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Modeling Study of Beach Placer Minerals using Artificial Neural Network: A Case Study

Pallavika, V.K. Kalyani[1] and V.J. Loveson

Central Mining Research Institute, Dhanbad – 826 001
[1] Corresponding Author's Email: vkkalyani@yahoo.com

Abstract

In recent years, artificial neural network (ANNs) have been found to be an attractive tool for steady-state/dynamic process modeling, and model based control in situations where the development of phenomenological or the empirical models just given either becomes impractical or cumbersome. ANN technology is well suited to solve problems in the mineral industry, and is expected to have a significant impact in many technological areas. Beneficiation plants for beach sand minerals are often very complex in nature with a number of alternative flow sheets are possible for the same mineral sand deposits.

Computer simulation is a very useful tool to study the different flowsheets and the combination of the flowsheet parameters. Such simulation study can be useful to predict the performance of the beneficiation plant when it is still on the drawing board. At the stage of experimentation, simulation can greatly help in substantially reducing the number of experiments necessary to arrive at the optimum flowsheet. In the present paper, a three layer feed forward artificial neural network (ANN) model, trained using the error back propagation algorithm, has been established to simulate the beneficiation of beach placer minerals. The network model validates the experimentally observed trends. The optimal model parameters in terms of network weights have been estimated and can be used for computing parameters of the process over wide-ranging experimental conditions.

INTRODUCTION

In recent years, artificial neural network (ANN) has been used widely for steady-state/dynamic process modeling, and model based control in situations where the development of phenomenological or the empirical models developed, either becomes impractical or cumbersome (Hernandez et. al 1992, Narendra et. al 1990). The ANN technology is well suited to solve problems in the mineral industry, and is expected to have a significant impact in many technological areas (Hunt et.al 1992, Tendulkar et. al 1998).

Beach sand is one of the major sources of heavy minerals like Ilmenite, Rutile, Zircon, Monazite, Sillimanite (Prabhaker et.al 2004), Garnet, Leucoxene and other amphibole and pyroxene group of silicate minerals. After the discovery of the Monazite in Quilon beach sands by Schorrberg, a German scientist, the beach placer industry started flourishing in India. Conventionally, beach placer beneficiation process consists of choosing and sizing appropriate process equipment, as well as fixing the nominal operating procedures (Kalyani et.al, 2005). Availability of a process model assumes considerable importance in the process design activity.

For a given process, a "first principle (phenomenological)" model can be constructed from the knowledge of mass, momentum, energy balances etc, as well as from other mineral processing principles. Owing to the lack of a good understanding of the underlying phenomena, development of phenomenological process models poses considerable difficulties. Moreover, nonlinear behavior, being a common feature of mineral processing units, leads to complex nonlinear models, which in most cases are not amenable to analytical solutions. Thus, computationally intensive numerical methods must be utilized for obtaining solutions. The difficulties associated with the construction and solutions of the phenomenological models necessitate the exploration of alternative modeling formalisms. Process identification via. empirical models are one such alternative. A fundamental deficiency of the empirical modeling approach is that model structure (form) must be specified a priori (Nandi et.al. 2001). Satisfying this requirement, especially for nonlinearly behaving processes is a cumbersome task, since it involves selecting heuristically an appropriate model structure from numerous alternatives. Artificial neural networks, although introduced by neuroscientist to model human learning behavior, have acquired numero-uno status in artificial intelligence (AI) technology. AI was conceived in mid 1950s with the goal of emulating on computers the human thought processes that needed intelligence. Towards this goal, AI research has been focused on developing software orientated computational approaches to mimic human intelligent behavior. The problem-solving route adopted by AI system is markedly different from the traditional numerical one employed by the scientific and engineering community in which well-defined algorithms solutions exist for a mathematically well-defined problem. Most note worthy applications of AI, prior to the resurgence of ANNs in the last decade, have been expert systems though the software based devises that play games and process natural languages have also been AI products.

