International Journal of Mining Science and Technology 24 (2014) 461–465

Contents lists available at ScienceDirect

International Journal of Mining Science and Technology

journal homepage: www.elsevier.com/locate/ijmst

Performance prediction of gravity concentrator by using artificial neural network-a case study

Panda Lopamudra *, Tripathy Sunil Kumar

Research and Development Division, Tata Steel Ltd., Burma Mines, Jamshedpur 831007, India

ARTICLE INFO

Article history:
Received 23 August 2013
Received in revised form 19 October 2013
Accepted 20 January 2014
Available online 18 June 2014

Keywords:
Chromite
Artificial neural network
Wet shaking table
Performance prediction
Back propagation algorithm

ABSTRACT

In conventional chromite beneficiation plant, huge quantity of chromite is used to loss in the form of tailing. For recovery these valuable mineral, a gravity concentrator viz. wet shaking table was used. Optimisation along with performance prediction of the unit operation is necessary for efficient recovery. So, in this present study, an artificial neural network (ANN) modeling approach was attempted for predicting the performance of wet shaking table in terms of grade (%) and recovery (%). A three layer feed forward neural network (3:3–11–2:2) was developed by varying the major operating parameters such as wash water flow rate (L/min), deck tilt angle (degree) and slurry feed rate (L/h). The predicted value obtained by the neural network model shows excellent agreement with the experimental values.

1. Introduction

Chromite ore plays an important role in industrial growth of any country. Major applications of chromite ore includes ferro-chrome production, making stainless steel, chrome plating, making anti corrosion alloy and also as a catalyst. India is the third largest chromite producer in world and approximately 98% of chromite ores deposits of India are present in Sukinda chromite belt of Odisha and out of which only 47% is of metallurgical grade [1].

Due to increase in demand of chromite ore, high grade chromite deposits are diminishing day by day. Therefore, it has become an essential part for mineral industry to enrich chromite values from the tailings. COB (Chrome Ore Beneficiation) Plant, Sukinda produces 50 TPH of tailings, which contains chromite along with other associated gangue minerals like goethite, kaolinite, quartz, gibbsite, etc [2–4]. These generated tailings not only cause natural loss of resources, but creates environmental problems also. For addressing the above problems, one solution could be to enrich the chromite value from tailings. Different attempts were taken by many researchers. They had used different beneficiation techniques like magnetic separation, floatation, multigravity separator, wet shaking table and floatex density separator etc, for enrichment of chromite value from tailings [2–6]. Further enrichment of these tailing values are possible by the wet shaking table if this unit operation can be included the beneficiation circuit and can be operated with proper optimised condition.

Moreover continuous operation of wet shaking table in commercial plant needs prompt control system and for this one needs correlation between input and output variables. Substantial research work was reported on wet shaking table including developing models and developing correlation between the operating parameters by using statistical analysis [3,7]. However limited progress has been made in developing a predictive model which is useful in building a control system in commercial scale.

So in this present investigation, an attempt was made to develop an artificial neural network (ANN) approach for developing predictive models for the gravity concentrator (wet shaking table) which will provide the requisite correlation between the input and output parameters. The operating parameters such as wash water flow rate, deck tilt angle and slurry feed rate of wet shaking table considered in this preliminary study as the input parameters for developing the predictive ANN model whereas grade (%) and recovery (%) of the concentrate fraction were considered as the output parameters.

2. Materials and methods

2.1. Feed characterisation

About one tone of representative tailing samples were collected from a typical tailing pond of chromite beneficiation plant of Sukinda, India. The collected samples were dewatered and dried

* Corresponding author. Tel.: +91 657 6648960.
E-mail address: l.panda@tatasteel.com (L. Panda).

http://dx.doi.org/10.1016/j.ijmst.2014.05.007
2095-2686/

Table 1
Chemical analysis of chromite tailing sample.

Cr_2O_3 (%)	Fe (%)	Al_2O_3 (%)	SiO_2 (%)	MgO (%)	LOI
24.26	23.51	13.61	17.58	5.35	7.60

to remove moisture. The dried sample was mixed properly and sample has been prepared for characterisation and beneficiation test work. The chemical analysis of the feed sample is given in Table 1. From the table it is evident that the feed sample contains huge amount of iron as gangue content along with chromite. The characterisation of the feed sample includes size analysis and size wise chemical analysis. The size distribution of the feed sample was carried out by using standard sieves and the distribution is shown in Fig. 1. It can be observed that about 33% of the feed sample having the size below 25 μm and 80% of the sample is passing below 250 μm, so the feed sample contains huge quantity of slime material. In addition to this, size wise chemical analysis was carried out and the results are given in Table 2. From the table it can be envisaged that the maximum amount of Cr_2O_3 is distributed at intermediate size fraction. It was also reported that the tailing sample contains chromite along with other associated gangue minerals like goethite, hematite, gibbsite, quartz and kaolinite [3–5].

