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ESTIMATION OF GAS HOLDUP AND INPUT POWER IN FROTH FLOTATION USING ARTIFICIAL NEURAL NETWORK

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Abstract: *Multivariable regression and artificial neural network procedures were used to modeling of the input power and gas holdup of flotation. The stepwise nonlinear equations have shown greater accuracy than linear ones where they can predict input power, and gas holdup with the correlation coefficients of 0.79 thereby 0.51 in the linear, and R2=0.88 versus 0.52 in the non linear, respectively. For increasing accuracy of predictions, Feed-forward artificial neural network (FANN) was applied. FANNs with 2-2-5-5, and 2-2-3-2-2 arrangements, were capable to estimating of the input power and gas holdup, respectively. They were achieved quite satisfactory correlations of 0.96 in testing stage for input power prediction, and 0.64 for gas holdup prediction.*

Keywords: *Flotation; Input Power; Gas Holdup; Regression; Artificial Neural Network*

1. INTRODUCTION

Gas dispersion properties include bubble size (d_{32}), gas holdup (ε_g ,%), while bubble surface area flux (S_b), and input power (P) which are effective parameters related to flotation performance. During the last 10 years, some investigations have been carried out to measure these parameters in mechanical flotation cells [1-7]. The gas holdup as a function of broad groups of chemical, operational, and machine variables presents in froth flotation [8-12]. The gas holdup is related to bubble size (a function of frother characteristics, concentration, solids coverage, and air flow rate), slurry flow rate, and solids content. It also defines the bubble flow density (or the bubble surface area flux), which is related to flotation kinetics [13]; Therefore, determination of the gas holdup for diagnosing, and controlling a flotation cell during the operation should be fruitful.

Based on an operating aspect, the impeller rotational speed (N_s) provides an opportunity to control the specific input power (P) to the flotation cell slurry, and impeller tip speed. Recent studies have highlighted the important influence of local turbulent energy dissipation (ε) on the both frequency of bubble–particle collision, and stability efficiency of the particle–bubble aggregate [14-16]. Because there is difficulty in establishing the exact spatial average of local energy dissipation for a given turbulent mixing system, the mean energy dissipation ($\bar{\varepsilon}$) in a flotation cell containing mass (M) of slurry is determined by the equation below [17]:

$$\bar{\varepsilon} = \frac{p}{M} \tag{1}$$

Typical mean energy dissipation values in industrial flotation cells change from 1.0 to 5.0 W/kg, depending upon the cell size, installed motor power, transmission losses, and slurry density [18]. It is well recognized that energy dissipation is a local function, and also the maximum value near the impeller may be higher than the mean energy dissipation across the entire cell (10–20 times higher) [19].

It is thought useful to develop empirical models to estimate gas dispersion factors in different conditions because of poor understanding of gas dispersion phenomena, and difficulty in measuring them in flotation cells. In other words, these models could be used readily for applications such as cell comparison,

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selection, new cell installation, scale-up for plant design, cell optimization, circuit modeling, and simulation, etc. Using the laboratory data, computing techniques have been applied to many aspects of mineral processing that were mentioned in the references [20-25].

The aim of the present work is prediction of gas holdup (ε_g ,%), and input power (P,W) according to effective variables on froth flotation (Impeller peripheral speed (N_s , m/s), superficial gas velocity (J_g , cm/s), and pulp density (P_d , %) using experimental data obtained at a laboratory scale. The multivariable regression, and feed forward artificial neural network (FANN) were used for those estimations.

2. EXPERIMENTAL PROCEDURE

All flotation experiments were carried out in a laboratory Denver flotation cell. An impeller diameter of 0.07 m was used for agitation in a cell with a square section of 0.12 and 0.1 m height. The type of impeller was a Rushton turbine with 8 paddles, and a stator was used around the rotor. All tests were done without any baffling in the flotation cell. MIBC (methyl iso-butyl carbinol), and Quartz particles (solid density of 2.65 g.cm^{-3} and particle size of -500) were used for flotation experiments. Concentration of the frother was 22.4 ppm.

