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Arch. Min. Sci. **64** (2019), 1, 119-130

Electronic version (in color) of this paper is available: http://mining.archives.pl

DOI 10.24425/ams.2019.126275

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THE INCREASE OF THE PERFORMANCE OF ULTRAFINE COAL FLOTATION BY USING EMULSIFIED KEROSENE AND THE PREDICTION OF THE FLOTATION PARAMETERS BY RANDOM FOREST AND GENETIC ALGORITHM

POPRAWA EFEKTYWNOŚCI FLOTACJI WĘGLA DROBNOZIARNISTEGO PRZY WYKORZYSTANIU EMULSJI NAFTOWEJ ORAZ PROGNOZOWANIE PARAMETRÓW PROCESU FLOTACJI PRZY UŻYCIU METODY LASÓW LOSOWYCH ORAZ ALGORYTMU GENETYCZNEGO

In this study, emulsified kerosene was investigated to improve the flotation performance of ultrafine coal. For this purpose, NP-10 surfactant was used to form the emulsified kerosene. Results showed that the emulsified kerosene increased the recovery of ultrafine coal compared to kerosene. This study also revealed the effect of independent variables (emulsified collector dosage (ECD), frother dosage (FD) and impeller speed (IS)) on the responses (concentrate yield (γ_C %), concentrate ash content (ϑ %) and combustible matter recovery (ε %)) based on Random Forest (RF) model and Genetic Algorithm (GA). The proposed models for γ_C %, ϑ % and ε% showed satisfactory results with R^2. The optimal values of three test variables were computed as ECD = 330.39 g/t, FD = 75.50 g/t and IS = 1644 rpm by using GA. Responses at these experimental optimal conditions were γ_C % = 58.51%, ϑ % = 21.7% and ε % = 82.83%. The results indicated that GA was a beneficial method to obtain the best values of the operating parameters. According to results obtained from optimal flotation conditions, kerosene consumption was reduced at the rate of about 20% with using the emulsified kerosene.

Keywords: ultrafine coal flotation, emulsified kerosene, random forest, genetic algorithm

W pracy zbadano możliwość wykorzystania emulsji naftowej do poprawy efektywności flotacji węgla drobnoziarnistego. W tym celu wykorzystano środek powierzchniowo czynny NP.-10 do utworzenia emulsji naftowej. Badania wykazały, że zastosowanie nafty w formie emulsji poprawiło wskaźniki odzysku węgla w porównaniu do procesów z wykorzystaniem nafty. W pracy badano także wpływ zmiennych zależnych (dozowanie emulsji w kolektorze ECD, dozowanie środka pianotwórczego FD, prędkość wirnika IS na wyniki procesu (uzysk koncentratu (γ_C %), zawartość popiołów (ϑ %) i stopień odzysku materii palnej (ε %), w oparciu o metodę lasów losowych i algorytm genetyczny. Proponowane modele pozwoliły na uzyskanie zadawalających wyników dla wskaźników γ_C %, ϑ %, ε %, w odniesieniu do współczynnika R^2.

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Optymalne wartości badanych zmiennych ECD = 330.39 g/t, FD = 75.50 g/t and IS = 1644 obrotów na minutę obliczono przy wykorzystaniu algorytmu genetycznego. Wyniki procesu prowadzonego w warunkach optymalnych, określonych eksperymentalnie to γ_C % = 58.81 %; ϑ % = 21.7 %; ε % = 82.83 %. Uzyskane wyniki wskazują, że wykorzystanie algorytmu genetycznego jest metodą umożliwiającą otrzymanie najkorzystniejszych wartości parametrów pracy. Na podstawie wyników flotacji uzyskanych w najkorzystniejszych warunkach stwierdzono, że zużycie nafty obniżone zostało o ok. 20% dzięki zastosowaniu nafty w postaci emulsji.