Neural networks are the models inspired by the structure and functions of biological neurons. A neural network is composed of neurons, or nodes, which represent the neuron bodies. Neurons are interconnected, and these interconnections are quantified by connecting weights. The ANNs can approximate complex nonlinear relationships existing between independent (ANN input) and dependent (ANN output) variables to an arbitrary degree of accuracy (Nahas et.al 1992). The advantages of a neural network based process model are: (i) it can be developed solely from the historic process data (i.e., without invoking process phenomenology); (ii) even multiple input – multiple output relationships can be approximated easily and simultaneously, and (iii) the model possesses a good generalization ability owing to which it can accurately predict the outputs corresponding to a new set of inputs that were not part of the data used for constructing the ANN model (Nandi et.al 2001, Narendra et. al 1990)

DEVELOPMENT OF ANN MODEL

The structure of ANNs forms the basis for information storage and governs the nets learning process (Hunt et.al 1992). The ANNs comprise inter connected simulated neurons as shown in Fig. 1. A neuron (node) is an entity capable of receiving and sending signals, and is simulated by means of software algorithm on a computer. Each simulated neurons in a given layer receives signals from other neurons in the preceding layer, sums these signal and transforms this sum usually by means of a linear function y=x or a non-linear function like sigmoid function as shown below

$$y = \frac{1}{1+e^{-x}}; \ \frac{dy}{dx} = y(1-y) \tag{1}$$

and sends the result to other neuron in the next layer (Hornik et.al 1989). A weight that modifies the signal being communicated is associated with each of the connections between neurons. The information content of the net is embodied in the set of all these weights, which together with the net structure constitute the model generated by the net. Such a structure has been inspired by our understanding of how human brain works. Of the many possible ANN configurations, Back Propagation net is particularly relevant as far as mineral processing is concerned (Hernandez et. al 1992).

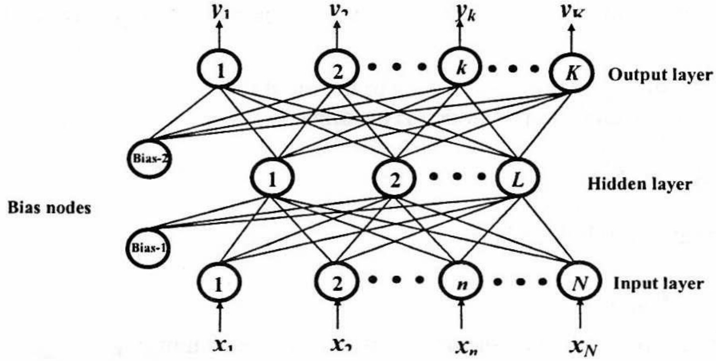

Fig. 1: Multilayer Perceptron Neural Network Model

Network Training

A network first needs to be trained before interpreting new information (Nahas et.al 1992). Several different algorithms are available for training of neural networks but the back-propagation algorithm is the most versatile and robust technique, which provides the most efficient learning procedure for multilayer neural network Hernandez et.al 1992, Poggio et.al 1990). Also, the fact that back-propagation algorithms are especially capable of solving and predicting problems that makes them popular. The feed forward back propagation neural network (BPNN) always consists of at least three layers: input layer, hidden layer and output layer. Each layer consists of number of elementary processing units, called neurons, and each neuron is connected to next layer through weights i.e. neurons in the input layer will send its output as input for neurons in the hidden layer and similar is the connection between hidden and output layer. Number of hidden layers and number of neurons in the hidden layer change according to the problem to be solved. The number of input and output neuron is same as the number of input and output variables (Hornik et.al 1989).