3. RESULTS AND DISCUSSION

3. 1. Gas Hold Up

The gas holdup (ε_g ,%) was measured using a device similar Jameson and Allum [26]. According to Fig. 1, it consisted of a 50 milliliter volume cylinder with a plunger attached to a central rod. The plunger had an O-ring for an air tight fitting when it moved inside the cylinder. The plunger drew into the cylinder, encapsulating a volume of aerated pulp in the space between the cylinder and plunger.

The pulp-air mixture encapsulated between the cylinder, and plunger was emptied into a measuring cylinder at which point the air escaped into the atmosphere. The volume of the space between the cylinders was determined by water

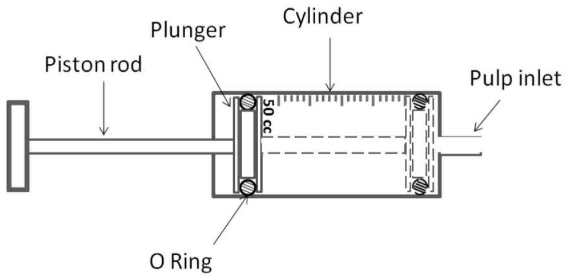

Fig. 1. Schematic of a device for measuring gas holdup

calibration. By calculating the difference between the measured volume of slurry, and the calibrated volume of water, the volume of air in the aerated pulp was obtained, finally ε_g was the volume fraction of air in each sample.

For $2.93 < N_s < 6.12$ m/s, $0.32 < J_g < 0.94$ cm/s, and $0 < P_d < 15.6$ %, gas holdup was obtained $3.04 < \varepsilon_g < 22\%$.

3. 2. Input Power

For calculating net power consumption, at first equipment power consumption was determined without pulp. Then, flotation cell was filled with pulp and power consumption was measured again. Net power consumption was calculated by reducing these two measured powers.

For $1.83 < N_s < 6.12$ m/s, and $0 < P_d < 40$ % input power was achieved $0.05 < P < 52.58$ W. In mechanical flotation cells, power intensity of 1 to 2 kW.m^{-3} is common [27]. Thus, an impeller peripheral speed of $2.93 < N_s < 3.66$ (impeller diameter of 0.07 m and impeller speed of 800 to 1000 rpm) is suitable for the flotation process.

3. 3. FANN Procedure

Few years, artificial neural networks (ANNs), and particularly feed forward artificial neural networks (FANNs) have been extensively studied in academia as process models, and are increasingly being used in industry [28]. Neural networks of multi-layer perceptron (MLP) type are often used as black-box models of systems where the underlying relations are poorly known or extremely complex [29]. The main advantages

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of neural network over conventional regression analysis are: free of linear supposition, large degrees of freedom, and more effectively deal with non-linear functional forms [30].

A Feed forward neural network of multi-layer perceptron type can be used as a nonlinear

black-box model in data-mining tasks, and typically consists of an input layer, hidden layers with sigmoid activation functions, and an output layer with linear activation function. Each node in the input layer is linked to all the nodes in the hidden layer using weighted connections. Similar connections exist between hidden, and output layer as also between nodes of hidden layers [31]. The number of nodes in the layers is adjustable parameters, whose magnitudes are governed by issues such as the desired prediction accuracy, and generalization performance of the FANN model. FANN is one of the most popular, and well documented neural network models, which has a good software support. In this study, two FANN models have been developed for predictions of gas holdup (ε_g ,%), and input power (P, W).

3. 4. Regression

By a least square mathematical method, inter correlations between input, and output variables were calculated (table 1). From the mentioned results it can be concluded that the worthy relationships are for impeller speed with positive effect on both power, and gas holdup. In addition, the increase of gas velocity rates have negative effect on input power, and in contrary term, have positive effect on gas holdup. The results show that there is no significant correlation between pulp density and gas holdup.

