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Modeling and Prediction of Zinc Extraction Efficiency from Concentrate by Operating Condition and Using Artificial Neural Networks

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***Abstract*—**PH, temperature and time of extraction of each stage, agitation speed and delay time between stages effect on efficiency of zinc extraction from concentrate. In this research, efficiency of zinc extraction was predicted as a function of mentioned variable by artificial neural networks (ANN). ANN with different layer was employed and the result show that the networks with 8 neurons in hidden layer has good agreement with experimental data.

***Keywords*—**Zinc extraction, Efficiency, Neural networks, Operating condition.

I. Introduction

THE roasting of zinc sulphide concentrates produces zinc, iron and other metal oxides (known as calcine), which are readily leached in sulphuric acid solutions [1], [2], with zinc ferrites one of the major species in the leaching residues [1], [3]. These ferrites can be very refractory to chemical attack and one method for their zinc recovery is to leach these residues with hot, concentrated sulphuric acid solutions, although this step will always dissolve a considerable amount of iron. This also requires a large quantity of acid during leaching and then a series of downstream iron and impurity metal removal steps [1], [3].

Several processes to remove dissolved iron have been applied at zinc industries, such as the jarosite $[XFe_3(So_4)_2(oH)_6]$, goethite $(FeOOH)$, hematite (Fe_2o_3) and paragoethite (ferrihydrite) processes; each of them having its own advantages and disadvantages [1], [4]. Notwithstanding, a small iron concentration in the zinc process is beneficial.

Raghavan et al. have proposed that there are two major steps to remove impurities from the zinc sulphate solution to those levels required for the electrolyte [5]. The first stage takes place in the neutral leaching step where co-precipitation of several deleterious impurities such as antimony, arsenic and germanium occurs, along with that of iron hydroxide (1). The second step comprises cementation with zinc dust.

$$2\,FeSo_4+3\,Zn\,o+Mn\,o_2+2\,H_2So_4+H_2o \rightarrow 2\,Fe(oH)_3+3\,Zn\,So_4+Mn\,So_4 \quad (1)$$

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In the case of silicate concentrates, Souza has devised an integrated process to treat zinc silicate concentrates in the same plant that processes zinc sulphide concentrates by the RLE process (the integrated process) [6]. Among the different options available, the A.D. Souza [1] has suggested only one step of zinc silicate leaching where stepwise addition of sulphuric acid dissolves the silicate with a minimum silica gel formation. The neutralisation of the residual acidity with lime or limestone to pH 4.0 provides good settling and filtration properties of the leaching residue. This leaching approach, industrially applied at the Três Marias Zinc facility, presents high zinc recovery (N98%), treating 350,000 tonnes /year of zinc silicate concentrate [1], [7].

II. Artificial Neural Networks

A multi-layer feed forward network structure with input, output, and hidden layer(s) was used in this study as shown in Fig. 1.

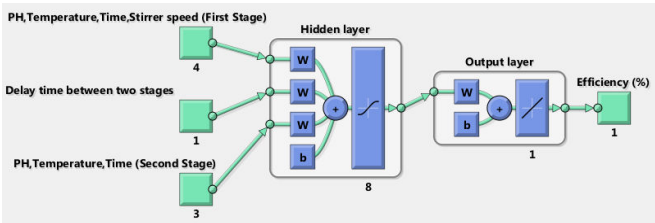

Fig. 1 A schematic diagram of multilayer artificial neural network used in this study

Several ANN models were trained using the training data set. The back-propagation algorithm was utilized in training of ANN models. [8], [9] A hyperbolic-tangent transfer function was used in all cases. The back-propagation algorithm uses the supervised training technique where the network weights and biases are initialized randomly at the beginning of the training phase. For a given set of inputs to the network, the response to each neuron in the output layer is calculated and compared with the corresponding desired output response. The errors associated with desired output response are adjusted in the way that reduces these errors in each neuron from the output to the input layer. The error minimization process is achieved using gradient descent rule [8], [9]. To avoid the potential problem of over-fitting or memorization while employing the back- propagation algorithm, the option of saving the best configuration was selected where the network with the best

result is saved during the selected long number of training cycles of 2,000. The SaveBest option allows running train/test cycles and saving the network with the best result during the run. One of the problems that can occur with the back propagation and associated network is the problem of over-fitting.