2.2. Methods

The experimental campaign was carried out in a wet shaking table which is slime deck having rectangular shape of 350 mm × 1000 mm dimension with linoleum as surface material. The wet shaking table used in the study was supplied by M/s the Deister Concentrator Company Inc., USA. The experimental set up consists of feed slurry tank, a peristaltic pump and the wet shaking table. The feed slurry tank having 100 liters capacity was attached with a stirrer to keep the solids in uniform suspension throughout the experimental run. The peristaltic pump was used to feed the desired quantity of slurry to the separation unit. The process

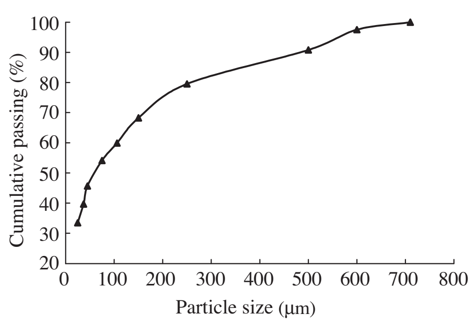

Fig. 1. Size distribution of the chromite plant tailing sample.

Table 2
Size wise chemical analysis of the chromite tailing sample.

Size (μm)	*Wt* (%) retained	Assay value (%)				
		Cr_2O_3	Fe(T)	Al_2O_3 (%)	SiO_2 (%)	MgO
+600	2.47	23.76	19.20	11.80	11.21	5.80
−600 + 500	6.74	23.18	22.20	14.35	13.10	4.50
−500 + 250	11.26	18.20	21.86	16.14	18.00	3.70
−250 + 150	11.26	21.20	21.87	16.40	18.77	4.34
−150 + 106	8.35	27.50	18.90	14.50	17.80	6.10
−106 + 75	5.80	26.30	18.90	15.00	21.10	5.70
−75 + 45	5.97	28.52	14.32	13.66	21.40	6.20
−45 + 37	6.22	29.26	15.19	12.12	18.14	6.26
−25	33.45	21.00	23.61	12.16	14.74	5.60

Table 3
Process variable ranges used in the laboratory test work.

Process variables	Parameter values	
	Lower value	Higher value
Wash water flow rate (L/min)	2.5	7.5
Deck tilt angle (degree)	2	6
Slurry feed rate (L/h)	100	160

variables such as wash water flow rate, deck tilt angle and feed slurry flow rate was varied to observe the effect on performance of wet shaking table. For all the experimental runs solid percentage were kept constant at 20%. The detail scopes of experiments have shown in the Table 3. The products of each test in wet shaking table was analysed for grade (%) and recovery (%). The obtain results from the experiments were subjected for developing the predictive models by using artificial neural network which is explained in the next section.

3. Artificial neural network

Artificial neural network is a modeling tool which can be successfully applied to complex non linear systems where it is difficult to establish correlations between the inputs and output variables. Artificial neural network (ANN) performs like a neuron system present in the human brain. Similar to a human brain the ANN gets trained from the existing set of data and then the trained ANN predicts the unknown output from a given set of input data. Among different types of neural network, multilayer perception (MLP) feed forward neural network is the most commonly used [8–11]. The MLP neural network normally consists of an input layer, an output layer and one or more hidden layer(s) based on the complexity of the problem in hand. The signal passes from the input layer to the output layer through hidden layer(s). The input layer receives the incoming data then these data are processed in hidden layer and the outcomes of the model are given by output layer. Generally MLP, it trends between non linear function between non linear inputs to target output for reducing the error function.

$$E(n) = \frac{1}{N}\sum_{i=1}^{N}(d_i - Y_i)^2 \tag{1}$$

where $E(n)$ is the mean square error function; d_i the target response and Y_i the actual output response.

In the current study a three layer feed forward ANN architecture (3:3–11–2:2) has been proposed for predicting grade and recovery of the tabling process. The optimised ANN architecture is shown in Fig. 2. Among different learning algorithms back propagation

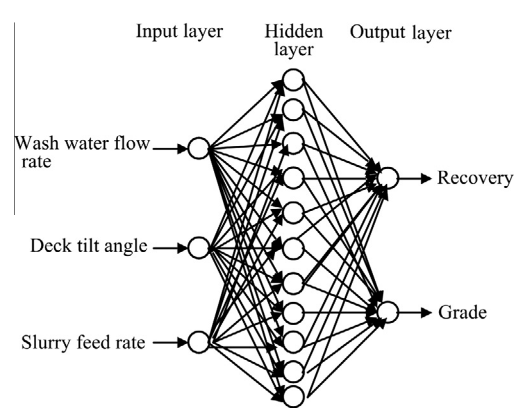

Fig. 2. Optimized MLP architecture for grade and recovery.