Słowa kluczowe: flotacja węgla drobnoziarnistego, emulsja naftowa, metoda lasów losowych, algorytm genetyczny

1. Introduction

Fine (1 mm - 0.15 mm) and ultrafine (–150 μm) coals at varying rates are present in run-of-mine coal. The fine coal is typically upgraded by watered based density separators like spirals and water-only cyclones. Ultrafine coal is cleaned using flotation or discarded to waste pond (Zhang, 2008). This method is on the basis of differences in the surface chemical characteristics of the coal and gangue minerals (Wang et al., article in press). There are quite many variables affecting the effect of froth flotation, collector dosage, froth dosage, stirring speed, and so on (Ye et al., article in press). The types and quantity of the reagents are the most important elements of the flotation process (Bulatovic, 2007; Vazifeh, 2010).

Non-polar oily materials, like diesel oil and kerosene are the most important collectors for coal flotation (Brown, 1966; Jia & Fuerstenau, 2002). The natural hydrophobicity of the coal leads to low reagent consumption in flotation in higher-rank coals (Jia & Fuerstenau, 2002). Li et al. (2013) stated that according to Polat et al. (2003), the collector disperses into droplets in the pulp and these droplets collide with, adhere to and coat the coal particles, thus increasing their hydrophobicity. It is frequently difficult to disperse these non-polar oils. The oil droplets has usually a large size, which leads to high collector consumption and very low flotation performance (Li et al., 2013). For this reason, one of significant factors affecting flotation results is the performance of flotation agent. It is important to use efficient and cost effective agents so that flotation costs decrease, flotation effect improves and economic efficiency increases (Weiwei et al., 2012). It is possible to disperse non-polar oils into smaller droplets via emulsification (Laskowski, 1992; Song et al., 1999; Duong et al. 2000). The studies on use of emulsions as flotation reagents also have reported flotation of coal in particular. It is clearly evident that emulsified reagents may improve the recovery of flotation and flotation rate, decrease consumption of reagents, and enhance the flotation selectivity of coal slime (Renhe et al., 2000; Yoon et al., 2002; Huang et al., 2009; Shi et al. 2015). While mechanical emulsification is mostly stable only for a short time, emulsions produced with surfactants are stable for a long time (Yu et al., 1990; Cebeci, 2002). It was revealed that approximately 20 μm droplets were produced as a result of the emulsification of the kerosene with high intensity stirring; whereas, the size of droplet was reduced to about 1.2-2 μm with emulsification with addition of surfactants (anionic and cationic) (Laskowski & Yu, 1998; Cebeci, 2002).

The common frothers are pine oil or methyl-isobutyl-carbinol (MIBC) for coals. Chaves (1983) states that pine oil froth is very heavy; therefore, it can carry (mechanically drag) the carbonaceous particles. However, as MIBC produces thinner froths and larger bubbles, thus leading to better water draining and smaller mass recovery but greater selectivity (Chaves & Rui, 2009).

The use of machine learning algorithms in predictive modelling and in the specific case of time series forecasting has increased significantly in the recent times (Bontenmpi et al., 2013; Tyralis& Papacharalampous, 2017). The random forest (RF) is a machine learning algorithm introduced in (Breiman, 2001), to be employed for classification and regression (Tyralis & Papacharalampous, 2017). It is considerably used since it is suitable for various prediction problems, has a few parameters to arrange, it is easy-to-use, it is successful for solution of many practical problems, and it is appropriate for small sample sizes, high-dimensional spaces, and complicated data structures (Scornet et al., 2015; Biau & Scornet, 2016; Tyralis & Papacharalampous, 2017). Representative applications can be found in many scientific fields including engineering, environmental and geophysical sciences, financial studies, and medicine. However, RF was not widely applied in modeling of mineral processing and separation problems (Shahbazi et al., 2017). Coal flotation has a complex process. The particle interaction frequently occurring in the flotation systems leads the case to be more complex (Bokany, 2016). RF, one of the soft computing methods, can be applicable to overcome complexity of flotation modeling (Chelgani et al., 2016; Shahbazi et al., 2017). Moreover, it is necessary to determine the optimal operating conditions to achieve the maximum combustible matter recovery with high weight recovery and minimum ash content. Genetic Algorithm (GA) is the most widely used meta-heuristic approach for hard optimization problems (Boussai et al., 2013; Eiben &Smith, 2003; Elyan & Gaber, 2017).

