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Estimating of gold recovery by using back propagation neural network and multiple linear regression methods in cyanide leaching process

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ABSTRACT

In this study, two techniques – back propagation neural network (BPNN) and multiple linear regression (MLR) were applied to estimate gold recovery in cyanide leaching process. The designed neural network has three layers including input layer (seven neurons), hidden layer (ten neurons) with tansing activation function and output layer (one neuron) with linear activation function. The comparison between the estimated recoveries and the measured data resulted in the correlation coefficients, R, 0.952 and 0.884 for training and test data using BPNN model. However, the R values were 0.786 and 0.767 for training and test data respectively, by MLR method. In addition, the root mean square (RMS) error obtained 1.08 and 1.22 for BPNN and MLR methods, respectively. Finally, the results indicate that the BPNN can be used as a viable method to rapidly and cost-effectively estimate gold recovery in cyanide leaching solution.

KEYWORDS

Gold recovery;
Back propagation neural network;
Multiple linear regression;
Cyanide leaching.

INTRODUCTION

Leaching is a process that dissolves valuable metals contained in ores into solutions. The cyanide leach is commonly employed in the treatment of gold ores[1]. Cyanide leaching is one of the most important and widespread hydrometallurgical technologies used in the extraction of gold and silver from ores and concentrates[2]. This process involves the dissolution of gold (and of any silver present in soluble form) from the ground ore in a dilute cyanide solution (usually NaCN or KCN) in the presence of lime and oxygen[3] according to the reaction:

$$4Au + 8CN^- + O_2 + 2H_2O \rightarrow 4Au(CN)_2^- + 4OH^-$$

There are many parameters that affect the performance of cyanide leaching. The major factors affecting leach performance, namely cyanide and oxygen concentration, Lime addition, solid percent, pulp density, particle size, retention time, temperature, pH, surface area of gold exposed, degree of agitation and mass transport, gold purity and presence of other ions in solution[2,4]. Identification, determination and effects of parameters involved are usually associated with considerable cost in experimental and semi industrial stages. Besides, the cost of raw material, preparation, test conducting, samples analysis, and other different cost are daily increased. In mineral processing application, there are input and output variables that we need to find models which are capable of not only expressing the variability within input or output variables but which are also most predictive of the output. Hence, some new methods should be used to obtain knowledge about the studied systems. Ideally multiple linear regression seems to be the simplest method which satisfies these requirements. However, it does not offer a meaningful solution in the presence of noisy correlated data[5]. In the other hand, the neural network has proven is a powerful tool and has been applied successfully in many area including industrial processes[6], modeling the greenhouse effect[7], bioleaching of metals[8], simulation N_2O emissions from a temperate grassland ecosystem[9], prediction of materials properties such as steel[10-12], prediction of coal microbial, chemical desulphurization and operational parameters[13-16] as well as coal Hargrove grindability index[17-18], gold content estimation in pyrometallurgy[19], Prediction of pre-oxidation efficiency of refractory gold concentrate by ozone in ferric sulfate solution[20], Prediction of heavy metals in acid mine drainage[21] and etc. Moreover, there are many other reports that the neural network approach has been used in material science based research as discussed by Sha and Edwards[22].

The literature review indicated that ANN approach and MLR method can be very good choices in this regard, as they exhibit significant ability in estimating of output and simulating various process especially ANN method. The purpose of this study is to estimate of gold leaching recovery and to simulate of cyanide leaching process using ANN and MLR methods. The results obtained from estimations of these two ways are compared with the actual determined recoveries in laboratory.

EXPERIMENTAL

Cyanidation experiments were conducted on representative ore sample with grade of 3 g/t Au next grinding process in 2 L capacity glass jacketed leaching cells[23-25]. The lime and dilute sulfuric acid, sodium cyanide, oxygen used were all certified reagent grade chemicals. The lime was used as pH regulator that it concentration was monitored by titration with dilute sulfuric acid. Distilled water was used. Experiments carried out using 500 g of ore sample based on a fractional factorial design. The duration of these experiments was 72 hours.

The studied operating parameters were: pH, solids content, sodium cyanide concentration, O_2 concentration, particle size, retention time, and temperature. Each factor was varied over three levels while the other operational parameters were kept constant. The levels of the parameters are shown in TABLE 1. TABLE 2 shows the results of a fractional factorial design from experiment of cyanide leaching tests on samples and responses measured for each experiment. Test No.33 is the average of 3 centre point experiments.

