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Evaluation of effects of operating parameters on combustible material recovery in coking coal flotation process using artificial neural networks

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Abstract

In this research work, the effects of flotation parameters on coking coal flotation combustible material recovery (CMR) were studied by the artificial neural networks (ANNs) method. The input parameters of the network were the pulp solid weight content, pH, collector dosage, frother dosage, conditioning time, flotation retention time, feed ash content, and rotor rotation speed. In order to select the most efficient model for this work, the outputs of different models were compared with each other. A five-layer ANN was found to be optimum with the architecture of 8, 15, 10, and 5 neurons in the input layer, and the first hidden, second hidden, and third hidden layers, respectively, as well one neurons in the output layer. In this work, the training, testing, validating, and data square correlation coefficients (R2) were achieved to be 0.995, 0.999, 0.999, and 0.998, respectively. The sensitivity analysis showed that the rotor speed and the solid weight content had the highest and lowest effects on CMR, respectively. It was verified that the predicted ANN values coincided very well with the experimental results.

1. Introduction

Coals can be classified into three primary coal ranks including low-rank coal, bituminous coal, and anthracite coal. Bituminous coal is also known as coking coal and is primarily used to produce coke. Eventually, the mentioned coke is applied in mineral metallurgy [1, 2]. In some cases, run of mine coking coal has a high ash content and it cannot be used to produce coke without an upgrading process [3]. The gravity separation technology is usually applied to coarse coals (> 0.5 mm), while flotation is applied to fine coals (< 0.5 mm) [4-7].

Froth flotation is an effective separation method for fine coal cleaning utilizing the differences in the surface hydrophobicity between the organic and mineral matters and has been widely used to treat fine coking coal [3, 5, 8-12].

The artificial neural network (ANN) technique is a relatively new branch of the 'artificial intelligence' (AI), developed since 1980s. At the present time, the ANN technique is considered to be one of the most intelligent tools for modeling complex problems. This technique has the ability of generalizing a solution from the pattern presented during training. Once the network is trained with a sufficient number of sample datasets, for a new input of relatively similar pattern, predictions can be done on the basis of previous learning [12]. The use of neural networks in flotation industry has been studied by many researchers [13-16].

In the present research work, we intend to study the effects of various parameters of coking coal flotation on combustible material recovery (CMR) percent and their limitations using the ANN modeling. The main purpose is to find the important factors that have the most dominant impacts on the CMR percent along with

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optimizing the process by 33 groups of data obtained from coking coal flotation datasets in batch experiments. An ANN model is used for simulation and recovery estimation of CMR percent.

2. ANN modeling

2.1. Theoretical background

The ANN models have been studied for about two decades, with the objective of achieving human-like performance in many fields of knowledge engineering. Neural networks are powerful tools that have the ability to identify the underlying highly complex relationships from the input-output data only [17, 18].

The fundamental part of a neural net is the neurons. They are arranged in layers, and are categorized as the input (I), hidden (H), and output (O) neurons depending on the layer in which they are located. Malinov and et al. (2001) and Lee and et al. (1999) have described the procedure of ANN modeling [19, 20].

Various algorithms are available for training neural networks but the back-propagation algorithm is the most versatile and powerful technique, which provides the most efficient learning procedure for multi-layer perception (MLP) neural networks [21].

For this investigation, a five-layer ANN was found to be optimum with architecture of fifteen, ten, and five neurons in the first, second, and third hidden layers, respectively, and one neuron in the output layer. To differentiate between various processing units, bias values are introduced in the transfer functions. In BPNN, with the exception of input layer neurons, all other neurons are associated with a bias vector and a transfer function [22]. Figure 1 illustrates a flowchart of a typical two-hidden-layer BPNN model [23].

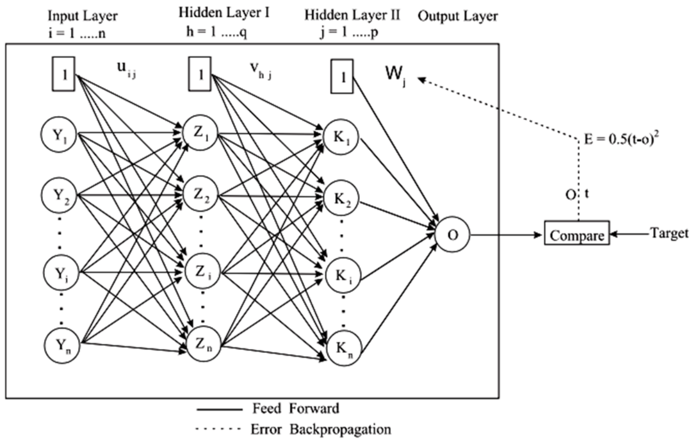


Figure 1. A flowchart of a typical two-hidden-layer BPNN [23].

Figure 1 shows the operation of feed forward in a BPNN. During this operation, each input neuron Yi receives an input signal and broadcasts this signal to the connected neurons Z1, ..., Zn in the first hidden layer. The total input parameters to the Zj neuron from the input layer is [23]:

$$e_j = z(in)_j = \sum_{i=1}^{n} o_i w_{ij} + \theta_j \quad (1)$$

The equations for the input and output relations for the first and second hidden layers are the same as Equation (1) [24].

Finally, the output neuron yields the network output according to the activation function (o=f[o(in)o]). The activation function is the same for all neurons in any particular layer of a neural network.

The second step of learning process is backward pass, which is concerned with error computation and connection weight updates. The network computes its own output pattern using its (mostly incorrect) weights and thresholds. Then the actual output is compared with the desired output to determine the error. An objective function is defined as E = 0.5(t-o)2, and the connection weights are updated using the generalized delta rules [12, 23].

The usual procedure for an ANN modeling is as follows:

1. Choosing the ANN parameters
2. Collecting the data
3. Pre-processing the database
4. Training ANN
5. Simulation and prediction using the trained ANN

In this research work, the above-mentioned stages were used in developing the model.