To differentiate between the different processing units, values called biases are introduced in the transfer functions. These biases are referred to as the temperature of a neuron. Except for input layer, all neurons in the back propagation network are associated with a bias neuron and a transfer function. The bias is much like a weight, except that it has a constant input of 1, while the transfer function filters are summed signals received from his neurons. These transfer functions are designed to map a neurons or layers net output to its actual output and they are simple step functions either linear or non-linear functions. The application of these transfer functions depends on the purpose of the neural network. The output layer produces the computed output vectors corresponding to the solution.

During training of the network, data is processed through the input layer to hidden layer, until it reaches the output layer (forward pass). In this layer, the output is compared to the measured values (true output). The difference or error between both is processed back through the network (backward pass) updating the individual weights of the connections and the biases of the individual neuron. The input and output data are mostly represented as vectors called training pairs. The process as mentioned above is repeated for all the training pairs in the data set, until the network error converged to a threshold minimum given by the root mean squared error (RMS) or summed squared error (SSE).

Back Propagation Algorithm

The weights for each connection are initially taken as random numbers. When the net undergoes training, the errors between the results of the output neurons and the desired corresponding target values, are propagated backward through the net. The backward propagation of the error signals is used to update the connection weights. Repeated iterations of this operation result in a converged set of the connection weights, yielding the desired net. Following equations govern the back propagation algorithm.

1. Apply the input vector, Xp= (x_{p1}, x_{p2}, …, x_{pn}) to the input units.
2. Calculate the net-input values to the hidden layer units:

$$net_{pj}^{h} = \sum_{i=1}^{n} w_{ji}^{h} x_{pi} + \theta_{j}^{h}$$

3. Calculate the outputs from hidden layer:

$$i_{pj} = f_{j}^{h}(net_{pj}^{h})$$

4. Move to the output layer. Calculate the net-input values to each unit:

$$net_{pk}^{o} = \sum_{j=1}^{L} w_{kj}^{o} i_{pj} + \theta_{k}^{o}$$

5. Calculate the outputs:

$$o_{pk} = f_{k}^{o}(net_{pk}^{o})$$

6. Calculate the error terms for the output units:

$$\delta_{pk}^{o} = (y_{pk} - o_{pk}) f'^{o}_{k}(net_{pk}^{o})$$

7. Calculate the error terms for the hidden units:

$$\delta_{pj}^{h} = f'^{h}_{j}(net_{pj}^{h}) \sum_{k} \delta_{pk}^{o} w_{kj}^{o}$$

8. Update weights on the output layer:

$$w_{kj}^{o}(t+1) = w_{kj}^{o}(t) + \eta \delta_{pk}^{o} i_{pj}$$

9. Update weights on the hidden layer:

$$w_{ji}^{h}(t+1) = w_{ji}^{h}(t) + \eta \delta_{pj}^{h} x_{i}$$

10. Calculate the error term

$$E_{p} = \frac{1}{2} \sum_{k=1}^{M} \delta_{pk}^{2}$$

Since this quantity is the measure of how well the network is learning. When the error is acceptably small for each of the training-vector pairs, training can be discontinued.

CASE STUDY AND RESULTS

In the present paper, ANN has been used to simulate the Cross Flow separator [Matthew Donnel Eisenmann, 2001]. The cross flow separator is comprised primarily of a rectangular tank that is divided into two regions, an upper separation chamber and the lower dewatering cone. In this novel device, feed is presented tangentially across the upper position of the unit. This tangential feed entry system allows for a lower velocity introduction of feed across the top of the classifier. This feed presentation design allows the unit to operate more efficiently than other conventional apparatuses. The factors determined for this process are:

- Feed Rate
- Bed Level
- Elutriation Water rate

- Feed percent Solids
- Feed TiO_2 Grade
- Feed Heavy Minerals Grade

Although feed rate, water rate and bed level are relatively easy to control using but the others are not. In present study, ANN model has been developed using the above algorithm. The input process variables are Feed rate, Bed level, and Elutriation water rate. The ANN model has been developed using the data (Matthew Donnel Eisenmann, 2001) on Cross Flow Separator. The back propagation algorithm has been used to simulate the results.