TABLE 1 : Selected parameters and their actual and coded levels to estimate gold recoveries

Factor	High level	Medium level	Low level
NaCN concentration(ppm)	1000	600	200
Concentration(ppm) O_2	16	8	0
Solid Content (%)	50	40	30
Temperature(°C)	40	30	20
pH	11.5	10.5	9.5
Size (micron) (P_{80})	75	50	25
Retention Time (h)	48	30	12

ESTIMATING OF GOLD RECOVERY USING ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural network description

Artificial neural network (ANN) is an empirical modeling tool, which is analogous to the behavior of biological neural structures[26]. Neural networks are powerful tools that have the abilities to identify underlying highly complex relationships from input–output data only[27]. Nevertheless, they are an alternative statistical prediction method inspired by studies on the

TABLE 2 : Cyanidation experiments results

Run	NaCN (ppm)	O_2 (ppm)	Solid Percent (%)	Temperature (ºC)	pH	P_{80} (micron)	Retention Time (h)	Recovery (%)
1	200	0	30	20	11.5	25	48	90.32
2	1000	16	50	20	9.5	25	48	91.15
3	1000	16	30	40	11.5	25	48	91.21
4	1000	0	50	20	9.5	75	12	90.11
5	200	16	50	40	11.5	25	48	90.66
6	200	0	30	20	9.5	75	12	90.14
7	1000	16	50	40	9.5	25	12	91.15
8	200	16	30	20	9.5	25	48	87.87
9	1000	0	50	40	9.5	75	48	85.75
10	1000	0	30	20	9.5	25	12	91.44
11	200	0	50	40	11.5	75	12	89.37
12	1000	16	50	20	11.5	75	12	91.32
13	1000	16	30	40	9.5	75	12	91.03
14	1000	0	50	20	11.5	25	48	90.86
15	200	16	50	40	9.5	75	12	83.22
16	200	0	30	40	11.5	25	12	91.7
17	1000	0	30	20	11.5	75	48	90.34
18	200	16	50	20	9.5	75	48	86.21
19	200	0	30	40	9.5	75	48	88.85
20	1000	16	30	20	11.5	25	12	92.87
21	200	16	30	20	11.5	75	12	91.09
22	200	16	30	40	9.5	25	12	92.3
23	200	0	50	20	9.5	25	12	89.05
24	1000	0	50	40	11.5	25	12	91.24
25	1000	16	30	20	9.5	75	48	90.57
26	200	0	50	40	9.5	25	48	84.05
27	1000	16	50	40	11.5	75	48	90.6
28	1000	0	30	40	11.5	75	12	91.95
29	1000	0	30	40	9.5	25	48	92.1
30	200	0	50	20	11.5	75	48	89.68
31	200	16	50	20	11.5	25	12	90.69
32	200	16	30	40	11.5	75	48	90.86
33	600	8	40	30	10.5	50	30	90.803

human nerve and brain system. Intelligence is embedded into a neural network by teaching and training them by using a series of examples and patterns. The information acquired through the training is retained and represented by a set of connection weights within the neural network structures. The nature of neural network memory leads to efficient responses (i.e., giving answers) when presented with previously unseen inputs.

Generally, a neural network contains one input layer, one or more hidden layers, and one output layer. Each layer comprises one or more neurons. The neurons are interconnected using weight factors. A neuron in a given layer receives information from all the neurons in the preceding layer. It sums the information, weighted by factors corresponding to the connection and the bias of the network, and transmits this sum to all the neurons of the next layer using a mathematical function[28-29].

The mechanism of the ANN is based on the four major assumptions[30]: 1) information processing occurs in many simple elements that are called neurons (processing elements), 2) signals are passed between neurons over connection links, 3) each connection link has an associated weight, which, in a typical neural network, multiplies the signal being transmitted, 4) each neuron applies an activation function (usually nonlinear) to its net input in order to determine its output signal.

The main advantage of ANN is the ability to modeling a problem by the use of examples (i.e. data driven), rather than describing it analytically. Unlike multiple linear or nonlinear regression techniques, which require a predefined empirical model, neural networks can identify and learn the correlative patterns among the input and corresponding output values once a training data set is provided. Neural networks learning algorithms can be divided into two main groups that are supervised and unsupervised. According to learning algorithms several types of neural networks such as Back propagation Neural Network (BPNN), Probabilistic Neural Network (PNN) and General Regression Neural Network (GRNN) have been designed in MATLAB software [27, 30-31]. Since Back propagation Neural Network (BPNN) method is used in this study, it is therefore described below briefly.

BPNN model description

A BPNN model is one of the most commonly used neural network[32]. In BPNN model, the neurons are arranged in layers and are connected so that the neurons in a layer receive inputs from the preceding layer and sends out outputs to the following layer. External inputs are applied at the first layer and system outputs are taken at the last layer. The intermediate layers are called hidden layers. A single hidden layer of the back-propagation has been proven to be capable of providing accurate approximations to any continuous function provided there are sufficient hidden units[33].