2.2. Datasets

One of the most important stages in the ANN technique is data collection. The data was divided into the training, testing, and validating parts to maintain the statistical consistency. The same datasets were used for all networks to make a comparable analysis of different architectures. In this work, a total number of 33 datasets were collected. One third of these (10 datasets) were used for testing and validating. The data was obtained from the laboratory experiments, as explained below.

The coking coal flotation was carried out in the bench scale experiments by the following composition: pH (4-10), gasoline (collector) dosage (200-500 g/ton), flotation retention time (0.5-5 min), solid weight content (8-15%), MIBC (frother) dosage (0-81 g/ton), conditioning time (1-4 min), feed ash (41.5-44.07%), and rotor speed (800-1300 RPM). The particle size range of flotation feed was 0-300 microns. The ranges of the main parameters are shown in Table 1.

Table 1. The ranges of variables in coking coal flotation (as determined).

Raw	Operating Parameter	Min	Max	Mean	St. Dev.
1	Conditioning Time (min)	1.00	4.00	2.94	0.44
2	Collector Dosage (g/ton)	200.00	500.00	343.75	104.53
3	Flotation Retention Time (min)	0.50	5.00	3.06	0.78
4	Frother Dosage (g/ton)	0.00	81.00	58.41	23.87
5	Solids Weight Content (%)	8.00	15.00	13.06	2.15
6	Rotor speed (RPM)	800.00	1300.00	1187.50	75.13
7	Feed Ash	41.50	44.07	43.25	0.80
8	pH	4.00	10.00	7.88	0.87

2.3. Input Parameters

In this investigation, the parameters used as the inputs to NN included the pH, solid weight content (%), conditioning time (min), collector dosage (g/ton), flotation retention time (min), rotor speed (RPM), frother dosage (g/ton), and feed ash to predict CMR (%).

2.4. Training and testing model

As mentioned above, the input layer has six neurons and the output layer has one neuron, which denote the amount of CMR. A schematic presentation of the whole process is shown in Figure 2.

The non-linear (LOGSIG, TANSIG) and linear (PURELIN) functions can be used as the transfer functions (Figures 3 and 4). The logarithmic sigmoid function (LOGSIG) can be defined as [22, 24]:

$$f = \frac{1}{(1+e^{-e_x})} \tag{2}$$

whereas the tangent sigmoid function (TANSIG) can be defined as follows:

$$f = \frac{e^{e_x} - e^{-e_x}}{e^{e_x} + e^{-e_x}} \tag{3}$$

where e_x is the weighted sum of the inputs for a processing unit.

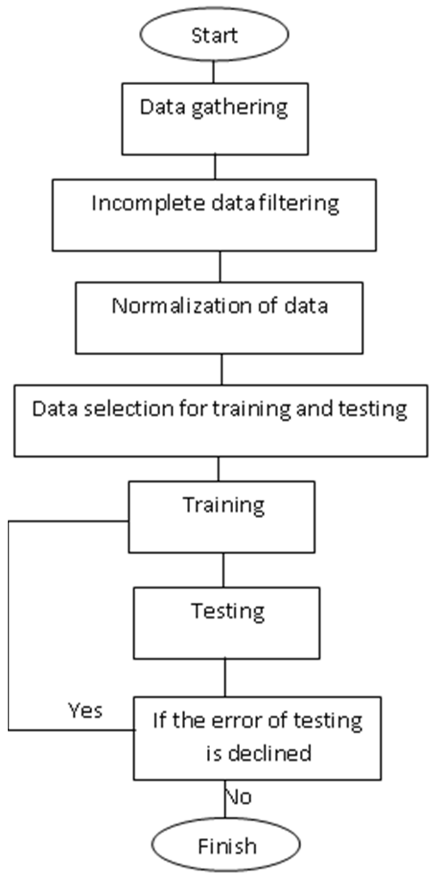
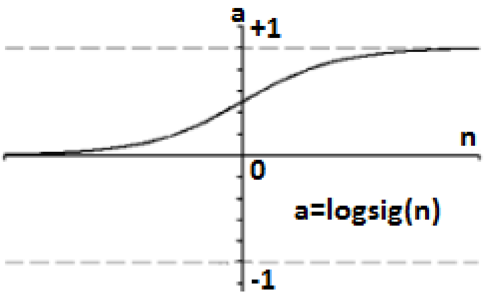


Figure 2. An ANN process flowchart.



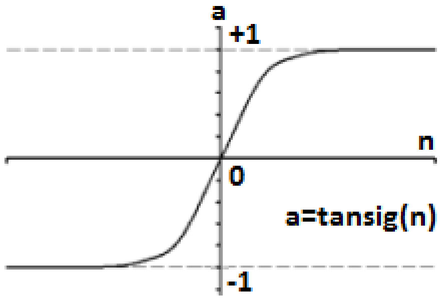


Figure 3. Sigmoid transfer functions [24].

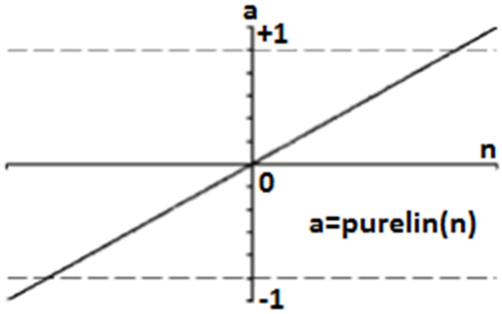


Figure 4. Liner transfer function [24].

2.5. Results and discussion

To select the most appropriate network architecture, the MLP networks with one and two hidden layers were examined, which showed unacceptable results. In the next try, a three-hidden layer network was used (Table 2). To determine the optimum network, SSE was calculated for various models using the following formula:

$$SSE = \sum \left(\frac{T_i - O_i}{N}\right)^2 \tag{4}$$

WhereT_i, O_i, and N represent the measured output, predicted output, and number of input-output data pairs, respectively [24].