The stepwise variable selection procedure was used to prepare regression equations. The best linear, and non linear multivariable equations between the froth flotation operational conditions with input power (P, W), and gas holdup (ε_g ,%) can be presented as the following equations:

$$P(wat) = -34.137+11.775N_s - 12.969J_g+ 0.164P^2_d \qquad R^2= 0.79 \qquad (2)$$

$$P(wat)=7.809-6.824N_s+1.718N^2_s+293.254P_d-70.134P^2_d+5.493P^3_d - 0.141P^4_d-6.748J_g \qquad R^2=0.88 \qquad (3)$$

$$\varepsilon_g(\%)= -7.285 + 3.282 N_s+ 5.961 J_g \qquad R^2=0.51 \qquad (4)$$

$$\varepsilon_g(\%)= -12.634+ 3.288 N_s+ 43.729 J_g-76.673J^2_g + 45.548J^3_g \qquad R^2=0.52 \qquad (5)$$

The distribution of difference between power,

Table 1. Inter- item correlation matrix for input, and output variables

Parameters	Input power (wat)	Impeller peripheral speed (m/s)	Pulp density (%)	Gas velocity (cm/s)	Gas holdup (%)
Input power (wat)	1	0.85	0.06	-0.28	0.30
Impeller peripheral speed (m/s)	0.85	1	-0.02	-0.05	0.64
Pulp density (%)	0.06	-0.02	1	0.05	-0.07
Gas velocity (cm/s)	-0.28	-0.05	0.05	1	0.28
Gas holdup (%)	0.30	0.64	-0.07	0.28	1

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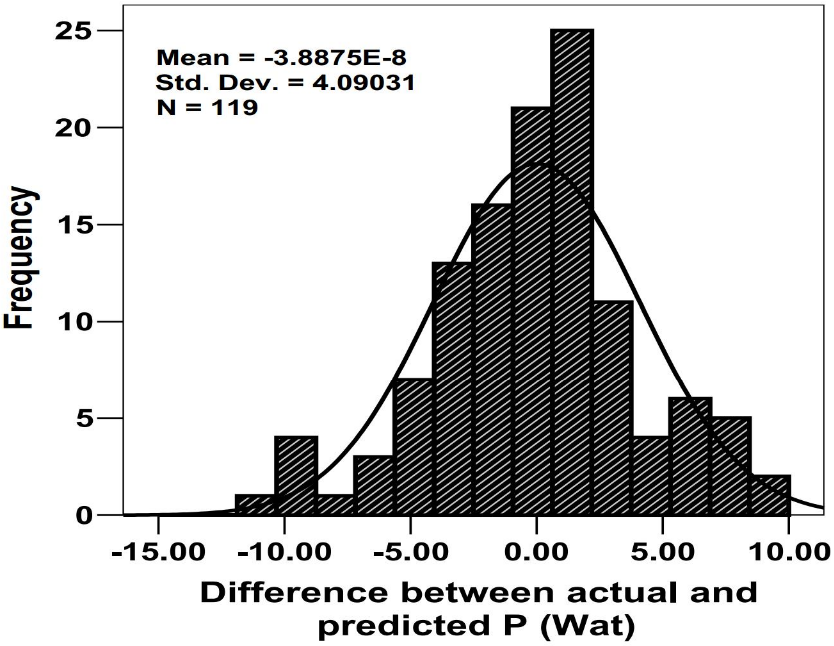

Fig. 2. Distribution of the difference between measured power values and estimated power values obtained from multivariate regression Eq. (2)

and gas holdup predicted from Eq. (3), and (5) with actual determined amounts of them according to their frequency are shown in Fig. 2, and 3, respectively.

3. 5. FANN Results

According to the Eqs. (2), and (4), the selected variables were determined as the best variables for the predictions of P, and ε_g. Therefore these variables were chosen as inputs to FANN for the improvement of estimations.

If certain preprocessing steps (normalizing processes) were performed on the network inputs and targets, neural network training can be made more efficient; therefore, before training, it is often useful to scale the inputs, and targets because they always fall within a specified range. For ANN work, all input, and output data were scaled using the following model:

$$N_p = (A_p - \text{mean}A_{ps}) / \text{std } A_p \qquad (6)$$

Where, A_p is actual parameter, mean A_{ps} is mean of actual parameters, stdA_p is standard deviation of actual parameter and N_P is normalized parameter (input). The mean, and standard deviation of input, and output variables for pre-processing are given in Table 2. After determining the number of input variables by

