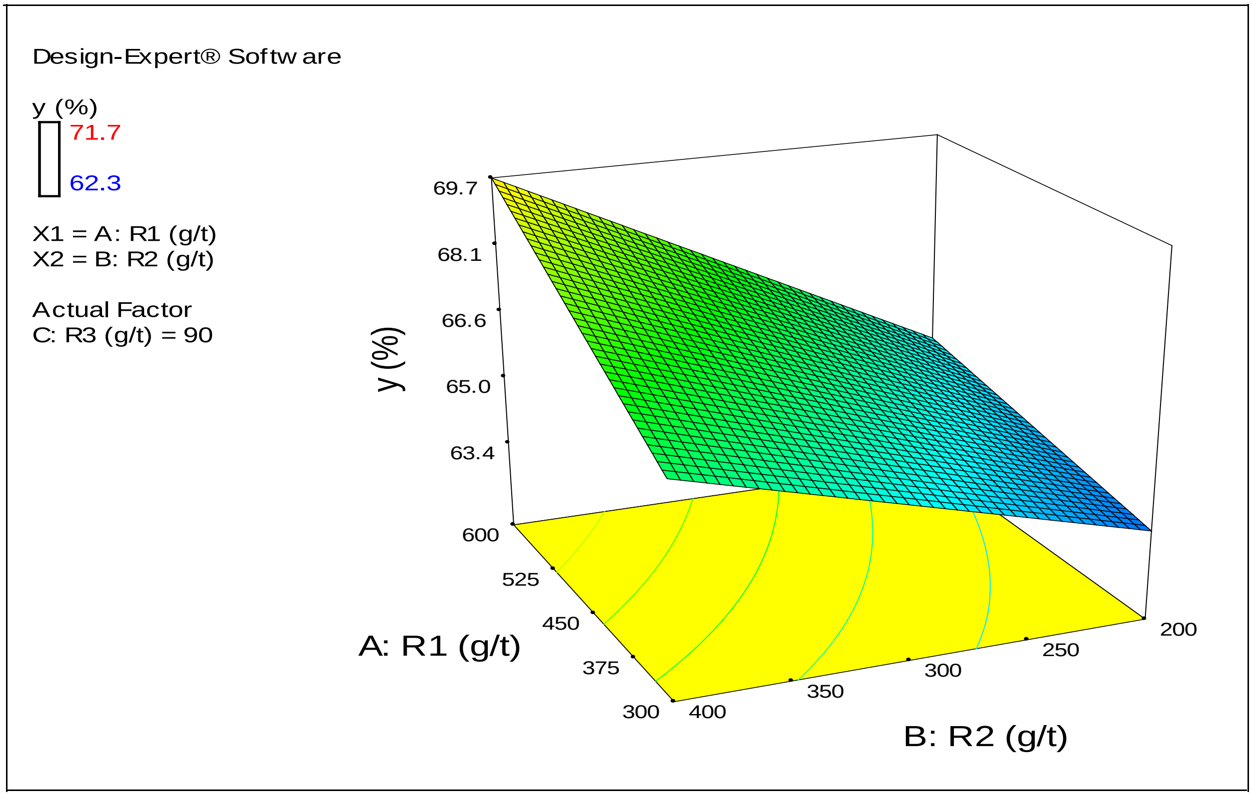

Figure 6: Response surface according to R_1-R_2.