The network with the architecture 8-15-10-5-1, which gives the minimum SSE, is considered as the optimum model. This network is shown in Figure 5. The results of the performance of the mentioned networks are shown in Figure 6.

For evaluation of the model, comparisons were fulfilled between the predicted and measured values of CMR. For this purpose, the mean square error (MAE), Ea, and mean relative error (Er) were used. Ea and Er were computed as follow [25]:

$$E_a = \left|T_i - O_i\right| \tag{5}$$

$$E_r = \left(\frac{\left|T_i - O_i\right|}{T_i}\right) \tag{6}$$

Where T_i and O_i represent the measured and predicted outputs, respectively.

For the selected model, Ea and Er were equal to 15.28 and 0.008, respectively. A comparison between the measured and predicted CMR for the data is shown in Figure 7. A correlations between the measured and predicted CMR from training, testing, and validating, and all the data indicate that the network has a high ability to predict CMR (Figures 7-9).

Table 2. Results of a comparison between some models.

Number	Transfer Function	Model	SSE
1	LOGSIG-PURELIN	8-8-1	6.8
2	LOGSIG-TANSIG-PURELIN	8-10-5-1	7.99
3	LOGSIG-LOGSIG-PURELIN	8-10-5-1	2.64
4	LOGSIG-LOGSIG-PURELIN-PURELIN-PURELIN	8-15-10-5-1	17.3
5	LOGSIG-PURELIN-TANSIG-LOGSIG-PURELIN	8-15-10-5-1	11.1
6	TANSIG-TANSIG-TANSIG-TANSIG-PURELIN	8-15-10-5-1	6.88
7	LOGSIG-LOGSIG-LOGSIG-PURELIN-PURELIN	8-15-10-5-1	0.15
8	LOGSIG-LOGSIG-LOGSIG-LOGSIG-PURELIN	8-15-10-5-1	0.006

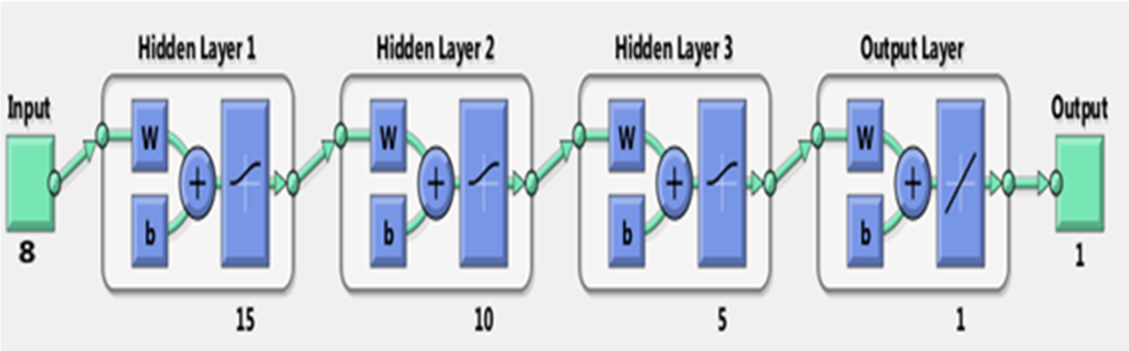


Figure 5. Architecture of the ANN model for coal flotation.

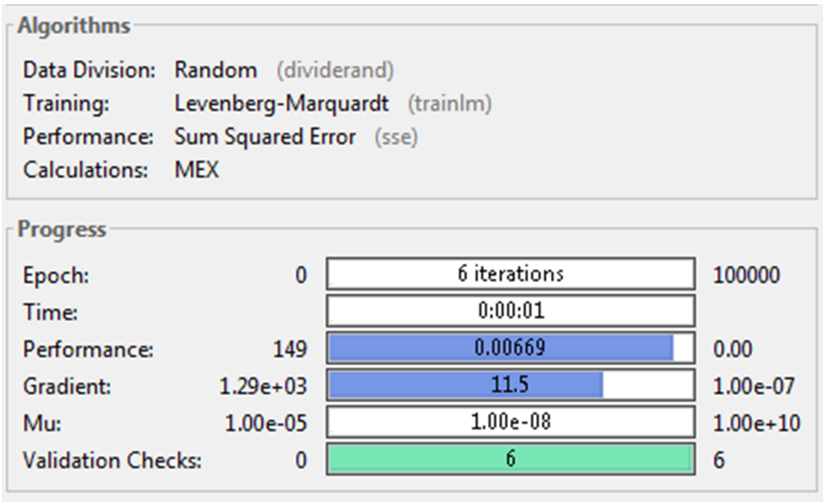


Figure 6. Results of network performance after the training process.

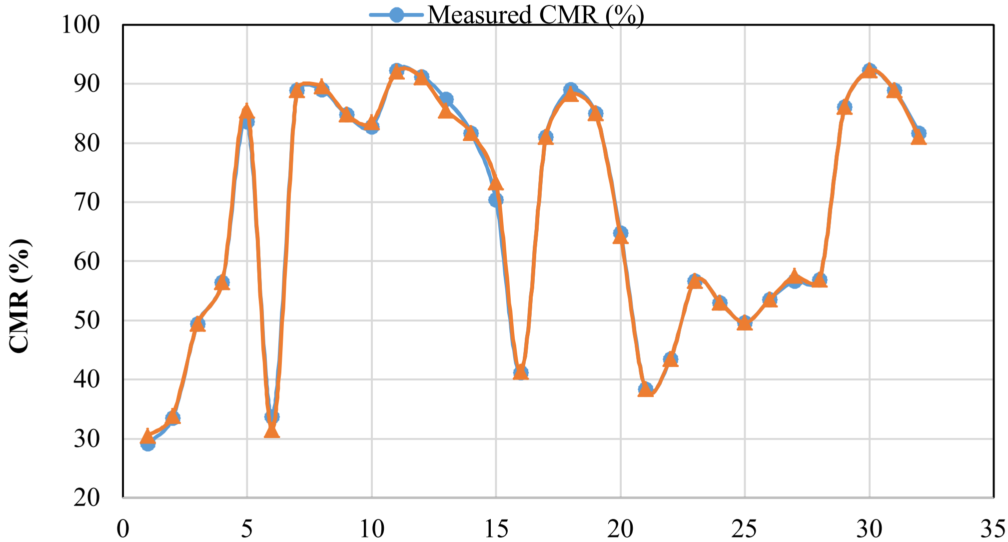


Figure 7. Comparison between the measured and predicted CMR for different samples for all data.