The symptom of this is when the network is performing well on the training data, but poorly on independent test data. SaveBest is one of a number of ways to deal with this [8], [10].

III. Experimental Data

Efficiency of zinc extraction was experimented by Atashy H. and et al. [11]. These experimental data are shown in Table I.

TABLE I
EFFICIENCY OF ZINC EXTRACTION IN DIFFERENT OPERATING CONDITION [11]

	First stage				Second Stage				
Number of Experiment	PH	Temperature (°C)	Time (Min)	Agitation speed	T_m	PH	Temperature (°C)	Time (Min)	Efficiency (%)
1	3.5	45	240	50	30	6	45	210	45.1
2	3.5	50	240	50	30	6	45	210	48.5
3	3.5	50	240	80	30	6	45	210	51.2
4	3.5	50	240	200	30	6	45	210	57.5
5	3	60	240	200	30	6	60	210	62.4
6	3	60	240	200	30	5.5	60	210	67.5
7	3	60	240	200	30	6.5	60	210	53.4
8	3	60	240	200	30	5.3	60	210	73.5
9	3	60	240	200	30	4.5	60	210	49.5
10	3	60	240	200	30	5.1	60	210	69.2
11	3	70	240	200	30	5.3	70	210	75.2
12	3	80	240	200	30	5.3	80	210	77.6
13	3	90	240	200	30	5.3	90	210	78.2
14	2.5	90	240	200	30	5.3	90	210	77.3
15	2	90	240	200	30	5.3	90	210	77.9
16	2	90	200	200	30	5.3	90	200	78.2
17	2	90	180	200	30	5.3	90	180	78.3
18	2	90	170	200	30	5.3	90	170	78.2
19	2	90	160	200	30	5.3	90	160	79.9
20	2	90	180	200	30	5.3	90	160	78.1
21	2	100	180	200	30	5.3	100	180	78.9
22	2	100	180	200	30	5.3	100	160	78.9
23	2	100	180	200	30	5.3	100	150	78.2
24	2	100	180	200	30	5.3	100	180	76.8
25	2	105	180	200	30	5.3	105	180	79.8
26	2	105	180	200	30	5.3	105	160	79.2
27	2	105	160	200	30	5.3	105	180	79.4
28	2	105	180	200	30	5.3	100	180	79.6
29	2	105	180	200	30	5.3	90	180	78.3
30	2	105	180	200	30	5.3	105	180	80
31	2	30	180	100	30	5.3	30	180	79.02
32	2	30	180	50	30	5.3	30	180	78.08
33	2	30	170	50	30	5.5	30	180	74.01
34	2	30	180	50	30	5.5	30	190	75.81
35	2	30	180	50	30	5.5	30	170	74.91
36	2	30	180	50	30	5.5	30	180	75.85
37	2	30	180	50	30	6	30	170	69.91
38	2	30	170	50	30	6	30	180	70.41
39	2	30	180	50	30	6	30	180	71.86
40	2	30	180	50	30	6	30	190	71.84
41	2	30	180	50	30	6	30	200	71.85
42	2	30	190	50	30	6	30	200	71.82
43	2	30	200	50	30	6	30	200	70.92
44	2	30	200	50	30	6	30	210	70.91
45	2	30	210	50	30	6	30	210	68.04
46	2	30	230	50	30	6	30	210	65.03