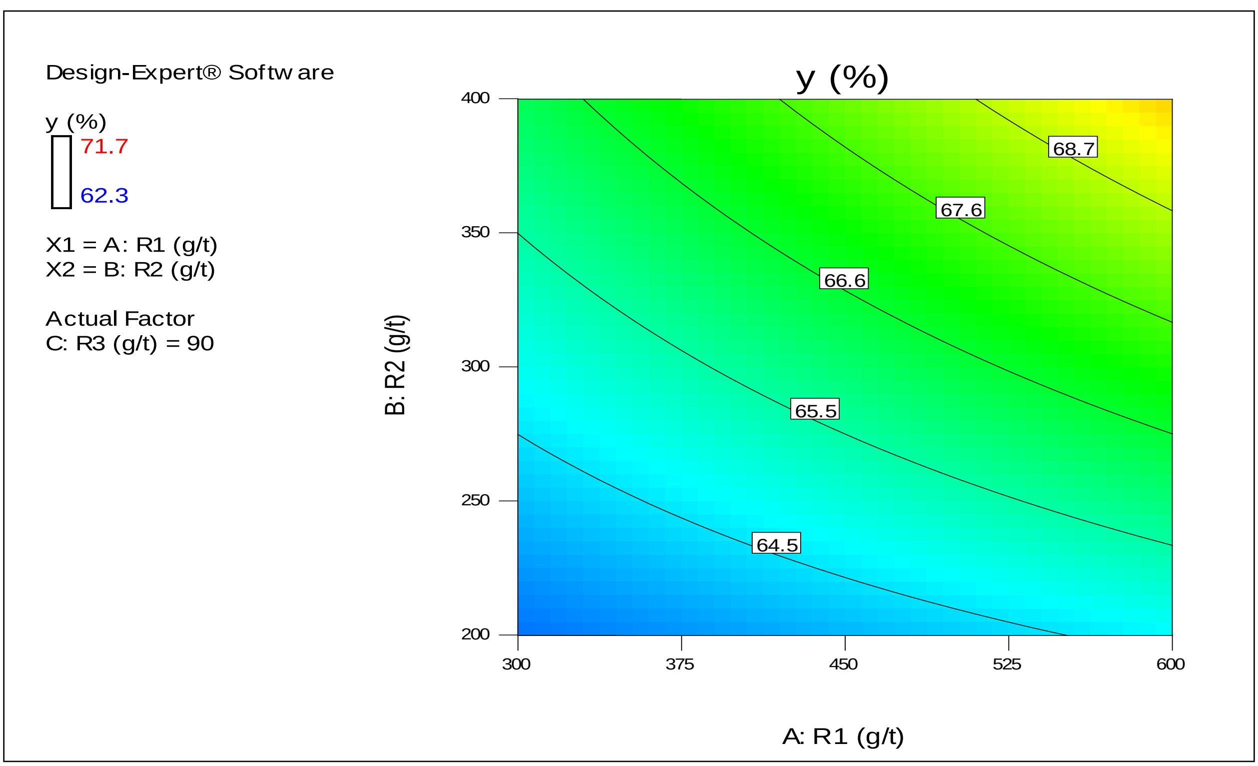

Figure 7: Contour graph according to R_1-R_2.