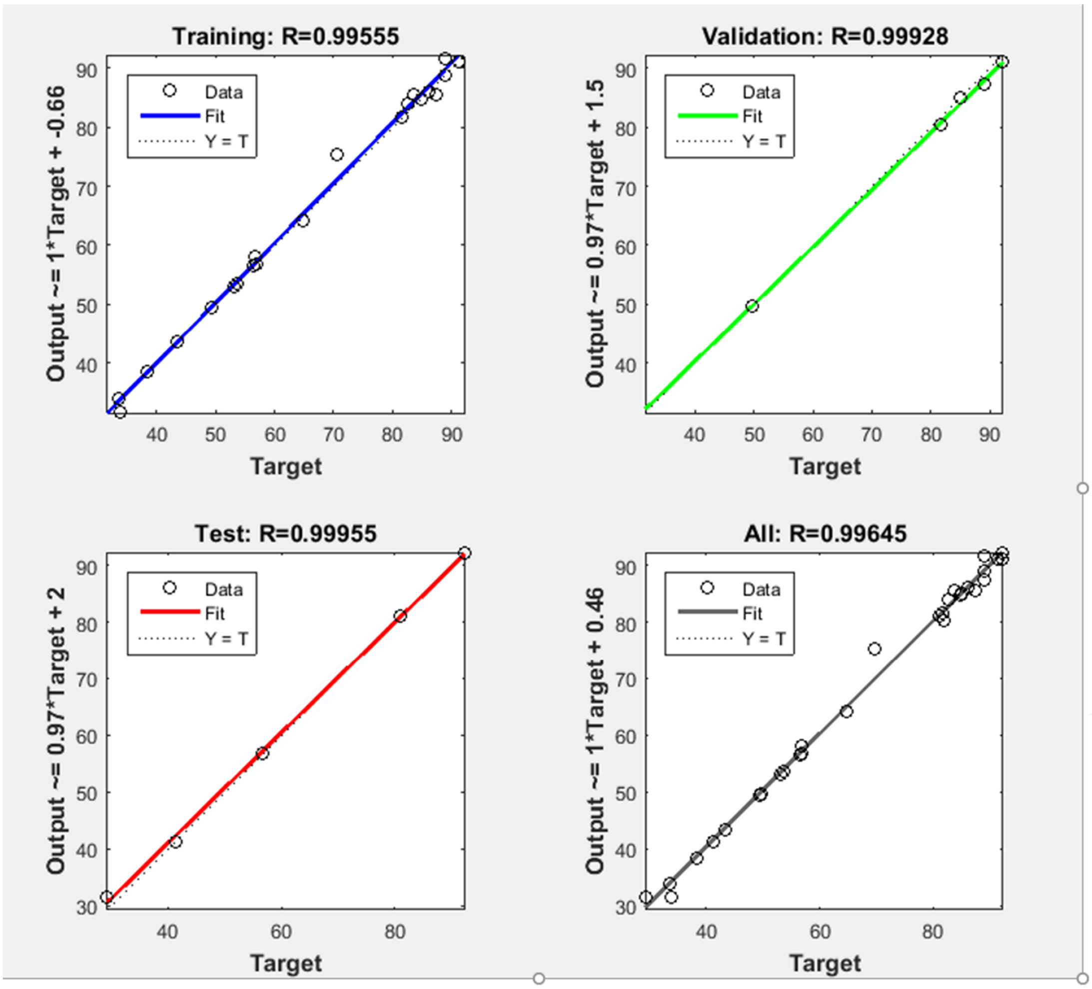


Figure 8. Correlation between the measured and predicted CM for training, testing, validation, and all data.

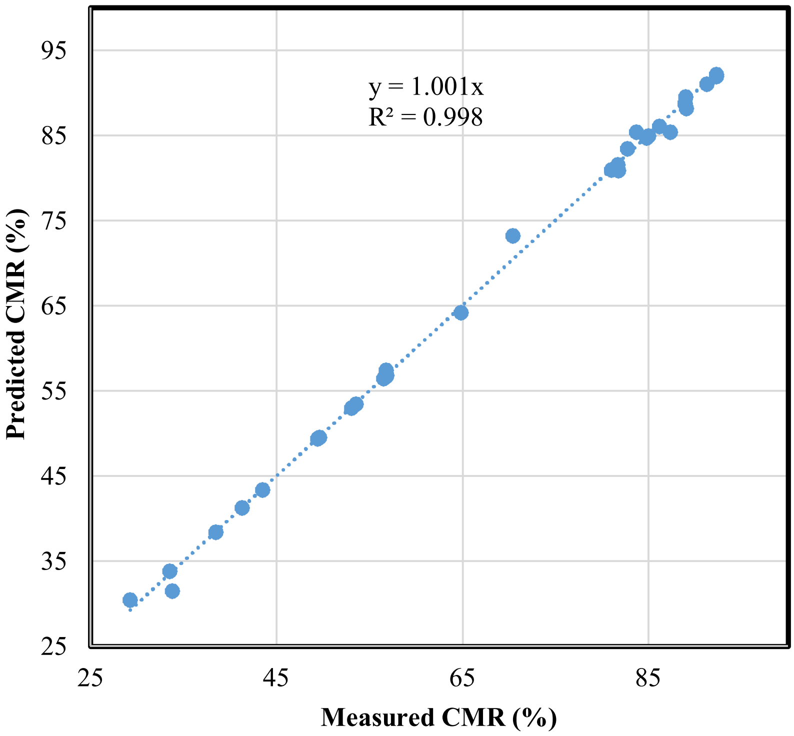


Figure 9. Correlation between the measured and predicted CMR for all data.