Back-propagation neural networks are trained by feeding a series of examples of associated input and target output values. Each hidden and output unit processes its inputs by multiplying each input by its weight, summing the product and then processing the sum using a non-linear transfer function to produce a result. During training the network tries to match the outputs with the desired target values. Learning starts with the assignment of random weights. The output is then calculated and the error is estimated. This error is used to update the weights until the stopping criterion is reached. It should be noted that the stopping criteria is usually the average error or epoch.

The over fitting phenomenon is one of the most common problems in the training process occur. This problem occurs mostly in case of large and too complicated networks when the error on the training set is driven to a very small value, but when new data is presented to the network the error is large. Therefore, the network will not generalize well on the testing data.

A common heuristic approach to avoid “over fitting” is “early stopping”. This approach involves monitoring the generalization error and stopping training when the minimum testing error is observed. However, some care is needed in deciding when to stop, since the validation error surface may have local minima or long flat regions preceding a steep drop-off[34]. Moreover, to overcome these limitations, Mackay (1991) and Neal (1992) proposed the use of Bayesian back propagation neural networks which minimizes a combination of squared errors and weights and then determines the correct combination so as to produce a network which generalizes well[35-36].

In this study, the Bayesian regularization method was used and trained with back propagation algorithm (BP). The necessary coding was added through MATLAB multi-purpose commercial software. The available data is divided into two subsets. The first subset is the training set, which is used for computing the gradient and updating the network weights and biases. The second subset is the test set. This model worked by modifying the performance function. The typical performance function that is used for training feed forward neural networks is the mean sum of squares of the network errors (mse) ((Eq.1)).

$$\mathbf{mse} = \frac{1}{n}\sum_{i=1}^{n} e_i^2 = \frac{1}{n}\sum_{i=1}^{n}(t_i - \alpha_i)^2 \qquad (1)$$

Where, n represents the total number of data, a_i is the estimated value, t_i denotes the measured value and e_i is the error.

We can improve this function with adding mean sum of squares of the network weights and biases (Eq.2):

$$\mathbf{msereg} = \gamma.\mathbf{mse} + (1-\gamma)\mathbf{msw}$$

$$\mathbf{msereg} = \gamma.\mathbf{mse} + (1-\gamma)\mathbf{msw} \quad (2)$$

Where msereg is the modified error, γ is the performance ratio, and

$$\mathbf{msw} = \frac{1}{n}\sum_{i=1}^{n} w_i^2 \quad (3)$$

Performance function will cause the network to have smaller weights and biases, and this will force the network response to be smoother and less likely to over fit[31].

Estimating of gold recovery using BPNN model (associated with Training and testing data)

The BPNN model was trained using 25 randomly selected data (accounting for 75% of the total data, approximately) while the remaining 8 data were utilized for testing of the network performance. In this study, Bayesian regularization algorithm (trainbr) was used as training function to prevent overtraining of the ANN models. This algorithm provides a measure of how many network parameters (weights and biases) are being effectively used by the network. Since the neural network performance can be made more efficiently by certain pre-processing steps, all input data and output in the present work were normalized. In this study, normalization of data (inputs and outputs) was done for the range of (-1, 1) using Eq. 4 and the number of training data (25) and test data (8) were then selected randomly.

$$P_n = 2\frac{P - P_{min}}{P_{max} - P_{min}} - 1 \quad (4)$$

Where P_n, P, P_{min} and P_{max} represent the normalized parameter, the actual parameter, minimum of the actual parameters and maximum of the actual parameters, respectively.

For the assessment of model performance, there are several criteria[37-38]. In the present work, the root mean square (RMS) error and efficiency criterion (R^2) were used to evaluate the effectiveness of each network and its ability to make accurate predictions. The root mean square error represents the discrepancy between the measured and estimated values. The lower the RMS error, the more accurate the prediction is. Moreover, efficiency criterion (R^2) indicates the percentage of the initial uncertainty explained by the model. Terms of RMS error and are defined as:

$$\mathbf{RMS(error)} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} y_i^2 - \frac{\sum_{i=1}^{n}\hat{y}_i^2}{n}} \quad (6)$$

Where , and denote the measured value, estimated value and the total number of data. The best fitting between measured and estimated values, which is unlikely to occur, would have RMS=0 and (TABLE 4).

Finally, a feed forward multilayer perceptron (because of powerful modeling capability)[27] with a 7-10-1 topology was selected as optimal network in this study. This network has one input layer with seven inputs, one hidden layer with ten neurons that each neuron has a bias and is fully connected to all inputs and utilizes sigmoid hyperbolic tangent (tansig) activation function as well as having one output layer that has one neuron with a linear activation function (purelin) without bias. Linear activation function can provide any range of data in output without any limitation for output values. Generally, the activation function is mathematical formula that determines the output of a processing neuron and the aim of it is to limit the amplitude of the output neurons. Schematic description of BPNN model is shown in Figure 1 and Figure 2. In this model, important parameters including, pH, solids content, sodium cyanide concentration, concentration, particle size, temperature and retention time were used as inputs, and gold recovery was the output of neural network model.