The aim of this study was to investigate the effect of the emulsified kerosene on ultrafine coal flotation and modeling of the effect of some operating variables on rougher flotation performance. In order to achieve these aims, experimental studies were conducted in two stages. The first stage involved several flotation tests conducted with using kerosene and emulsified kerosene. According to the results obtained from the first stage, prediction and optimization of some operating parameters were analyzed in the second stage. For this purpose, three factors (ECD, FD, and IS) were considered as main variables. γ_C %, ϑ % and ε % were defined as the process responses. RF was applied for modeling the effect of variables on flotation performance. After modeling the data, the optimal parameters were computed by GA. Flotation tests were also performed based on the optimum conditions determined by GA.

2. Materials and methods

2.1. Material

In this study, the bituminous coal was supplied from flotation feeding unit of Amasra coal preparation plant located in Zonguldak Province, Turkey. Currently, coals having approximately minus 1 mm (d_{80} = 0.7 mm) particle size were subjected to flotation process for obtaining a clean coal. Particle size distribution of –1 +0.15 mm is too large for the good efficiency of flotation process. Therefore, the sample was firstly divided into fine coal (–1 +0.15 mm) and ultrafine coal (–0.15 mm). Fine coal constitutes 81.35% of the raw coal feeding to the flotation unit and is enriched by Knelson concentrator in another study (Oney et al., article in press). In this study, ultrafine coal was subjected to the flotation process. The coal sample was screened at 0.106 mm, 0.074 mm, 0.053 mm and 0.038 mm. Table 1 shows the particle size distribution of the ultrafine coal sample. The sample had an ash content of 46.34%. The ash content of various fraction sizes was close to the total ash content and finer fractions had high values of ash.

TABLE 1

Particle size distribution of the Amasra ultrafine coal.

Size fraction (mm)	Yield (%)	Ash Content (%)	Cumulative weight of undersize (%)	Cumulative ash content of undersize (%)
0.15-0.106	42.44	44.23	100	46.34
0.106-0.074	19.24	46.72	57.56	47.89
0.074-0.053	16.99	47.95	38.32	48.48
0.053-0.038	12.79	48.43	21.33	48.90
–0.038	8.54	49.61	8.54	49.61
Total	100	46.34	—	—

2.2. Reagents

Emulsified kerosene and kerosene were used as collectors in the flotation tests. Kerosene was obtained commercially. The emulsified kerosene was prepared using the mixture of water and kerosene with addition of emulsifier. Nonylphenol Ethoxylate (NP-10) by Dow was used as emulsifier. Initially, 30 g water and 0.08 g NP-10 (0.02% of the total mass percentage of water and kerosene) were added into a 0.2 L beaker and stirred approximately for 5 minutes until the emulsifier was dissolved completely. Later, 10 g kerosene was added into solution and stirred for 5 minutes at the emulsification speed of 20.000 rpm by using an ultraturrax homogenizer (Ultra-turrax IKA-T18). As a result, the milky emulsified kerosene was prepared for the tests as seen in Figure 1. In addition, MIBC and Na_2SiO_3 were treated respectively as the frother and the depressant. MIBC was supplied by Sigma- Aldrich. Sodium silicate was supplied by PQ Cooperation.

Fig. 1. High shear disperser and emulsified kerosene

2.3. Method

Flotation tests were performed with one-liter flotation machine. During the flotation tests, the solid content was kept constant at 10% by weight and depressant dosage at 1000 g/t at natural pH (8). Once agitation process was performed for the slurry mixture in the flotation cell for 3 minutes in each test, the desired amount of collector, frother, and depressant were added respectively. During this process, suspension was conditioned for 3 minutes after addition of each reagent. Afterwards, the air was given into the cell and the froth product was collected for 3 minutes. Each flotation product was dehydrated and weighed. Then, the ash content measurement was performed (wt. % on dry basis). The experimental studies were carried out in two stages. In the first stage, the effect of the proper emulsified kerosene was investigated. In the second stage, performance and optimization of the operating variables were determined by using RF and GA.