2.6. Sensitivity analysis

A useful concept has been proposed to identify the significance of each input factor in the output using a trained network. This was performed by incorporating values of 'relative strength of effect' (RSEs) [24, 26].

RSEs are used to show the process to find the significant input factors for CMR in optimum ANN network input, weight, and output factors.

The larger the absolute value for RSE, the greater the effect the corresponding input unit is on the output unit. RSE is a dynamic parameter that changes with variance of input factors. Here, RSE will be used for a sensitivity analysis of the influence of factors on the back-break phenomenon predicted by a trained neural network. The RSE range is 0-1.

Figure 10 shows the average RSE values for the factors calculated for all the 33 field data used in the previous sections. It is assumed that the input parameters including the conditioning time, solid weight percentage, collector dosage, frother dosage, flotation retention time, rotor speed, feed ash, and pH are the most effective factors involved in the coking coal flotation recovery. It can be seen in Figure 10 that the solid weight content and rotor speed are the most and least sensitive parameters, respectively.

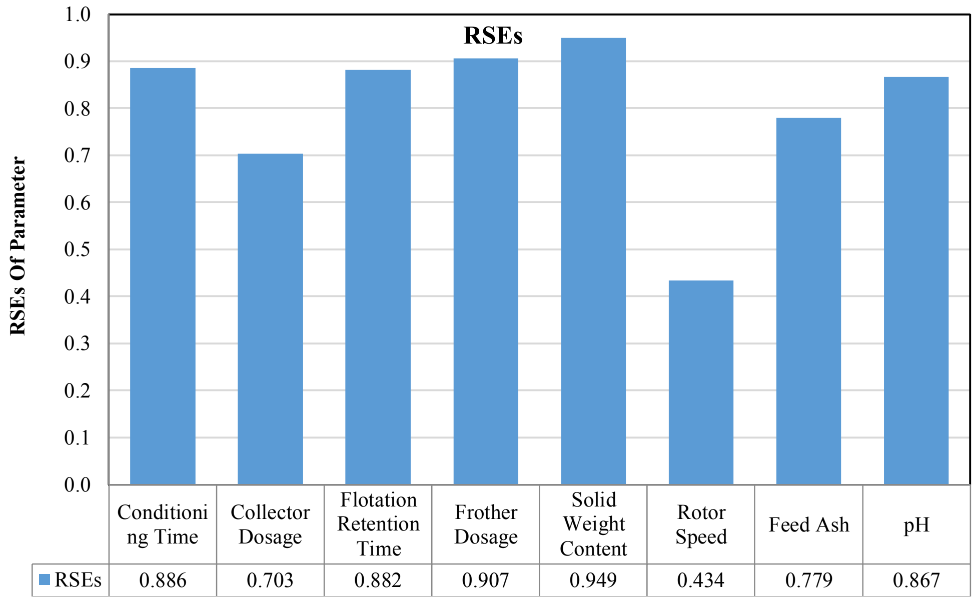


Figure 10. Sensitivity analysis between the CMR and coking coal flotation parameters.

3. Performance of ANN

In order to verify the veracity of the ANN model, 33 experiment data were chosen. The verified results reveal that the predicted values coincide well with the experimental results, as shown in Figures 7-9. It indicates that the ANN model has exactly reflected the correlation between the input and output layers. The functions of the coking coal flotation parameters influencing CMR have been found. In Figures 11-18, the measured and experimental values for (CMR) (%) are compared.

3.1. Effect of every factor on CMR

Figures 7-9 show that the ANN model has a good result as a whole, and can reflect the general effect of all factors involved in coking coal CMR. However, it is not known if the model can explain the specific effect of every factor on CMR. Eight group data has been chosen for every factor in order to verify the model. The results obtained are shown in Figures 11-18.

As seen in Figure 11, the predicted effect of pH on CMR using the ANN model is the same as the experimental results. By increasing the pH, the amount of CMR is improved. It is obvious that pH > 8 has a negative effect on CMR.

Figure 12 shows the influence of conditioning time on CMR. By increasing the conditioning time, the coal flotation recovery has been enhanced.

The effect of flotation retention time on CMR is shown in Figure 13. It can be verified that the predicted values for ANN coincide well with the experimental results. CMR increases obviously with increasing the flotation retention time from 0 to 4 min.

Figure 14 shows the effect of frother dosage on CMR. The results of the measured and predicted data are similar. By increasing the frother dosage, the amount of CMR will be improved. The RSE results of the network show that the rotor speed has the lowest influence on CMR. A rotor speed between 800 and 1200 RPM will have a direct effect on CMR. It is clear that over 1200 RPM, increasing the rotor speed has a reverse effect on CMR. Figure 15 shows the effect of this factor on CMR.

The effect of collector dosage on CMR, as seen in Figure 16, shows that CMR changes directly by alteration in the collector dosage.

The solid weight content has a great influence on CMR. Figure 17 shows that the amount of CMR increases significantly by decreasing the solid content. By decreasing the solid weight content below 10%, CMR of the process has been decreased. The optimum condition for the solid weight content is 10%. The predicted value gives the same results. Figure 18 shows the effect of feed ash on flotation CMR. The results shown in this figure shows that feed ash has a reverse effect on CMR. It is the reason why feed ash decreases because of decrease in the amount of combustible materials.

From such an analysis, it is believed that the ANN model not only exactly predicts CMR but also predicts the effect of every factor on CMR in the coking coal flotation process.

