USE OF ARTIFICIAL NEURAL NETWORK TO MODEL THE BIOLEACHING PROCESS OF PRECIOUS METALS FROM FURNACE FUEL ASH USING *ACIDITHIOBACILLUS FERROOXIDANS*

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Abstract
In this study, bioleaching modeling of precious metals including vanadium, nickel and copper in fuel oil ash furnaces is investigated using artificial neural networks. In the obtained models, the percentage of metal extraction as a function of pH factors (in the range of 1-2.5), the initial concentration of Fe^{2+} ions (in the range of 0-9 g/l), the percentage of bacterial inoculation (in the range of 1-10 %) and time (in the range of 0-15 days) has been examined. Three neural network models were proposed to estimate the percentage of each metal extraction. The error propagation method and Levenberg-Marquardt algorithm were used for network training. A quarter of the data was not used in the neural network training process and was used to evaluate the model. The mean relative error (MRE) for vanadium, nickel, and copper was 5.35%, 3.07% and 2.82%, respectively. Also, a value greater than 0.99 of the absolute fraction of variance (R^2) indicated the validation of the models developed using the neural network.

***Keywords*:** Modeling, bioleaching, neural networks, fuel oil ash

INTRODUCTION

Today, the tendency to sell secondary raw materials is increasing due to the reduction of rich mineral reserves, the application of strict environmental laws and the reduction of exports of primary raw materials by countries with mines and precious metal resources. One of these important secondary resources is the ash of power furnaces. This waste contains metals such as vanadium and nickel, which can cause serious damage to the environment. On the other hand, the widespread use of these metals in various industries has attracted more attention to these wastes. There are several technologies for the extraction of metals from industrial wastes, including pyrometallurgy and hydrometallurgy. Today, the use of pyrometallurgy and hydrometallurgy methods is challenged due to high energy requirements, toxic solvents, secondary environmental pollutions and high operation costs. In addition to these methods, the use of bioleaching method, which is based on the performance of microorganisms in the extraction of valuable metals, has received a lot of attention in recent decades. This interest is due to the many benefits of bioleaching including high safety, high-efficiency, low environmental impact, and low investment costs. Various bacteria have been used for bioleaching, including *Acidithiobacillus ferrooxidans*, *Acidithiobacillus thiooxidans*, and *Leptospirillum ferrooxidans*. Generally, the biological reactions are influenced by environmental, physical, and chemical factors such as pH, solid density, time, temperature, inoculation percentage, and energy sources. In previous bioleaching studies, conventional experiment design like one factor at a time or statistical optimization methods such as response surface methodology have been used. The purpose of this study is to present a neural network model to accurately predict the percentage of bio-extraction of vanadium, nickel and copper metals from power plant furnace ash. Metal extraction percentage as model output and initial pH, initial Fe^{2+} concentration, bacterial inoculation percentage and process time were considered as

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neural network inputs. The neural network is able to predict the output of the model with very high accuracy by using its many parameters (weights and biases). Providing a model with high estimation accuracy will reduce the need for more laboratory data and will allow determining the optimal parameters for equipment design.

MATERILAS AND METHODS

SAMPLE PREPARATION

In this research, fly ash was supplied by Neka power plant of Mazandaran, Iran. Samples were first crushed to the grain size of 75 μm. The resulting powder was used as a sample in all experiments.

BIOLEACHING EXPERIMENTS

The experiments were performed in a 250 ml Erlenmeyer flask containing 50 ml of culture medium for Acidithiobacillus ferrooxidans. The conditions of each experiment were determined by setting initial pH, initial ferric concentration, bacterial inoculation percentage, and time. The bacteria were PTCC 1647,obtained from the Iranian Research Organization for Science and Technology (IROST), Tehran, Iran. The prepared strain was added by sequential culture and adapted to a maximum of up to 4 g/l. This value was determined as the amount of waste in next experiments.

MEASURING DEVICES

pH and Eh were monitored using a portable pH meter. An inductively coupled plasma optical emission spectrometer (ICP-OES) (Vista-pro, Australia) was used following standard procedures to analyze the metals after bioleaching. The leaching yield was calculated based on the elemental content of the feed and the leach liquor as follows:

$$\text{Metal extraction (\%)} = \frac{C_1V_1/M_1}{C_2V_2/M_2} * 100 \qquad (1)$$

where C1, M1 and V1 indicate metal concentration from aqua regia, the solid mass before dissolution and liquid volume of the aqua regia, respectively. C2, M2 and V2 are corresponding values for the bioleaching experiment.

MODELING BY ARTIFICIAL NEURAL NETWORK

The neural network used in this study is a feed forward network that has been trained by the Levenberg–Marquardt (LM) back propagation algorithm. Based on this method, network weights and biases are frequently corrected by the LM method. Laboratory data were used to train and validate the model. Experimental data from previous research regarding the bio-extraction of vanadium, nickel and copper metals from plant furnace waste were used for modeling. Three neural networks were trained to estimate each of the metals. In each of the studied models, the target variable and metal extraction percentage were considered as a function of initial pH, initial Fe2+ concentration (CFe), bacterial inoculation percentage (Inoculum Percentage, IP) and process time (t). In the interconnected structure of the neural network, each connection has a weight (w), which represents the corresponding connection strength. The final output of the network is determined as follows:

$$Y = F_p\left\{\sum_{j=1}^{n} w_{kj}\left[F_t\left(\sum_{i=1}^{m} w_{ji}x_i + b_j\right)\right] + b_k\right\} \qquad (2)$$

Where Y is the final response of the network, x is the input of the network, w is the weight, b is the bias, n is the number of hidden layer neurons, m is the number of inputs, and i, j, k are related to the input, hidden and output layers, respectively. F is the transfer function or conversion function used to normalize the output data of each neuron. In this study, the transfer function of the hyperbolic sigmoid tangent was considered for the hidden layer and the linear function was considered for the output layer.