2.4. Random forest (RF)

Being a statistical learning algorithm RF utilizes a large ensemble of decision trees for both regression and classification tasks. Its strengths involve striking classification performance as well as relatively simple training and tuning (Menze et al., 2009; Mahreng et al., 2018). The algorithm shows performance based on the selected variables (Verikas et al., 2011; Genuer et al., 2010; Tyralis & Papacharalampous, 2017), the number of trees (Oshiro et al., 2012; Probst & Boulesteix, 2017) and the number of examples in each cell, below which the cell is not split (Biau, 2016; Tyralis & Papacharalampous, 2017). The data were split into nodes via a threshold which was selected to obtain the minimum residual sum of squares, called as the regression criteria (R_{ss}), given below (Kucukyıldız et al., 2017):

$$R_{ss} = \sum\nolimits_{left} \left(y_i - y_r \right)^2 + \sum\nolimits_{right} \left(y_i - y_r \right)^2 \tag{1}$$

Here, y_i is the value for the corresponding feature for the i-th sample, y_i and y_r are the mean values for the feature of the samples assigned to the left and the right nodes, respectively.

In this classification, the RF algorithm utilizes a set of classification trees, whereas each tree is built on a bootstrapped sample of the original data (Breiman, 2001; Mahreng et al., 2018). The classification trees are built according to recursive binary splits, as, a randomly-chosen subset of input variables is used to determine the best binary split for each split. The following formula was used to calculate the output of the RF (RO):

$$RO = \frac{1}{M} \sum\nolimits_{i=1}^{M} T_i \tag{2}$$

M is the number of the grown trees and T_i is the output of i-tree (Kucukyıldız et al., 2017).

2.5. Genetic algorithm (GA)

GAs are a heuristic solution-search or optimization technique, originally motivated by the Darwinian principle of evolution through (genetic) selection (Mcall, 2004). The GA can be easily adapted to the mathematical optimization problems which cannot be formulated in exact and accurate mathematical forms. GA has a number of advantages compared to the traditional techniques. These advantages are expressed as follows (Ghobadi et al., 2011):

- Due to its probabilistic quality, GA does not need initial guess of the decision variables and requires only their lower and upper bounds.
- GA works only with the objective functions instead of their gradients.
- GA can be used for solution of single-objective, multi-objective, and multi-modal optimization problems.
- GA can deal with a number of decision variables and constraints efficiently (Guria et al., 2005).

GA is also used for various applications in mineral processing as well as process control, circuit design, and pattern recognition of multivariate data, optimization of parameters, crushing, and comminution (Nakhaei et al., 2016).

3. Results and Discussion

3.1. The effect of emulsified kerosene

The flotation tests were carried out to determine the effect of emulsified kerosene on ultrafine coal with the rougher concentrate. Figure 2 shows the results.

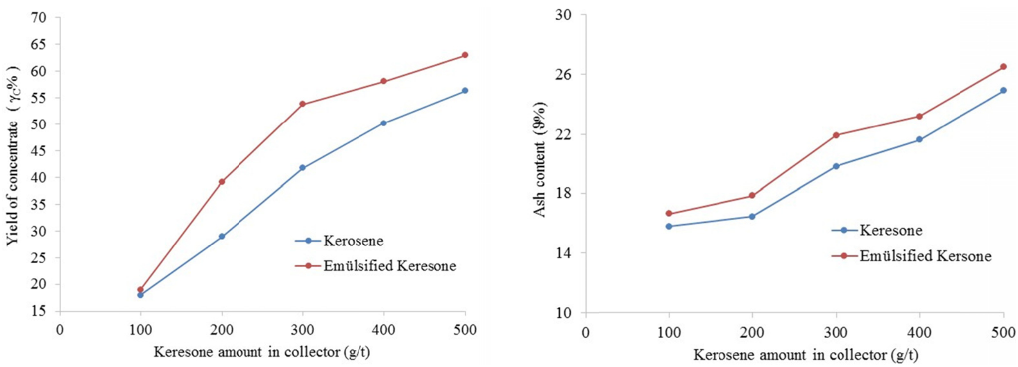

Fig. 2. The effect of emulsified kerosene on γ_C % (a) and ϑ % (b) (MIBC dosage: 75 g/t, Na_2SiO_3 dosage: 1000 g/t, impeller speed: 1400 rpm)