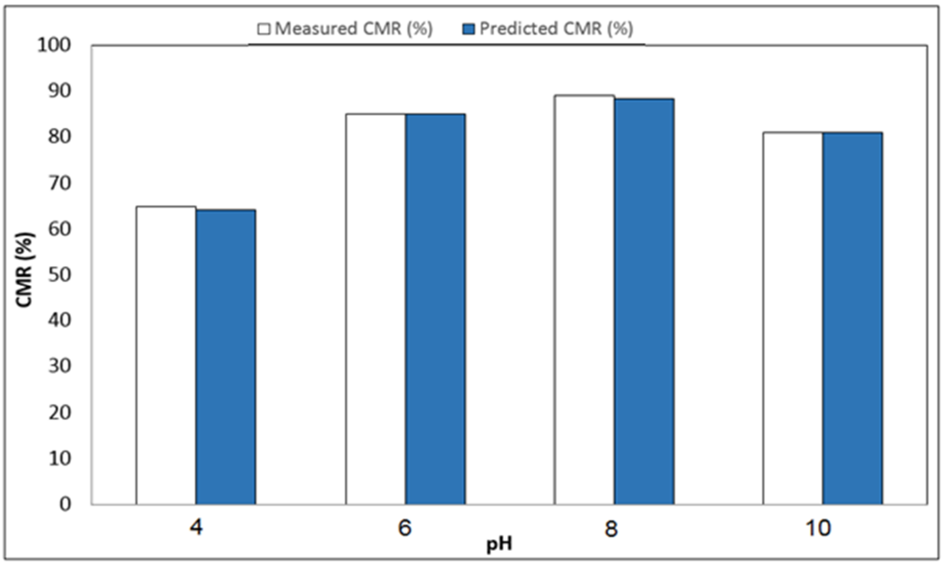


Figure 11. The predicted and experimental effects of pH on CMR: conditioning time, 3min; gasoline dosage, 500 g/ton; flotation retention time, 3 min; MIBC dosage, 50 g/ton; solid weight content, 12%; rotor speed, 1200 RPM; and feed ash, 43.5%.

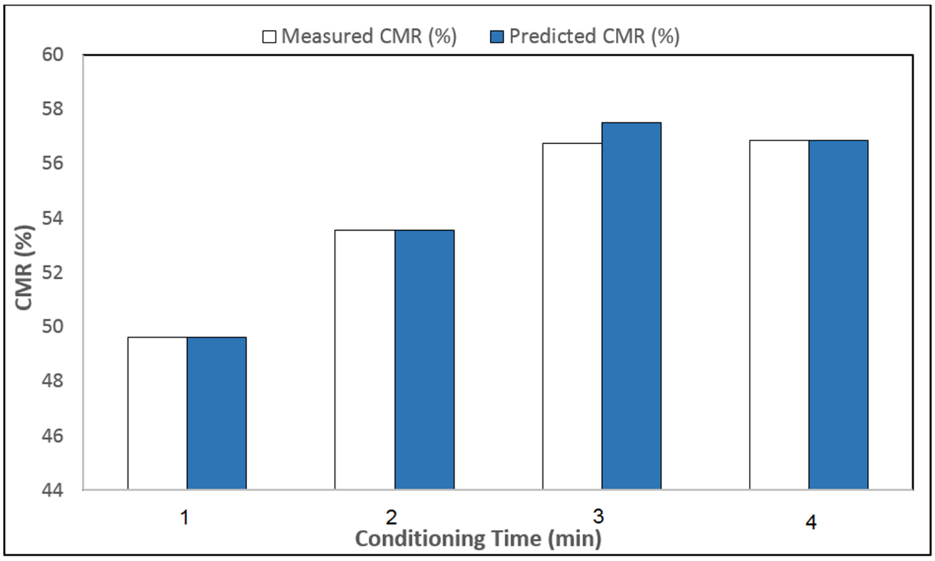


Figure 12. The predicted and experimental effects of conditioning time on CMR: pH, 8; gasoline dosage, 500 g/ton; flotation retention time, 4 min; MIBC dosage, 50 g/ton; solid weight content, 10%; rotor speed, 1200 RPM; and feed ash, 43.9%.

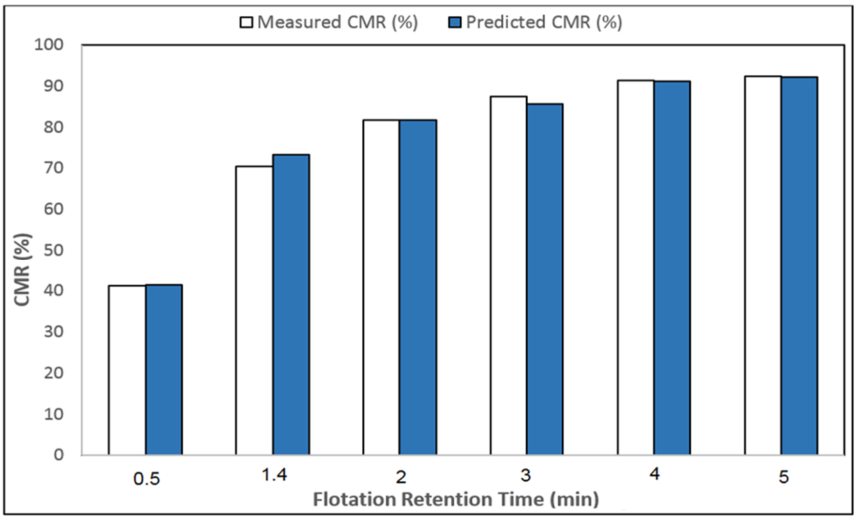


Figure 13. The predicted and experimental effects of flotation retention time on CMR: conditioning time, 3 min; gasoline dosage, 300 g/ton; pH, 8; MIBC dosage, 81 g/ton; solid weight content, 15%; rotor speed, 1200 RPM; and feed ash, 43.5%.