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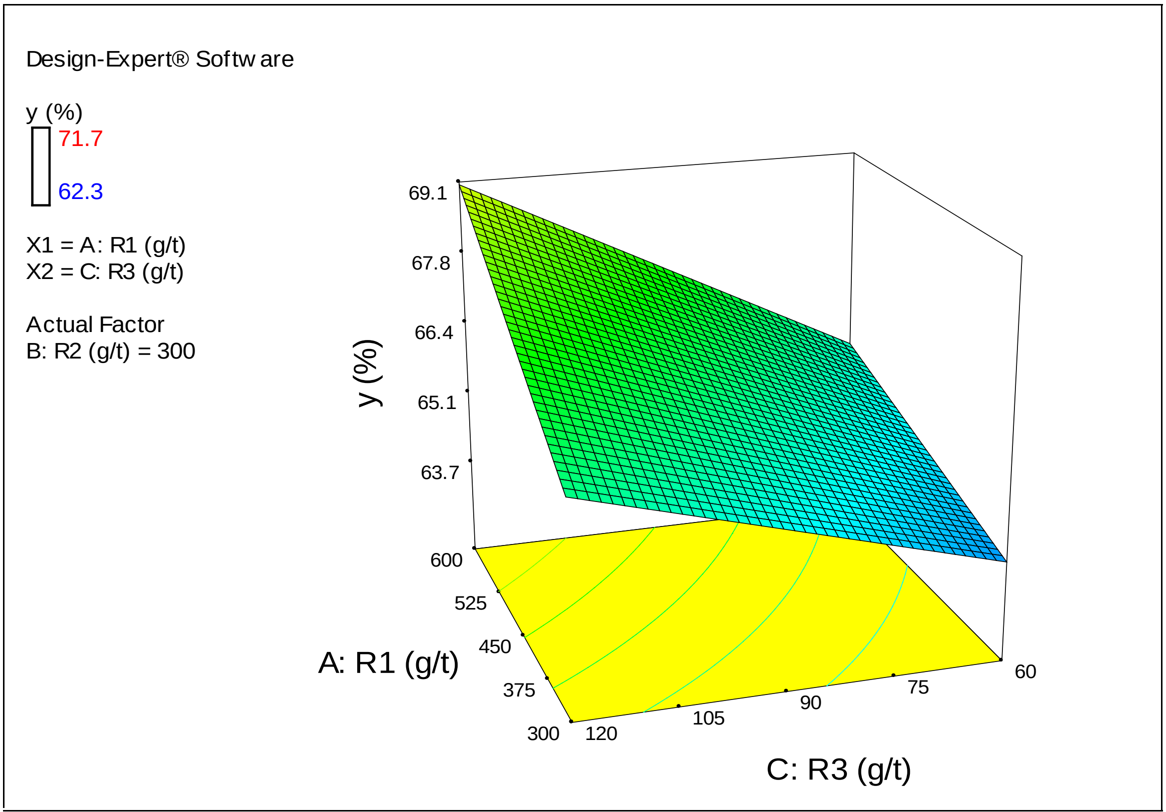

Figure 8: Response surface according to R_1-R_3.