Figure 2a shows that γ_C % increased with increasing collector dosages. At the lower collector dosage (100 g/t) γ_C % was nearly the same for the dosages of kerosene and emulsified kerosene. When the emulsified kerosene dosage increased from 100 g/t to 500 g/t, γ_C % increased from 18.95% to 62.90%. As for kerosene, γ_C % also increased from 17.92% to 56.28% for the same collector dosages. γ_C % obtained with the emulsified kerosene was higher compared to the kerosene for all the same collector dosages. As seen from Figure 2b, when collector dosage is increased from 100 g/t to 500 g/t, ϑ % increased from 16.64% to 26.46% for the emulsified kerosene and 15.79% to 24.89% for the kerosene. The ash content in the concentrate obtained from the emulsified kerosene was higher than kerosene. This could be associated with the fact that selectivity of the flotation process might have been decreased due to higher amount of surfactant adsorbed on the particle surface (Aktas & Woodburn, 1995; Asplin et al., 1998; Li et al., 2013).

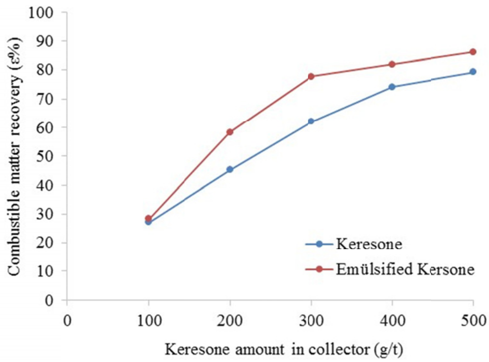

Fig. 3. The effect of collector dosage on ε % (MIBC dosage: 75 g/t, $Na_2\,SiO_3$ dosage: 1000 g/t, impeller speed: 1400 rpm)

As seen in Figure 3 ε % increased with increasing collector dosage. ε % values obtained using emulsified kerosene were higher compared to kerosene at all dosages. This difference was especially higher in the range of 200-400 g/t collector dosage. Experimental studies indicated that the usage of emulsified kerosene as a collector instead of kerosene improved the flotation recovery remarkably. It is necessary to predict the optimal operating variables to clarify the difference between emulsified kerosene and kerosene usage and reveal the efficiency of the process. This could be evaluated by FR and GA.

3.2. Prediction and optimization of the process by RF and GA

The aim of the coal flotation is to obtain low ash content of concentrates with high yield and combustible matter recovery. To achieve this phenomena, it is necessary to reveal the effect of main variables on the flotation performance and determine optimal parameters. For this purpose, RF and GA were employed to find out the correlation between the selected operating parameters (EMD, FD, and IS) and process responses (γ_C %, ϑ %, and ε %). Figure 4 shows the methodology used in this study.

A total of 19 tests were randomly performed using the laboratory flotation machine. Table 2 shows the range of the selected operating flotation parameters and actual responses.

The algorithms used in this study were developed in MATLAB environment, various values were tested and evaluated for parameters in order to determine the optimal RF model for prediction: ntree = 50-150 with step size 10. A totally of 19 tests were randomly performed in laboratory flotation machine. Randomly selected 15 samples of data were used for training of RF model and the remaining part of the data used for testing the RF model. Table 3 shows the variation of the RF Models' correlation coefficients owing to tree number.