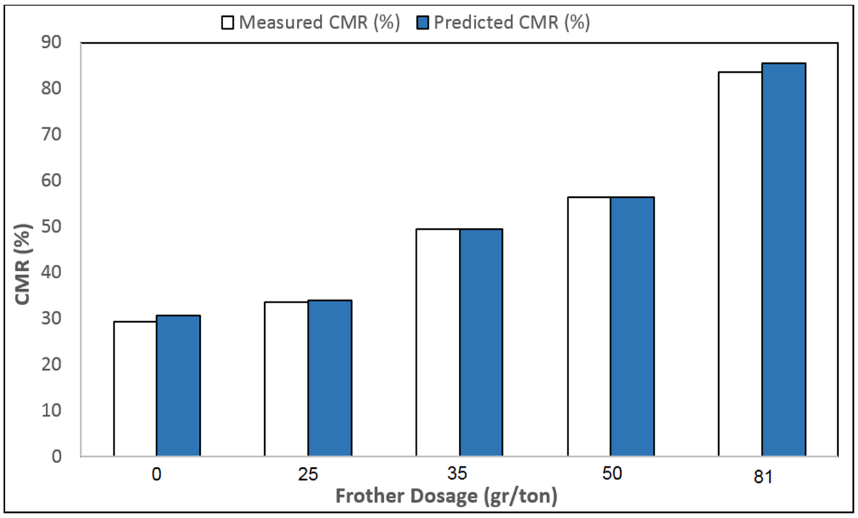


Figure 14. The predicted and experimental effects of MIBC (frother) dosage on CMR: conditioning time, 3 min; gasoline dosage, 300 g/ton; pH, 8; flotation retention time, 3 min; solid weight content, 15%; rotor speed, 1200 RPM; and feed ash, 43.6%.

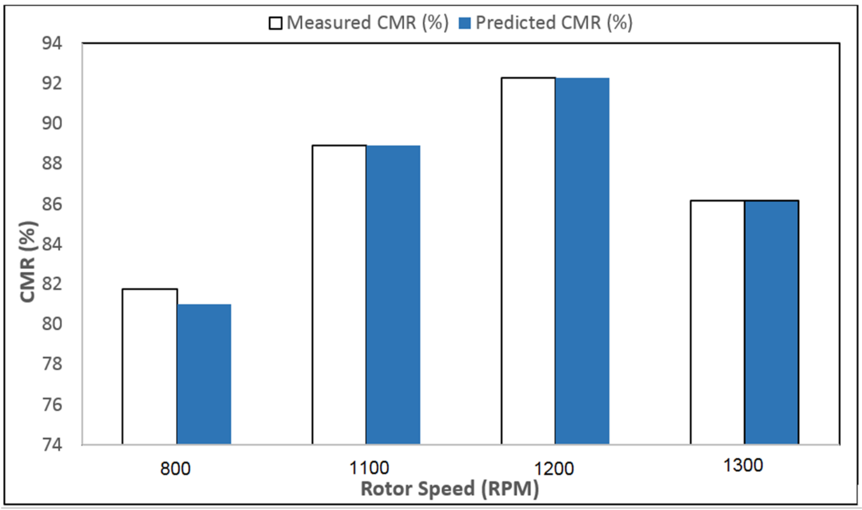


Figure 15. The predicted and experimental effects of rotor speed on CMR: conditioning time, 3 min; gasoline dosage, 300 g/ton; pH, 8; flotation retention time, 3 min; solid weight content, 15%; frother dosage, 25 g/ton; and feed ash, 43.9%.

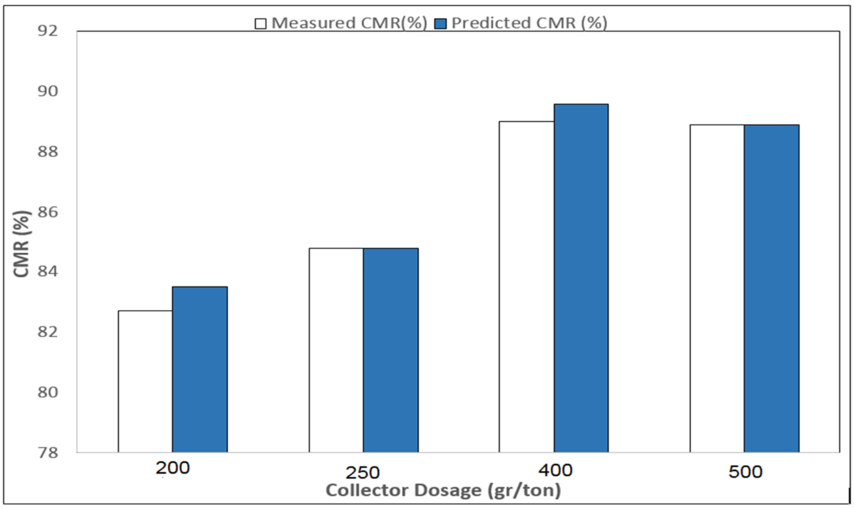


Figure 16. The predicted and experimental effects of gasoline (collector) dosage on CMR: conditioning time, 3min; rotor speed, 1200 RPM; pH, 8; flotation retention time, 3 min; solid weight content, 12%; frother dosage, 81 g/ton; and feed ash, 43.87%.

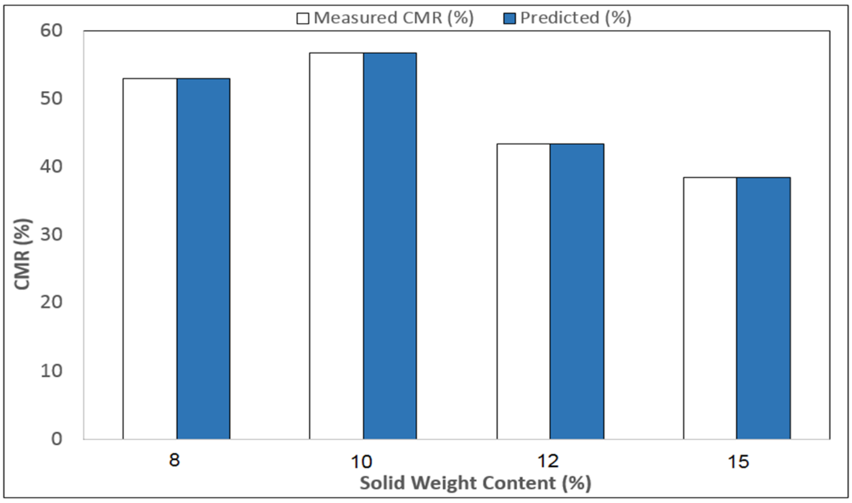


Figure 17. The predicted and experimental effects of solid weight content on CMR: conditioning time, 3 min; rotor speed, 1200 RPM; pH, 8; flotation retention time, 3 min; collector dosage, 250 g/ton; frother dosage, 50g/ton; and feed ash, 41.9%.