Since the input and output model have different units as well as different ranges, all data were normalized between zero and one before the training process, using equation 3, in order to increase the speed and accuracy of the network:

$$\text{Normalized data} = \frac{\text{Data value} - \text{Min}}{\text{Max} - \text{Min}} \qquad (3)$$

The range of variables used for modeling are pH (1-2.5), inoculation percentage (1-10), Fe2+ concentration (g/l) (0-9), process time (day) (0-15), percentage of vanadium extraction (18.51-82), percentage of nickel extraction (50.24-86.14), and percentage of copper extraction (45.81-87.75). The total of laboratory data, a quarter of the data were used for network training and the rest were used for model evaluation and validation.

In this research, the trial and error method was used, which is a common method in articles. This way a different number of neurons are used in the hidden layer, and finally the optimal number of neurons for the network is determined. This method prevents the preservation of educational data or the so-called overfitting of the artificial neural network.

RESULTS AND DISCUSSION

The neural network model was used in this study to predict the percentage of metal extraction. The trial and error method was used to determine the optimal number of neurons in the middle (hidden) layer. The mean relative errors (MRE), mean square errors (MSE) and absolute fraction of variance (R2) formulas were used to determine the error.

Fig.1 shows the relative error values for different structures (different number of neurons in the middle layer) to predict the percentage of metal extraction. The low number of neurons leads to the low accuracy of the model, and on the other hand, the high number of middle neurons leads to the complexity of the network and the preservation of educational data by the model. As shown in the figure, neural networks with 3, 4, and 4 intermediate neurons can be determined as the optimal structure to predict the percentage of extraction of vanadium, nickel, and copper metals, respectively.

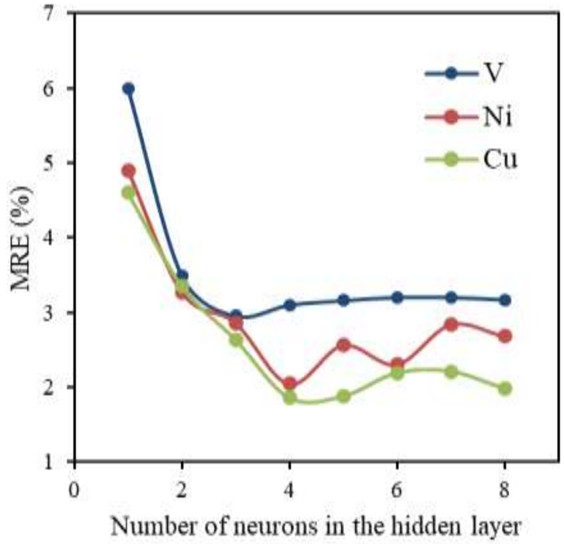

Figure 1. Relative error changes according to the number of neurons in the hidden layer.

The obtained weights and biases for vanadium networks is presented in Tables 1. By substituting weights and biases in Eq. (2), the percentage of metal extraction can be defined in terms of input variables.

Table1. Parameters (weights and biases) of the trained ANN for vanadium extraction.

Neuron	Wji				bj	bk= -5.266
	t	CFe	IP	pH		Wkj
1	-8.546	-35.223	-1.925	1.294	2.178	-5.645
2	-0.927	0.165	-0.982	-1.991	1.397	0.717
3	5.108	-1.045	3.1	1.543	2.966	0.305

A model is assessed as accurate when it can accurately estimate data that did not play a role in its training. A quarter of the laboratory data were used to evaluate the model. Fig. 2 shows the correlation of the values predicted by the neural network with the experimental data related to the vanadium metal for the training and the evaluation of the network. The points of this data are very close to the 45-degree line. This line represents a complete prediction. As can be seen, the network, is highly accurate in estimating evaluation data (one-fourth of the data), in addition to the training data. The MRE, MSE and R2 values obtained for the evaluation data were 5.35%, 10.08%, and 0.9971, respectively. The high accuracy of the trained neural networks for the evaluation data confirmed the validity of the model as well as the logical difference between the training data error and the evaluation.

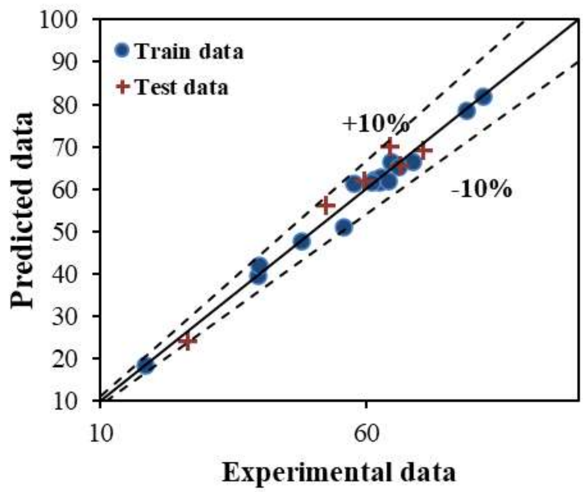

Fig. 2. Comparasion betweeen predicted and experimental data for training and testing

CONCLUSIONS

In this study, the extraction percentage of vanadium, nickel, and copper metals from ash by bioleaching was modeled using artificial neural network . Three separate neural networks were trained to estimate the extraction of each metal in terms of pH, initial Fe^{2+} concentration, bacterial inoculation percentage, and process time. The validity of the proposed models were assessed by data that were not used in the network training phase. The results indicate the high accuracy of artificial neural network modeling in estimating target variables.

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