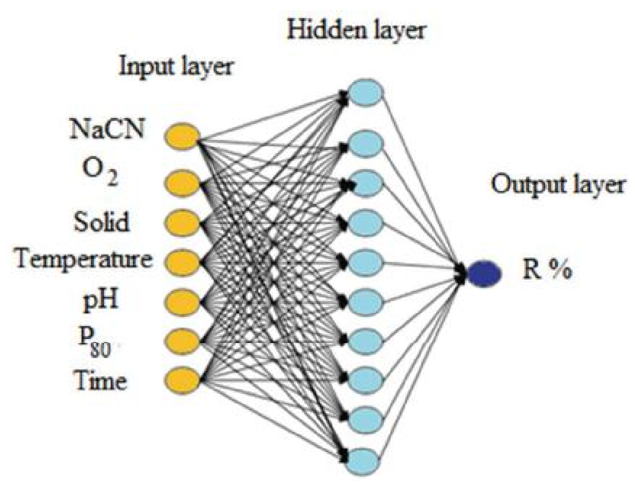

Figure 1 : Back propagation neural network architecture

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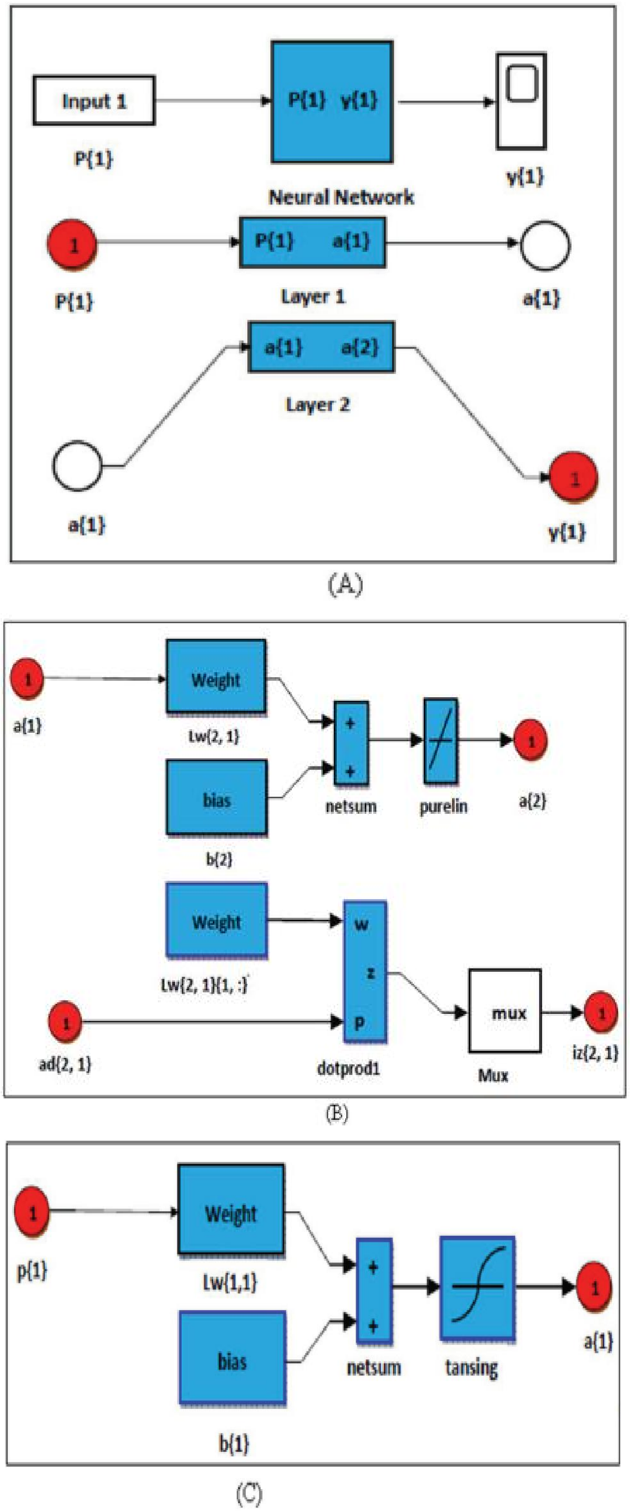

Figure 2 : The structure of BPNN model, (A)Schematic diagram of network and its layers, (B)Structure of network output layer and (C)Structure of network hidden layer (Layer 1)

Figure 1, Figure 2 (A), Figure 2 (B) and Figure 2 (C) indicate the back propagation neural network architecture, general schematic diagram of network and its layers (that layer 1 is hidden layer and layer 2 is output layer), the structure of network output layer and the structure of network hidden layer 1.