Table 2. Pre-processing parameters for ANN

Variable	Minimum	Maximum	Mean	Std. Deviation
Impeller peripheral speed (m/s)	2.93	6.12	4.58	0.84
Pulp density (%)	0	15.6	8.09	6.25
Gas velocity (cm/s)	0.11	0.94	0.46	0.22
Gas holdup (%)	2.8	19.8	10.48	4.16
Input power (wat)	2.01	38.19	15.22	11.72

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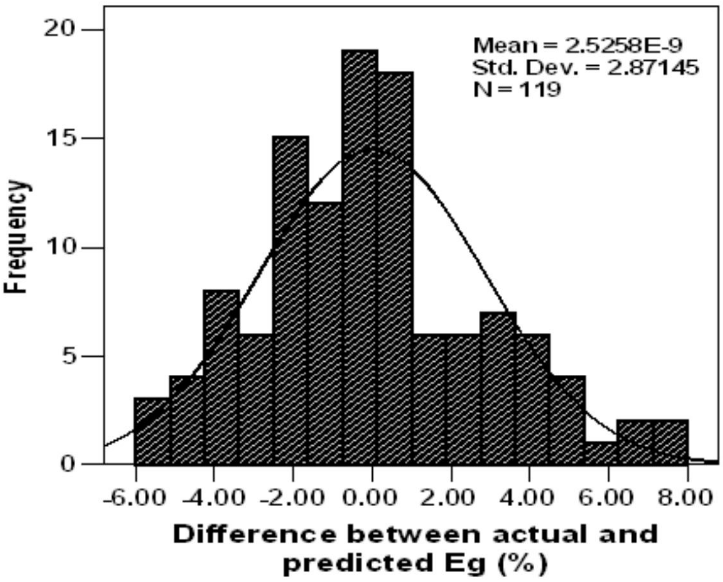

Fig. 3. Distribution of the difference between measured gas holdup values and estimated gas holdup values obtained from multivariate regression Eq. (3)

statistical means, the most appropriate architecture for the network was determined. From the total dataset (119 laboratory experiments) were used for the input power and gas holdup predictions by FANN, 100 samples were input for training, and 19 sets were used for testing the network. The training process was stopped after 3000 epochs.

Several FANNs were created, trained, and tested to achieve a suitable FANN topology, which is able to predict accurate values of outputs. The number of neurons in the hidden layers was obtained by the trial and error method so that the error between the desired, and estimated outputs was minimized. The 2–5–5–5, and 2-2-3-2-2 FANN models adequately

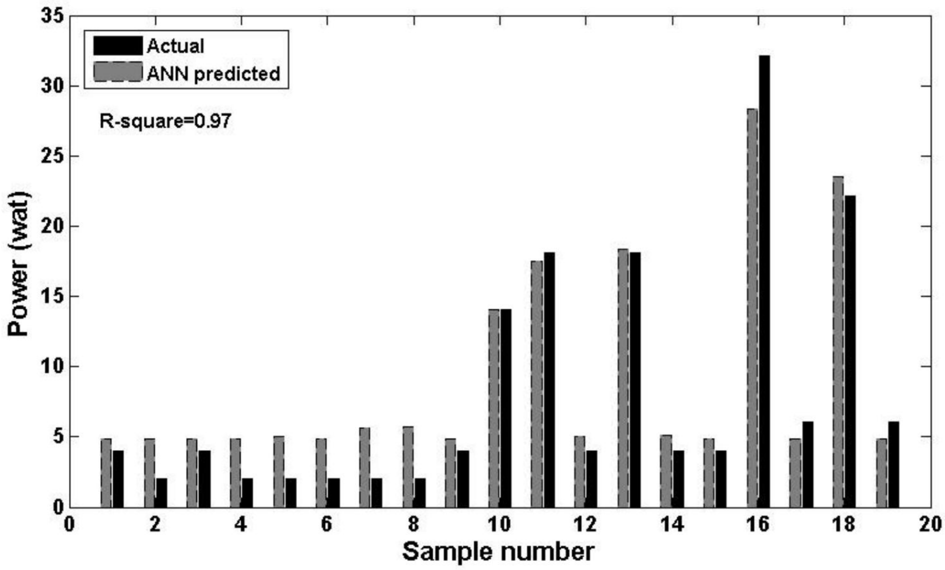

Fig. 4. Comparison between measured power values and estimated power values obtained from ANN