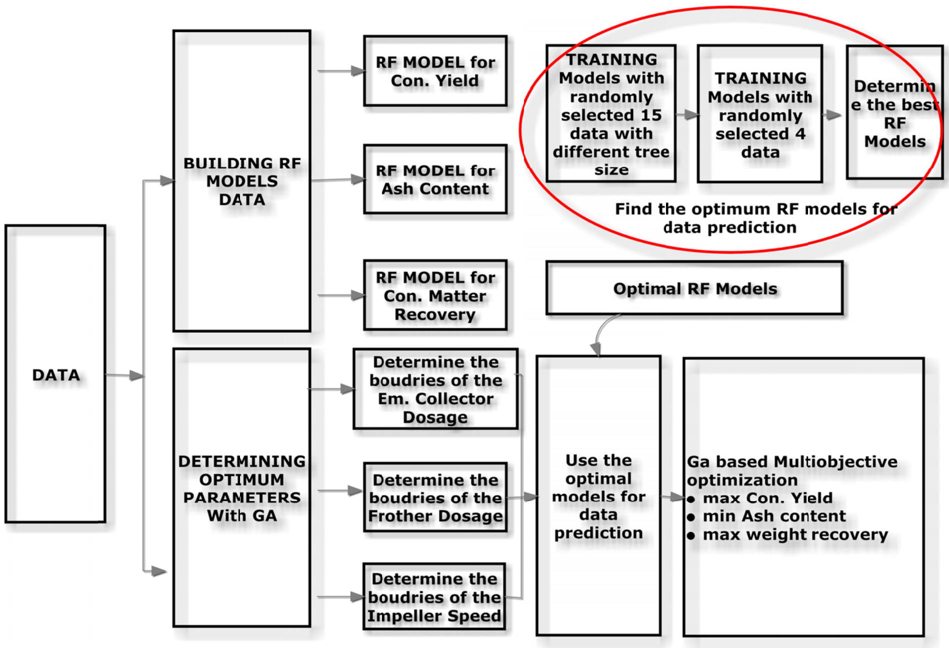

Fig. 4. Flowchart of the developed algorithm

TABLE 2

The range of operating parameters and actual responses

Variables		Minimum	Maximum	Mean	Std. Deviation
Inputs					
Emulsified kerosene dosage (ECD)	(g/t)	100	500	336.84	121.15
MIBC dosage (FD)	(g/t)	50	125	88.15	24.1
Impeller speed (IS)	(rpm)	1200	1800	1521	207.03
Outputs					
Con. yield (γ_C %),	(%)	35.76	67.27	55.94	8.14
Con. ash content (ϑ %)	(%)	16.11	26.46	23.55	3.32
Combustible matter recovery (ε %)	(%)	55.78	88.17	79.30	8.79

The performance of the model was analyzed by the determination coefficient (R^2). The training stages for the models were stopped after generation of 80 trees for γ_C % and ϑ % models and 110 trees for ε % model. Optimal models were determined by using the correlation coefficients R^2. R square for the concentrate yield of clean coal was calculated as 0.878 (Fig. 5a). In this case, the value of determination coefficient ($R^2 = 0.878$) indicated that three independent variables for the right side of the equation represent 87.8% of the variation in concentrate yield in the regression model. Likewise, R^2 values for the concentrate ash content and combustible recovery were calculated as 0.74 and 0.929, respectively (Fig. 5b and Fig. 5c). The results showed that RF models can predict the γ_C %, ϑ % and ε % based on the selected operating variables of EKD, FD, and IS.

TABLE 3

Correlation (R^2) coefficients for the RF Models

Tree Number	RF Model for γ_C %	RF Model for ϑ %	RF Model for ε %
50	0.151	0.091	0.002
60	0.040	0.039	0.732
70	0.066	0.091	0.002
80	0.878	0.740	0.001
90	0.840	0.039	0.732
100	0.066	0.057	0.001
110	0.066	0.039	0.929
120	0.006	0.039	0.001
130	0.040	0.740	0.002
140	0.878	0.039	0.929
150	0.066	0.057	0.001