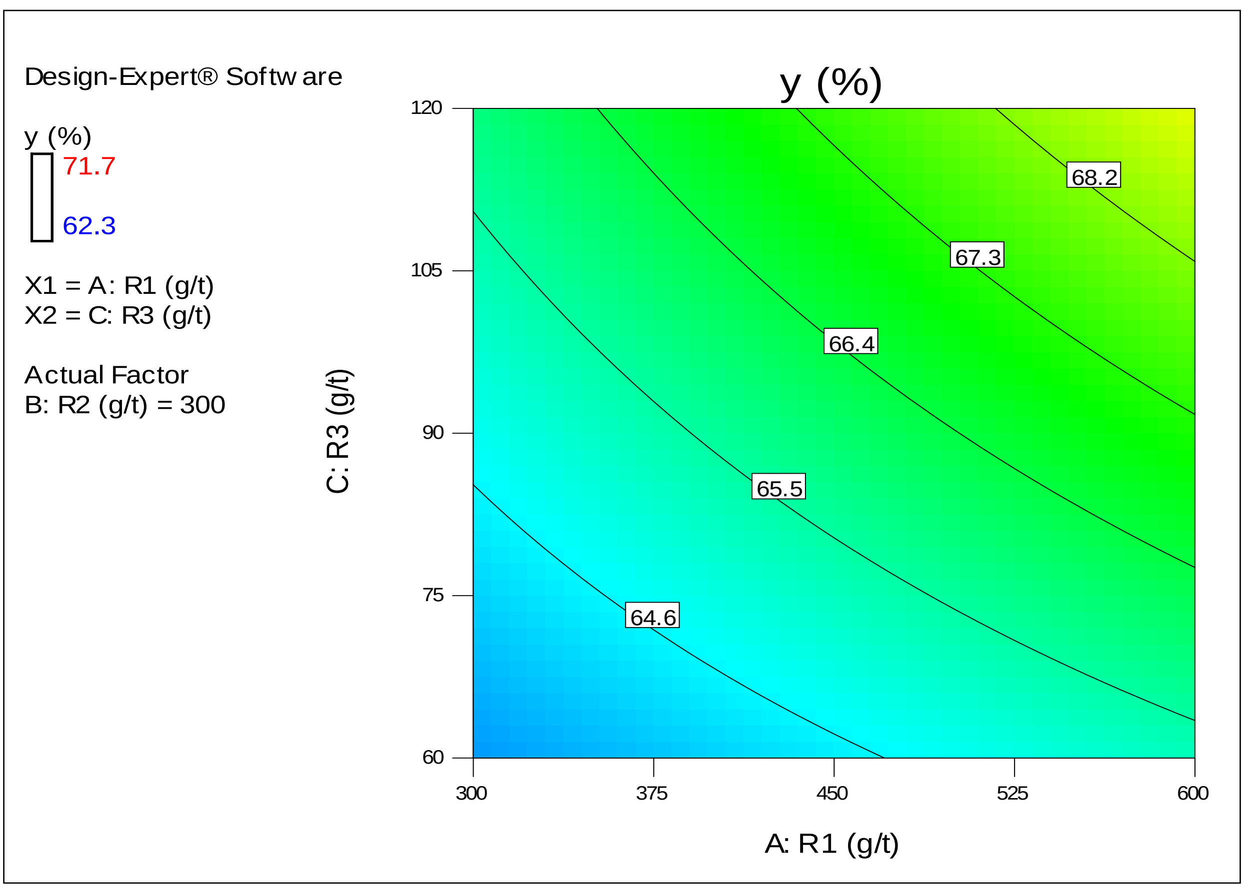

Figure 9: Contour graph according to R_1-R_3.

Figures 8 and 9 show that there is a strong interaction R_1-R_3. Indeed, the response surface indicates that the concentrate y (%) increases progressively with the increase of R_1 and R_3 consumption.

X. Results Interpretation

The increase of the concentrate y (%) with the increase in consumption of R_1, R_2 and R_3 is linked to several approaches; to the power of depression and precipitation of the concentrate particles because of the strong adsorption of R_1 on their surfaces that increases their masses and ensures their gravity in the recovered non-float product. This increase is due both to the strong collection of undesirable elements with R_2 and R_3 that improves their hydrophobicities and ensures their affinities with the air bubbles injected into the flotation pilot cell[20-21]. The undesirable elements are transported to the surface forming a foam (floating product) rich in percentages of undesirable elements. This migration or evacuation of the collected elements ensures an increase in the percentage of the concentrate particles in the non-floating product and thereafter the increase of the concentrate y (%) in the product (non-floating).

To validate these interpretations, figures 10 and 11 illustrate the concentrate y (%) maximum value obtained according to maximum consumption of flotation reagents.