After selecting the best possible architecture, the network was trained to reduce the error between the neural network output and the target output. Figure 3 indicated the training process of back propagation neural network by Bayesian regularization algorithm. This algorithm provides a measure of how many network parameters (weights and biases) are being effectively used by the network. The training may stop with the message "Maximum MU reached". This is a good indication that the algorithm has truly converged. In this present work, the algorithm was stopped in 367 epochs.

After the training process, the neural networks will be tested with another data set, which has not been used for the training process. The aim of this verification is to guard against overtraining, where the ANN has memorized or over-fitted the connection weights to the training patterns. The testing set is used to evaluate the confidence in the performance of the trained network.

Furthermore, diagrams of correlation between estimated values using BPNN versus measured values were used to evaluate the capability of designed neural network in training and testing stages (Figure 4 (A) and Figure 4 (B)). Also, the performance of the neural net-

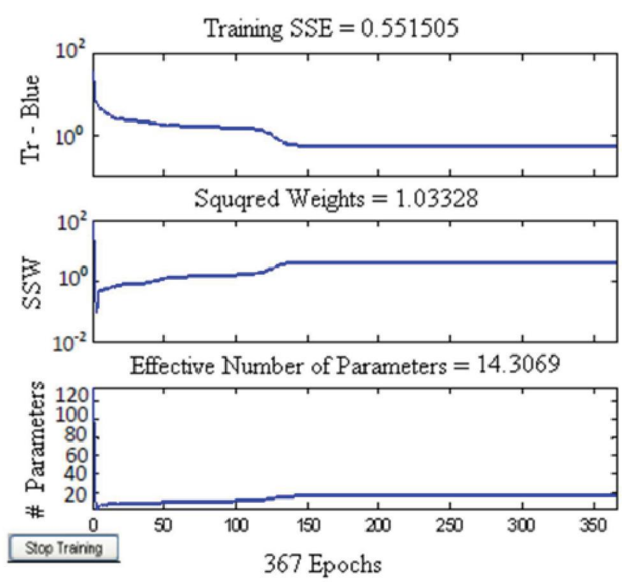

Figure 3 : Sum squared error, sum squared weighs and effective number of parameters versus the epoch in training step