	First stage				Second Stage				
Number of Experiment	PH	Temperature (°C)	Time (Min)	Agitation speed	T_m	PH	Temperature (°C)	Time (Min)	Efficiency (%)
47	3	30	230	50	30	6	30	210	45.02
48	3	35	230	50	30	6	35	210	45.8
49	3	45	230	200	30	6	45	210	46.9
50	1.5	30	420	200	30	5	30	180	80.01
51	1.5	30	350	200	30	5	30	180	80.02
52	1.5	30	300	200	30	5	30	180	79.11
53	1.5	30	280	200	30	5	30	180	79.01
54	1.5	30	250	200	30	5	30	180	78.91
55	1.5	30	220	200	30	5	30	180	78.71
56	1.5	30	200	200	30	5	30	180	78.13
57	1.5	30	180	200	30	5	30	220	78.02
58	1.5	30	180	200	30	5	30	200	78.02
59	1.5	30	180	200	30	5	30	180	78.02
60	1.5	30	170	200	30	5.3	30	170	77.91
61	1.5	30	170	200	30	5.3	30	180	78.08
62	1.5	30	180	200	30	5.3	30	180	79.02
63	2	30	180	250	30	5.3	30	180	80
64	2	30	180	200	30	5.3	30	180	80.01
65	2	30	180	150	30	5.3	30	180	79.51
66	2	105	180	200	30	5.3	105	180	80
67	2	105	180	200	25	5.3	105	180	80.98
68	2	105	180	200	20	5.3	105	180	82.01
69	2	105	180	200	15	5.3	105	180	82.98
70	2	105	180	200	10	5.3	105	180	84.01
71	2	105	180	200	5	5.3	105	180	85.09
72	2	105	180	200	0	5.3	105	180	86.01
73	2	105	180	200	35	5.3	105	180	79.08
74	2	105	180	200	45	5.3	105	180	78.91
75	2	105	180	200	60	5.3	105	180	77.01

IV. Result and Discussion

The input layer consisted of eight (8) neurons which corresponded to the PH, temperature, time and agitation speed of first stage, delay time between two stage, PH, temperature and time of second stage. The output layer had one neurons representing efficiency of zinc extraction (Fig. 1). The number of hidden layers and neurons within each hidden layer can be varied on the complexity of the problem and data set. In this study, the number of hidden layers was selected one. The number of neurons in hidden layer varied from two to 10 with increments of one. Table II show the result of different neurons in hidden layer.

TABLE II
Result of Different Neurons in Hidden Layer

Number of neurons in hidden layer	Regression coefficient	Error
1	0.9528	0.1870
2	0.9879	0.0302
3	0.9944	0.0196
4	0.9981	0.0057
5	0.9981	0.0057
6	0.9981	0.0057
7	0.9981	0.0057
8	0.9983	0.0051
9	0.9983	0.0051
10	0.9983	0.0051

Table II shows that, artificial neural network with 8 neurons in hidden layer has the best regression coefficient and minimum error. Regression coefficient of experimental data and predicting data is shown in Fig. 2.

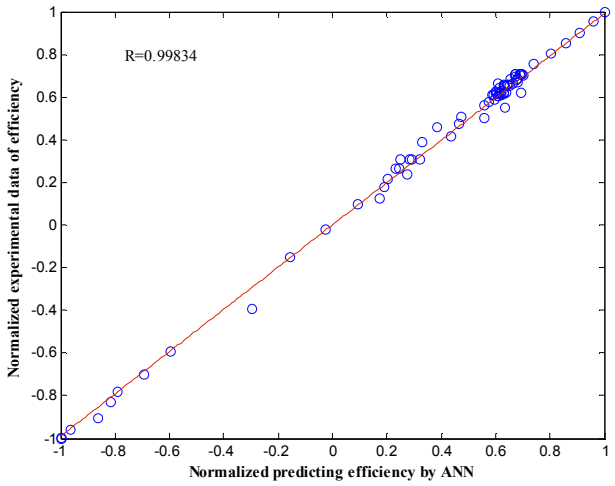

Fig. 2 Regression coefficient of experimental data and predicting data

This figure shows good agreement between experimental data and predicting data.

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