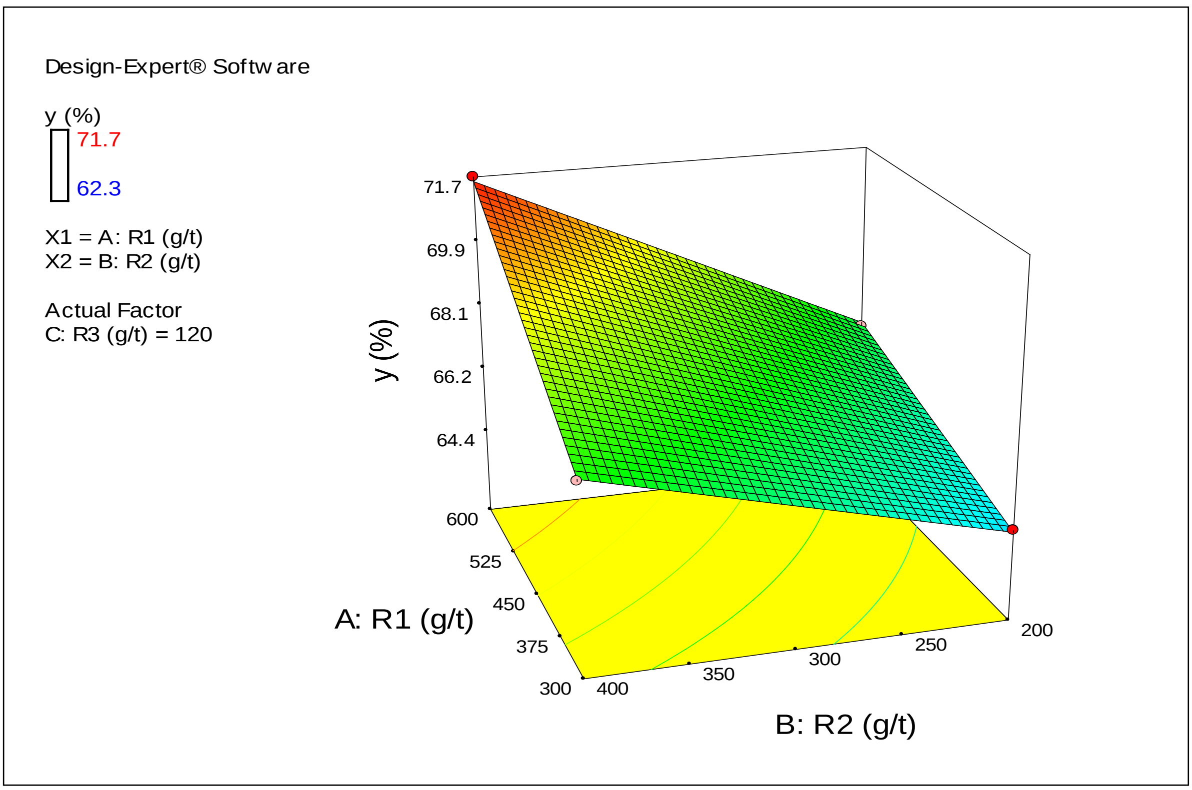

Figure 10: Response surface according to R_1-R_2 for a maximum constant R_3 value