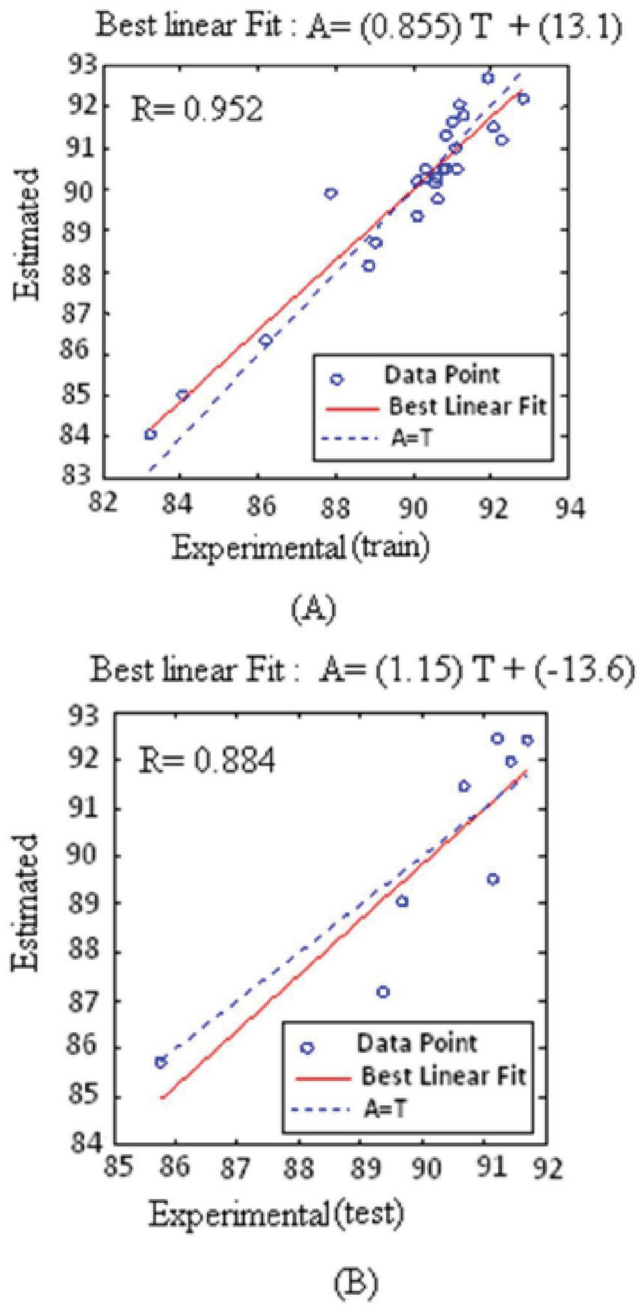

Figure 4 : Comparison of the estimated recoveries for training and test data using BPNN model versus determined values in laboratory (experimental data). A: Correlation between estimated recoveries using BPNN model and determined recoveries in laboratory (train data), B: Correlation between estimated recoveries using BPNN model and determined recoveries in laboratory (test data)

work was further evaluated using comparison between diagram of network estimations and experimental data in training and testing stage (Figure 5).

Figure 4 compares the estimated recoveries of gold by BPNN model with those obtained in laboratory for

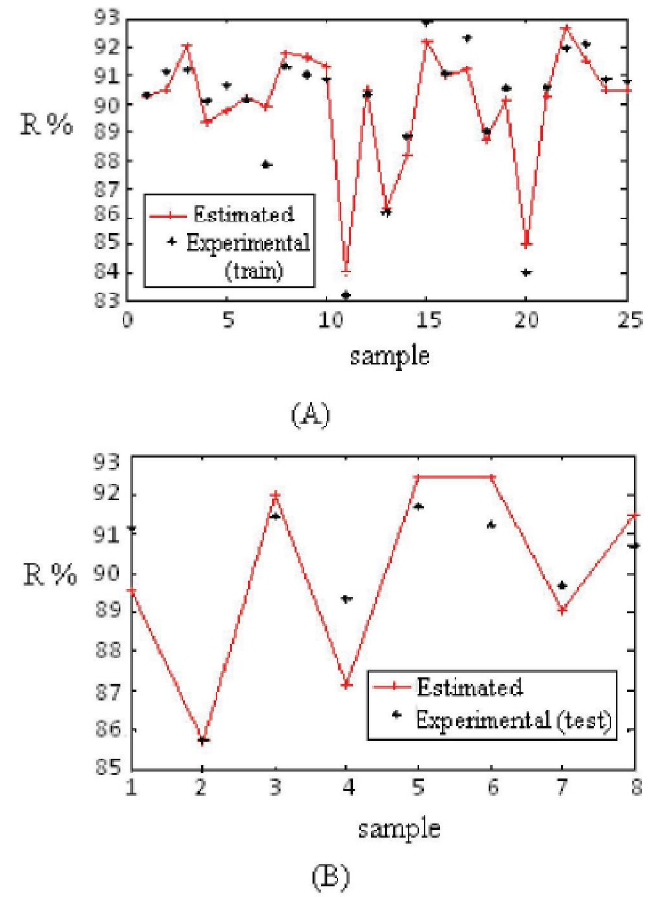

Figure 5 : Comparison of network estimations and experimental recovery for all data using BPNN ((A): training and (B): test data)

training and test data. It can be seen that selected neural network with 7-10-1 topology has given estimations of gold cyanidation recoveries for two data sets. These results were approved by Figure 5. The results indicate that the correlation coefficients (R) values of measured and estimated recoveries were 0.952 and 0.884 for training and test data, respectively. Also, the obtained root mean square (RMS) error using back propagation neural network was 1.08. Therefore, the selected BPNN provided a good-fit model for two data sets of recoveries. The correlation coefficient (R) values for the training and test data and the respective values of RMS for the two data sets are listed in TABLE 4.

ESTIMATING OF GOLD RECOVERY USING MULTIPLE REGRESSION ANALYSIS (MLR)

Multiple linear regression (MLR) description

Multiple (linear) regression is a statistical tool, based

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TABLE 3 : Statistical characteristics of the multiple linear regression model

Model	Independent Variables	Coefficient	Standard Error	Standard error of estimate	t value	Sig. level.	Determination coefficient (R^2)
1	(Constant)	86.521	4.332	.786	19.974	.000	0.786
	NACN	2.559E-03	.001		2.844	.011	
	O_2	2.156E-02	.045		.475	.641	
	SOLID	-.105	.036		-2.892	.010	
	T	-1.545E-02	.036		-.429	.674	
	PH	.775	.367		2.114	.050	
	P_{80}	-2.034E-02	.015		-1.392	.182	
	TIME	-2.442E-02	.021		-1.179	.255	