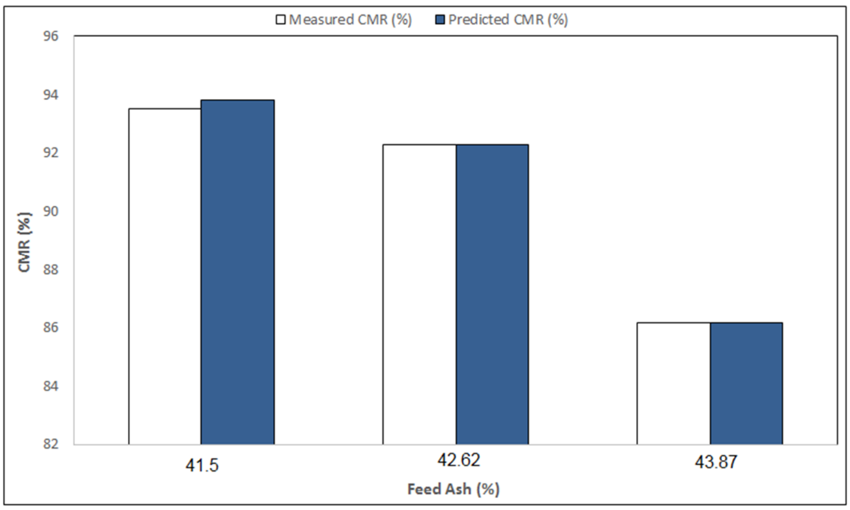


Figure 18. The predicted and experimental effects of feed ash on CMR: conditioning time, 3 min; rotor speed, 1200 RPM; pH, 8; flotation retention time, 3 min; collector dosage, 500 g/ton; frother dosage, 81g/ton; and solid weight content, 15%.

3.2. Application of model

From the simulation and predictions (see Figures 7-18) made using the ANN model, it is evident that the model could be a useful tool in assessing the correlations of CMR in the coking coal flotation process parameters. Thus the best combination of parameters for a high amount of CMR in the coking coal flotation can be obtained using this model.

4. Conclusions

The results of this work demonstrate that the optimum ANN architecture is found to be 8 neurons in the input layer, three hidden layers with 15, 10, and 5 neurons, respectively, and one neuron in the output layer. The results taken from ANN shows that square correlation coefficients of the training, testing, validating, and all data (R^2) achieve 0.9955, 0.9995, 0.9993, and 0.998, respectively. By applying the ANN method, it can be concluded that the most important factors involved in the coal flotation recovery are the solid weight content, frother dosage, flotation retention time, conditioning time, pH, and feed ash. The RSEs achieved from the results of the network showed that the solid weight content (0.949), frother dosage (0907), conditioning time (0.886), flotation retention time (0.882), pH (0.867), feed ash (0.779), collector dosage (0.703), and rotor speed (0.434) were the effective parameters on CMR. The RSE value for solid weight content was 0.949, and it had the highest effect on CMR. The results of the predicted data from neural network and experimented data showed that the conditioning time, frother dosage, flotation retention time, and collector dosage had positive effects on CMR. By increasing these parameters, CMR of coking coal flotation will be enhanced. The negative effects of the operating parameters were related to the feed ash and solid weight content. These parameters had reverse effects on CMR. The results of this work indicated that the optimum pH, solid weight content, and rotor speed for CMR in coking coal flotation were 8, 10%, and 1200 RPM, respectively.

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بررسی تأثیر پارامترهای عملیاتی بر بازیابی مواد قابل احتراق در فرآیند فلوتاسیون با استفاده از شبکه‌های عصبی مصنوعی

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چکیده:

در این پژوهش، تأثیر پارامترهای فلوتاسیون بر بازیابی مواد قابل احتراق (CMR) به روش شبکه عصبی مصنوعی (ANNs) مورد بررسی قرار گرفت. پارامترهای ورودی شبکه شامل درصد جامد، pH، غلظت کلکتور، غلظت کف‌ساز، زمان آماده‌سازی، زمان کف گیری فلوتاسیون، میزان خاکستر خوراک و دور روتور سلول بود. در این پژوهش، برای انتخاب مناسب‌ترین مدل، خروجی مدل‌های مختلف با یکدیگر مقایسه شد. یک شبکه عصبی با ساختار پنج لایه و با نرون‌های ۸، ۱۵، ۱۰ و ۵ نرون به ترتیب در لایه ورودی، اولین لایه پنهان، دومین و سومین لایه پنهان و یک نرون نیز در لایه خروجی شبکه عصبی به کار گرفته شد. در این شبکه عصبی داده‌ها آموزش، تست و اعتبار سنجی شد که مربع ضریب هم‌بستگی (R^2) برای داده‌های آموزشی، تست، اعتبار سنجی و کل داده‌ها به ترتیب ۰/۹۹۵، ۰/۹۹۹، ۰/۹۹۹ و ۰/۹۹۸ حاصل شد. همچنین خروجی شبکه عصبی مورد آنالیز حساسیت قرار گرفت. آنالیز حساسیت نشان داد که سرعت روتور و درصد جامد به ترتیب بیشترین و کمترین تأثیر را بر روی CMR دارند. مقادیر داده‌های خروجی شبکه عصبی با نتایج داده‌های حاصل آزمایش فلوتاسیون همبستگی بسیار زیادی داشت.

کلمات کلیدی: زغال کک شو، فلوتاسیون، شبکه عصبی مصنوعی، شبکه عصبی پس انتشار خطا، بازیابی مواد قابل احتراق.