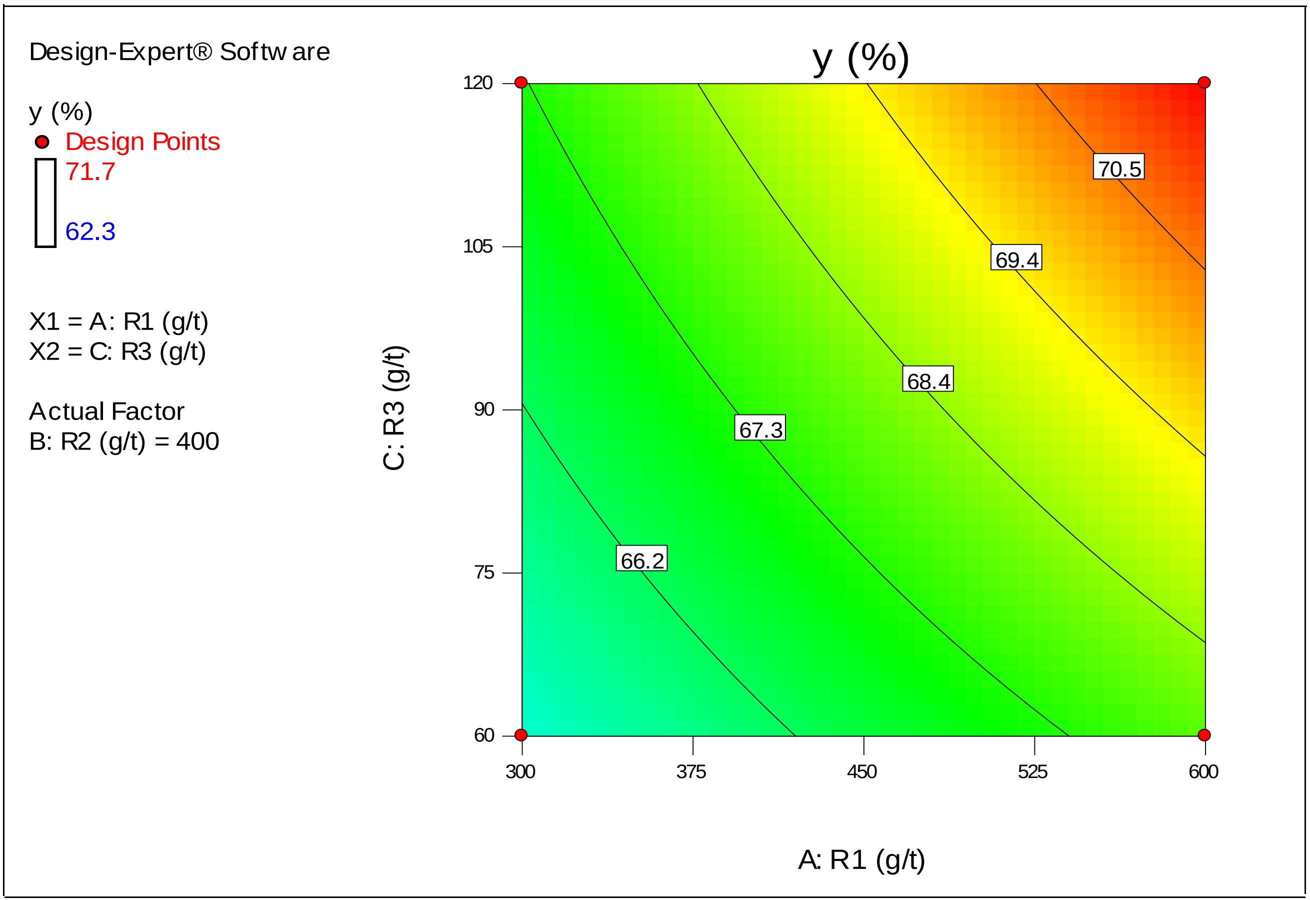

Figure 11: Contour graphaccording to R_1-$R_3$for a maximum constant R_2value

We can conclude, through these figures analysis, that the flotation process using important consumption of reagents (g/t) (R_1, R_2 and R_3) allows obtaining high concentrate values which reach 71.7%. This is convenient with approximations or appropriate approaches with the interpretations in the previous paragraph.

In order to improve the flotation process overall performance, several flow recycling case studies were considered. The reduction of the recycling ratio increases the specific consumption of Flotation reagents, however its progressive increment reduces the need for reagents up to an optimal level. Moreover, any increase results in an accumulation of fine particles in the circuits, which causes saturation and a reduction of the production capacity in the Flotation unit. According to the "AA" curve below, the industrial optimization led to a remarkable reduction of the specific consumptions for the same raw product profile and for the same level of the production capacity[22].

XI. Conclusion

This study has shown that the experimental design methodology allows developing an empirical model that allows a good understanding and describing, in a satisfactory way of the concentrate y (%) at every point of the experimental field. The influence of R_1 (g/t), R_2 (g/t) and R_3 (g/t) was performed on the concentrate y (%). The results show that the optimization and modeling of the concentrate y (%) using the factorial design method allows us to correctly describe the influence of these three experimental parameters on the effectiveness of the treatment. Statistical analysis showed that the two interactions R_1-$R_2$and R_1-R_3 are the most influential ones. This study shows that the model used is highly significant and in accordance with the experimental results.

Bibliographic References

1. W.J. Rankin, "Minerals, Metals and Sustainability: Meeting Future Material Needs", (2011).
2. D. Banyak, Frothers, "Bubbles and Flotation: A Survey of Flotation Milling in the Twentieth-Century Metal Industries", US Government Printing Office, National Park Service Intermountain support office, Denver, Colorado. (1998) 1-92.
3. J. Drzymala, "Mineral Processing, Foundations of Theory and Practice of Minerallurgy", 1st English edition, Oficyna Wydawnicza PWr, Wroclaw University of Technology. (2007) 344-362.