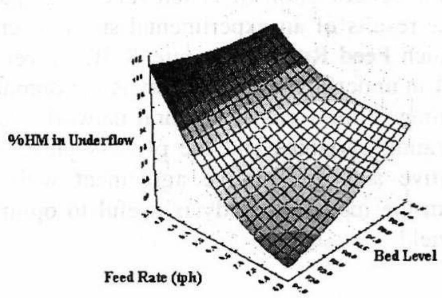

Fig. 2: Response Surface of %HM in Underflow with Feed Rate and Bed Level

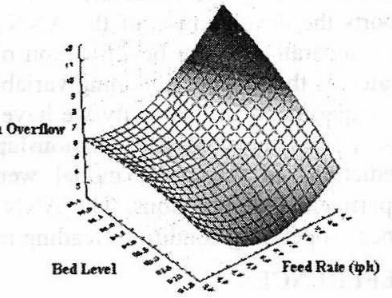

Fig. 3: Response Surface of %HM in Overflow with Feed Rate and Bed Level

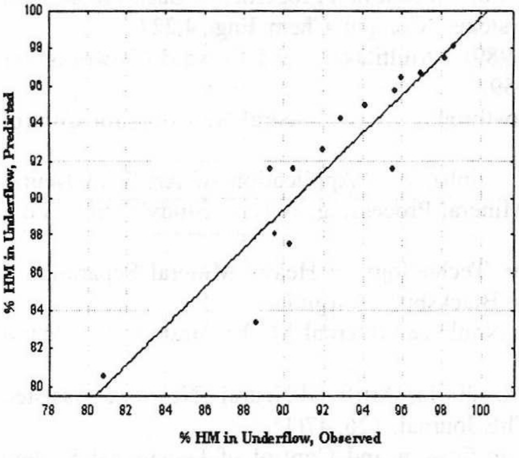

Fig. 4: Predicted Vs Actual of %HM in Underflow

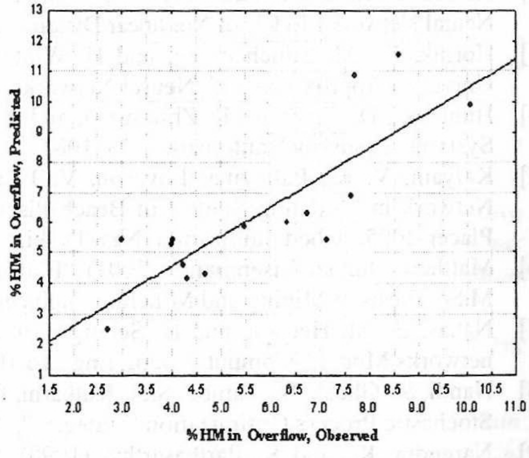

Fig. 5: Predicted Vs Actual of %HM in Overflow

The data set comprising of process operating variables forms the network's input space, and the corresponding Y values represent the network's desired (target) output space. An optimal multilayer perceptron (MLP) network model is developed in accordance with the network training procedure described earlier. An optimal MLP architecture obtained thereby has seven input nodes (nin =3), seven hidden layer nodes (nhn =8) and one output layer node (non =2). An MLP network with good function approximation and generalization abilities, results in small but comparable RMSE values for both the training set (E_{trn}) as well as the test set (E_{tst}). In the case of the MLP-based cross flow model, the E_{trn} and E_{tst} magnitude were 0.077 and 0.310 respectively. Additionally, values of the coefficient of correlation (CC) between the MLP-predicted and target Y values were calculated. The CC value for %HM in Underflow model is found to be 0.92 while the CC for %HM in Overflow model is found to be 0.83. Three-dimensional diagram has also been shown to visualize the behavior of input parameters on the output i.e. %HM in underflow and %HM in overflow. Response surface of %HM in underflow with feed rate Vs bed level and water rate Vs bed level is shown in Fig.-1 ~~and~~ Fig.-2 ~~respectively~~. The response surface of %HM in overflow with feed rate Vs bed level is shown in Fig.-3.The plots for MLP-predicted Vs actual values for %HM in underflow and %HM in overflow is shown in Fig.-4 and Fig.-5 respectively.