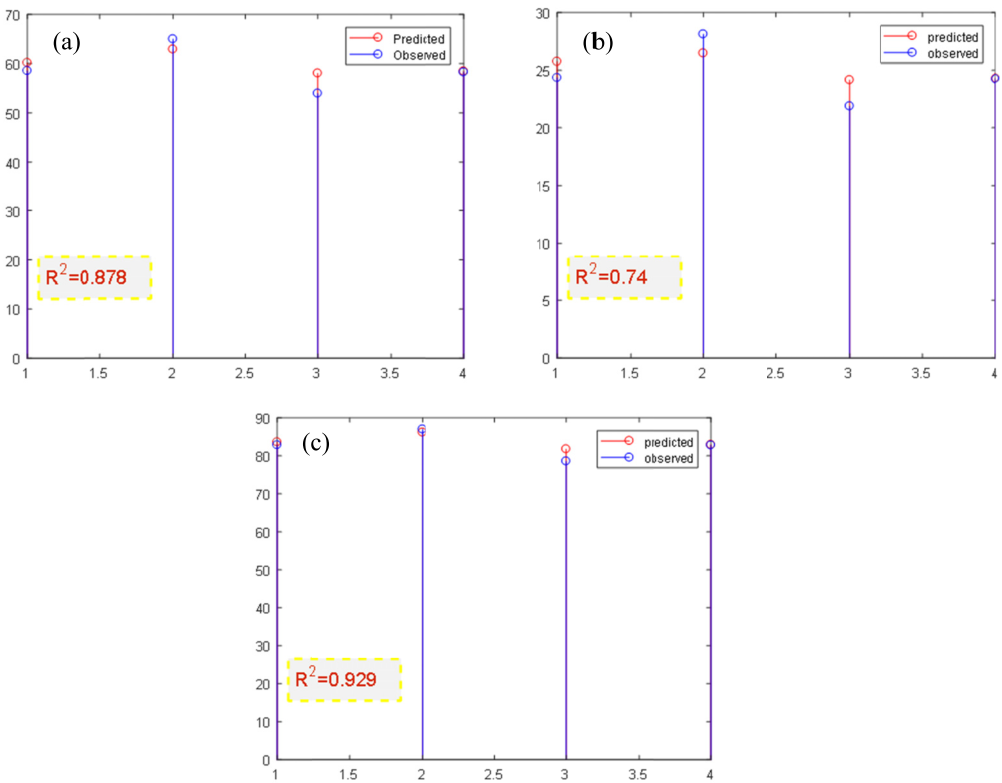

Fig. 5. Correlation between observed and predicted values for (a) γ_C %, (b) ϑ %, and (c) ε % by RF

In this study, the multiobjective fitness function of the GA was determined as maximum γ_C %, minimum ϑ %, and maximum ε %. Fitness function values of the optimization problem at each step were calculated with the optimal models which were built in training stage. Table 4 shows the results.

TABLE 4

Optimal results obtained with GA

Optimization Variables	Best results
Operating Variables	
Emulsified kerosene dosage (g/t)	330.39
MIBC dosage (g/t)	75.50
Impeller speed (rpm)	1644
Responses	
Concentrate recovery (%)	58.51
Ash content (%)	21.70
Combustible matter recovery (%)	82.83

Under optimal conditions, the experimental tests were carried out both using kerosene and emulsified kerosene to compare the test results. The results showed that kerosene consumption using the emulsified kerosene decreased by about 20% by disregarding the consumption of the surfactant.

4. Conclusions

This study indicated that the flotation performance of ultrafine coal was significantly improved by employing emulsified kerosene. Emulsified kerosene oil enhanced dispersion of the pulp, which would reduce the size of emulsified kerosene droplets by improving adsorption onto the ultrafine coal surface and so improving the flotation performance. Further, RF and GE were used to recognize some operating parameters on coal flotation and determine the optimal operating conditions. In this context, three important parameters affecting the flotation performance were examined. The results indicated that models obtained for γ_C %, ϑ % and ε % were statistically significant and could explain the correlation between flotation parameters and their responses. Results obtained from flotation tests carried out under optimal conditions determined by using GA were in good agreement with the predicted values.

Acknowledgement

The author gratefully thanks to Dr. Gurkan KUCUKYILDIZ for his supports evaluating the experimental results by using RF and GA algorithm.

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