4. S.M. Bulatovic, "Handbook of Flotation Reagents, Chemistry, Theory and Practice: Flotation of Sulfide Ores", Elsevier Science & Technology Books. 1 (2007) 105–178.
5. B. Nanthakumar, S. Kelebek, "Stagewise analysis of flotation by factorial design approach with an application to the flotation of oxidized pentlandite and pyrrhotite", Int. J. Miner. Process. 84 (2007) 192-206.
6. M.S. Sheridan, D.R. Nagaraj, D. Fornasiero, J. Ralston, "The use of a factorial experimental design to study collector properties of N-allyl-O-alkyl thionocarbamate collector in the flotation of a copper ore", Miner. Eng. 15 (2002) 333-340.
7. V.D. Smar, R.R. Klimpel, F.F. Aplan, "Evaluation of chemical and operational variables for the flotation of a copper ore Part I-collector concentration, frother concentration, and air flow rate", Int. J. Miner. Process. 42 (1994) 225-240.
8. D.J. Bradshaw, B. Oostendorp, P.J. Harris, "Development of methodologies to improve the assessment of reagent behaviour in flotation with particular reference to collectors and depressants", Miner. Eng. 18 (2005) 239–246.
9. M. Mäkelä, "Experimental design and response surface methodology in energy applications: A tutorial review ", Energy Conversion and Management. 151 (2017) 630–640.
10. M.J. Anderson, P.J. Whitcomb, DOE Simplified, "Practical Tools for Effective Experimentation Productivity Press", New York, NY, USA (2000).
11. N. Barka, M. Abdennouri, A. Boussaoud, A .Galadi, M. Baâlala, M. Bensitel, et al. "Full factorial experimental design applied to oxalic acid photo catalytic degradation in TiO2 aqueous solution", Arab. J. Chem. 7 (2014) 752-757.
12. A. K. Nayak, D. Pal, K. Santra, "Ispaghula mucilage-gellan mucoadhesive beads of met form in HCl: Development by response surface methodology", Carbohydr. Polym. 107 (2014) 41-50.
13. B.K. Korbahti, A. Tanyolac, "Electrochemical treatment of simulated textile wastewater with industrial components and Levafix Blue CA reactive dye: optimization through response surface methodology", Journal of Hazardous Materials. 151 (2008) 422-431.
14. M. Meloun, J. Militky, M. Hill, RG. Brereton. "Crucial problems in regression modelling and their solutions". Analyst. 127 (2002) 433-450.
15. J. Antony. "Design of experiments for engineers and scientists", New York : Butterworth-Heinemann (2003).
16. A. K. Nayak, D. Pal, "Development of pH-sensitive tamarind seed polysaccharide-alginate composite beads for controlled diclofenac sodium delivery using response surface methodology", International Journal of Biological Macromolecules 49 (2011) 784–793.
17. Z. Tan, S. Song, J. Han, Y. Wang, Y. Lu, Y. Yan, "Optimization of partitioning process parameters of chloramphenicol in ionic liquid aqueous two-phase flotation using response surface methodology", J. Iran. Chem. Soc. 10 (2013) 505–512.
18. A. Hooda, A. Nanda, M. Jain, V. Kumar, P. Rathee, "Optimization and evaluation of gastroretentive ranitidine HCl microspheres by using design expert software", Int. J. Biol. Macromol. 51 (2012) 691-700.
19. Abaamrane, S. Qourzal, M. El Ouardi, S. Alahiane, M. Belmouden, H. Bari, N. Barka, S. Mançour Billah, A. Assabbane, Y. Ait-Ichou, Desalin, ''Modeling of photocatalytic mineralization of phthalic acid in TiO2 suspension using response surface methodology (RSM)'' Water Treat. 53 (2015) 249-256.
20. B.L. Karger, R.B. Grieves, R. Lemlich, A.J. Rubin, F. Sebba, "Nomenclature recommendations for adsorptive bubble separation methods". Sep. Sci. 2 (1967) 401-404.
21. R. Lemlich "Adsorptive bubble separation methods", Ind. & Eng. Chem. 60 (1968) 10-16.
22. Alouani, A. Arbaoui, K. Benkhouja, "The Mineral Flotation Overall Performance Increase by the Improvement of Recycling", Global Journal of Researches in Engineering. 17 (2017) 3.

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