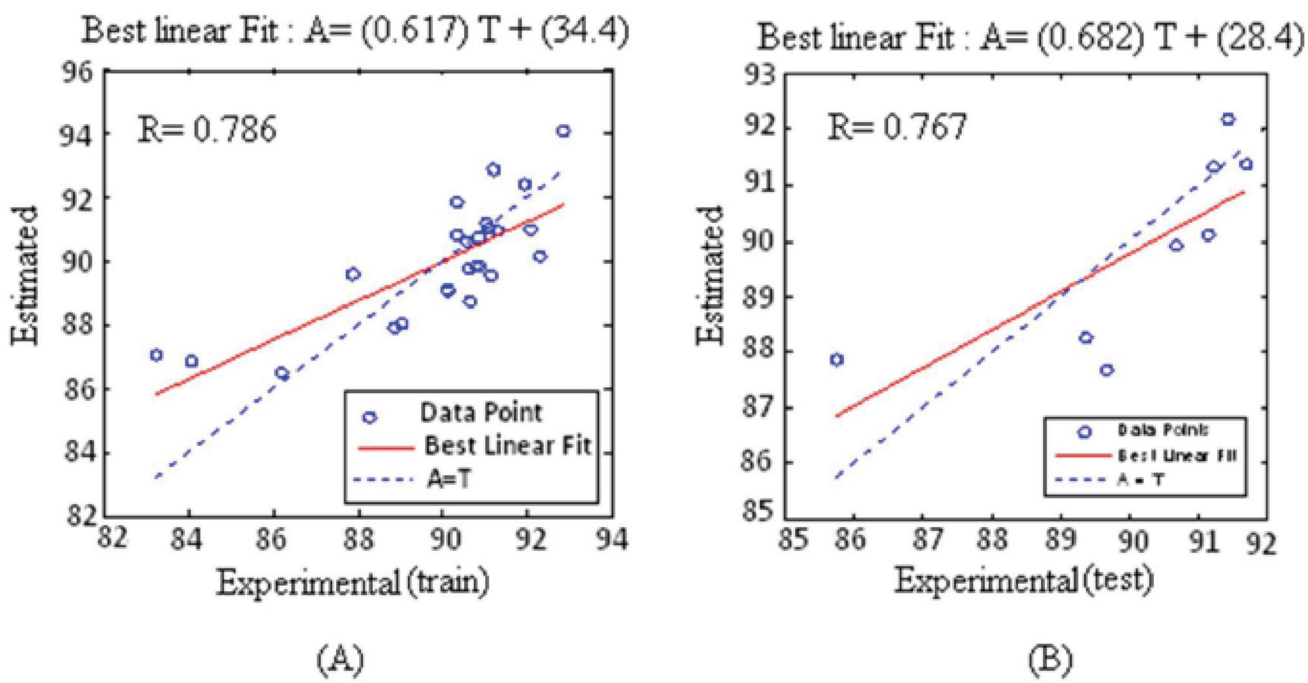

Figure 6 : Comparison of the estimated recoveries for training and test data using MLR model versus determined values in laboratory (experimental data). A: Correlation between estimated recoveries using MLR model and determined recoveries in laboratory (train data), B: Correlation between estimated recoveries using MLR model and determined recoveries in laboratory (test data).

on least-squares analysis of experimental (or observational) data to obtain a (linear) functional relationship between one dependent and several independent variables. The first step of a regression analysis is to find an appropriate model for the functional relationship[39]. This approach can be used either to test theories or models about how well a set of variables explains a phenomenon, or which particular set of variables do the best job in predicting it. It is one of the most widely used of all statistical methods.

Besides determining how much variance in a dependent variable can be explained by a set of predictors, multiple linear regression also can tell us the relative contribution or 'weight' each independent variable exerts. These weights can be used to construct prediction equations for the dependent variable. Such equations allow us to accurately estimate values of the dependent variable based on our foreknowledge of the independent variables. Here, the model to be fitted is:

$$y = b_0 + b_1x_1 + b_2x_2 + ... + b_nx_n + e \quad (7)$$

Where y is the dependent variable (gold recovery), is regression constant, the represent the k predictor (independent) variables, is a random error (or residual) which is the amount of variation in y not accounted for by the linear relationship and the b's are the regression coefficients. These regression coefficients represent the independent contributions of each predictor variable in explaining variation in (y). They are unknown and are to be estimated. There is usually substantial variation of the observed points around the fitted regression line. The deviation of a particular point from the regression line (its predicted value) is called the residual value. The smaller the variability of the residual values around the regression line, the better is model estimation.

In present study, regression analysis was performed using the training and test data employed in neural network data. Recovery was considered as the dependent variable and pH, solids content, sodium cyanide concentration, concentration, particle size, temperature and retention time were considered as the independent variables. A computer-based package called SPSS (Statistical Package for the Social Sciences) was used to carry out the regression analysis. The statistical result of the model for estimating of recoveries is presented in TABLE 3.