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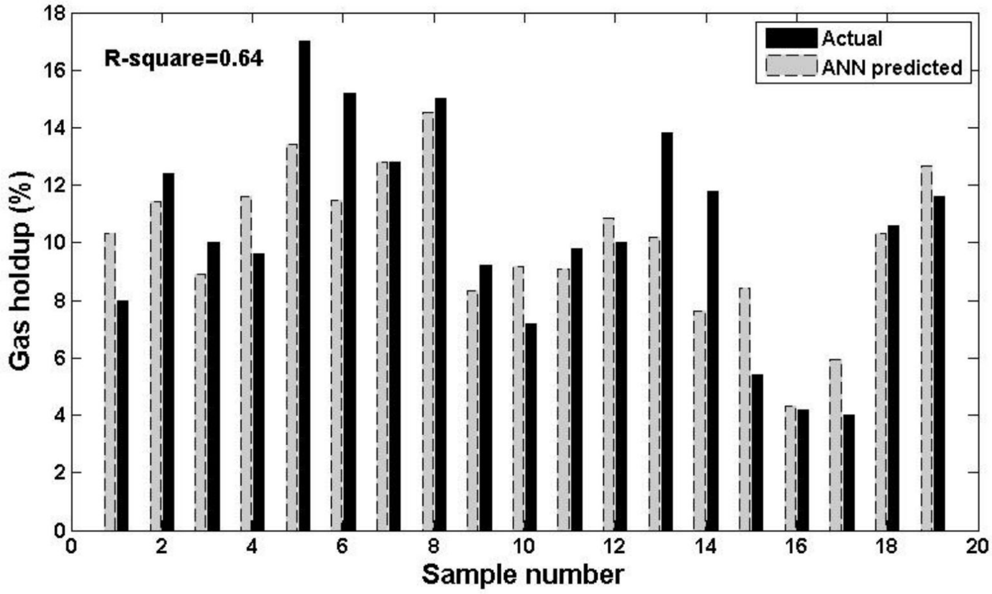

Fig. 5. Comparison between measured gas holdup values and estimated gas holdup values obtained from ANN

recognized the effects of different operational conditions on the outputs, and usefully predicted both input power, and gas holdup, respectively. Figs 4 and 5 show the relationship between estimated variables by FANN model from testing phase and their determined value by the laboratory methods. The testing sets, which actually test how good the models are, show that the models can estimate input power, and gas holdup quite satisfactorily. The correlation coefficient (R^2) values for testing sets are 0.96 and 0.64 for input power, and gas holdup predictions, respectively. Upon comparison with the regression results, the FANN models were shown to have greater accuracy in predicting values from the same inputs.

4. CONCLUSION

Predicting input power, and gas holdup using regression, and artificial neural network is put forward. 119 laboratory data sets were used for the prediction operations. The input-correlations between operational conditions with input power, and gas holdup show that with the increase of gas velocity rates both input power, and gas holdup values increase remarkably. Through the modeling data, the correlation coefficients between the prediction value, and the laboratory value of input power, and gas holdup were 0.88, and 0.52 for the non linear regression, where they can predict them with greater accuracy than linear ones with R^2=0.79, and 0.51. Using the FANN method for the modeling and predicting were achieved R^2=0.96, and 0.64 for input power, and gas holdup, respectively. The results showed that laboratory operational conditions can be used as predictors of input power, and gas holdup successfully, and can create accurate models. As a comparison between equations, and FANN models, it was found that the performances of FANN models are better than regression models. Therefore, it can be effectively used in estimations of input power, and gas holdup.

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NOMENCLATURE

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A_p	Actual parameter
N_p	Normalized parameter
$stdA_p$	Standard deviation of actual parameter
A_{ps}	Mean of actual parameters
N_s	Peripheral speed
ε_g	Local energy dissipation
d_{32}	Sauter mean diameter
P	Input power
ε_g	Gas holdup
J_g	Superficial gas velocity
P_d	Pulp density
$\overline{\varepsilon}$	Mean energy dissipation
M	Liquid mass
S_b	Bubble surface area flux
ρ	Fluid density

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