CONCLUSION

Artificial neural networks can be used effectively in solving modeling problems in mineral processing where conventional methods fail or are very complex. An artificial neural network is a novel approach that can be used for modeling of the column flotation for beneficiation of beach sand. This paper reports the development of the ANN model based on the results of an experimental study of cross flow separator for the beneficiation of beach sand in which Feed Rate, water rate & Bed level are treated as the process operating variables and percent HM in underflow and overflow is the output of the experiment. In this study we have provided a correlation in the form of a neural network model that defines the nonlinear relationship between the operating variables and the process yield. The predictions of the ANN model were in good qualitative and quantitative agreement with the experimental observations. The ANN weights obtained in the modeling study is useful to optimize process-operating conditions leading to maximization of yield.

REFERENCES

[1] Agarwal, M., (1997), "A Systematic Classification of Neural- Network- Based Control," IEEE Control Syst., 26 (2), 75.

[2] Hernandez, E., and Y. Arkun, (1992)," Study of the Control-Relevant Properties of Back-Propagation Neural Network Models of Nonlinear Dynamical Systems," Comput. Chem. Eng., 4,227.

[3] Hornik, K., M. Stinchcombe, and H. White, (1989), "Multilayer Feed forward Networks are Universal Approximators," Neural Networks, 2,359.

[4] Hunt , K., D. Sbarbaro, R. Zbikowski, and P. Gawthrop, (1992), " Neural Networks for Control Systems- A survey," automatica, 28, 1083.

[5] Kalyani, V. K., Pallavika, Loveson, V. J., and Sinha, A., "Application of Artificial Neural Network in Modeling Studies of Beach Placer Mineral Processing: A Case Study", Proc. Vol., Placer-2005, Allied publication, New Delhi.

[6] Matthew Donnel Eisenmann, (2001) "Elutriation Technology in Heavy Mineral Separation " M.Sc Thesis in Mining and Minerals Engineering, Blacksburg, Virginia.

[7] Nahas, E., M. Henson, and D. Seborg, (1992), "Nonlinear Internal Model Strategy for Neural networks Model," Comput. Chem. Eng., 16,1039.

[8] Nandi, S., Ghosh, S., Tambe, S.S., Kulkarni, B. D., (2001),"Artificial Neural –Network- Assisted Stochastic Process Optimization Strategies", AIChE Journal, 126, 47(1).

[9] Narendra, K., and K. Parthasarthy, (1990). "Identification and Control of Dynamical System Using Neural Networks." IEEE Trans. Neural Networks, 1, 4.

[10] Poggio, T., and F. Girosi, (1990), "Regularization Algorithms for Learning that are Equivalent to Multilayer Networks," Science, 247, 978.

[11] Prabhakar, S., G. Bhaskar Raju and S. Subha Rao, 2004, "Development of Semi-Commercial Flotation Column and Beneficiation of Sillimanite", Proc. Vol., Placer-2004, Eds. V. J. Loveson and D. D. Misra, Allied publication, New Delhi, pp-171-184.

[12] Ramasamy. S., S. S. Tambe, B. D. Kulkarni, and P. B. Deshpande, (1995),"Robust Nonlinear Control with Neural Networks," Proc. R. Soc. Lond. A., 449, 655.

[13] Tendulkar, S. B., S. S. Tambe, I. Chandra, P. V. Rao, R. V. Naik, B. D. Kulkarni, (1998), "Hydroxylation of phenol to Dihydroxybengene: Development of Artificial- Neural-Network-Bsed Process Identification and Model Predictive Control Strategies for a Pilot Plant Scale Reactor," Ind. Eng. Chem. res., 37, 2081.