TABLE 3 showed the estimated regression relationships for recoveries of gold in leaching process. Thus, recoveries were estimated according to Equation 8:

$$\begin{aligned} &\mathbf{R = 86.521 + 0.002559 \times NaCN + 0.02156 \times O_2 -} \\ &\mathbf{0.105 \times Solid - 0.01545 \times Temperature + 0.775 \times} \\ &\mathbf{pH - 0.02034 \times P_{80} - 0.02442 \times Time} \end{aligned} \qquad \mathbf{(8)}$$

Furthermore, Figure 6 compares the correlation between estimated recoveries using MLR method versus actual determined recoveries for training data (Figure 6 (A)) and test data (Figure 6 (B)).

As it can be seen correlation between the model predictions using MLR and actual data is almost low. It shows a relatively low ability of the MLR model to estimate recoveries.

TABLE 4 : The comparison of the results (R, RMS) of BPNN and MLR models in training and test data

Model	RMS (Train)	RMS (test)	Correlation coefficient (R) (train)	Correlation coefficient (R) (train)
Neural network	0.71851	1.0858	0.952	0.884
Multiple linear regression	1.7398	1.2262	0.786	0.767

TABLE 5 : Comparison of experimental data with those estimated by BPNN and MLR models in the train and test process

Run no.	Gold Recoveries (%) (experiments)	Estimated recoveries using MLR model for training and test data	Estimated recoveries using BPNN model for training and test data
Trainingstage			
1	90.32	90.80564	90.29782
2	91.15	89.5478	90.48904
3	91.21	92.8888	92.04327
4	90.11	89.06496	89.36567
5	90.66	88.7416	89.75867
6	90.14	89.11776	90.19387
8	87.87	89.6006	89.93672
12	91.32	90.95992	91.78801
13	91.03	91.20092	91.63498
14	90.86	90.75284	91.30635
15	83.22	87.05372	84.07919
17	90.34	91.83584	90.51104
18	86.21	86.4836	86.33209
19	88.85	87.92964	88.17113
20	92.87	94.07692	92.21623
21	91.09	91.01272	90.98865
22	92.3	90.17072	91.20352
23	89.05	88.03476	88.7249
25	90.57	90.6308	90.17165
26	84.05	86.84664	85.04233
27	90.6	89.7718	90.30003
28	91.95	92.40596	92.69725
29	92.1	90.99384	91.5086
32	90.86	89.8246	90.50169
33	90.803	89.8246	90.50169
Testing stage			
7	91.15	90.11792	89.5395
9	85.75	87.87684	85.7309
10	91.44	92.18196	91.996
11	89.37	88.25876	87.18182
16	91.7	91.37576	92.42003
24	91.24	91.32296	92.43288
30	89.68	87.68864	89.06599
31	90.69	89.92972	91.4663

COMPARISON OF MLR AND BPNN MODELS

The results obtained from the studied models for train and test set compounds are summarized in TABLE 4 and TABLE 5.

TABLE 4 compares the correlation coefficient R and root mean square error (RMS) of two techniques studied for training and test data. A close agreement can be seen between the estimated recoveries and actual data when the ANN method (BPNN) is used. In the other hand, estimated recoveries by BPNN and MLR Models accompanied by actual determined recoveries are listed in TABLE 5.

As can be observed in TABLES 4 and 5, the error estimates used for model performance evaluation, RMS error were lower for BPNN model. The correlation coefficients (*R*) given by BPNN model is also higher. This demonstrates that the performance of neural network is better than that of MLR model. Comparison of results from the models performance and estimated recoveries demonstrate that the BPNN model estimates the gold recoveries more accurately than MLR model for the train and test data sets.

CONCLUSION

Back-propagation neural network (BPNN) and multiple linear regressions (MLR) were applied to estimate the gold leaching recovery. The input data for the BPNN and MLR models have been selected on the high values of the correlation coefficients between gold recovery and effective parameters including NaCN concentration, concentration, solid content, temperature, pH, retention time.

The designed neural network (BPNN model) has three layers including input layer (seven neurons), hidden layer (ten neurons) with tansing activation function and output layer (one neuron) with linear activation function.

The comparison between estimated gold recoveries and actual determined values in cyanidation process indicated that correlation coefficients (R) (for training, test data) and the root mean square (RMS) error were (0.953 and 0.88) and 1.08 and (0.786, 0.767) and 1.22 using BPNN and MLR methods, respectively.

Finally, the results demonstrated that low correlation values between the model estimations using MLR method and experimental data described its low capability in estimation recoveries. In addition, the results indicated high capability of BPNN method in estimation gold recoveries and simulation cyanide leaching process. Therefore, it can be a very powerful tool for treating the experimental data in other similar cyanide leaching process.

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