Petroleum Science and Technology
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/lpet20

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Published online: 30 Jan 2014.

To cite this article: A. Hafizi , M. Koolivand-Salooki , A. Janghorbani , A. Ahmadpour & M. H. Moradi (2014) An Investigation of Artificial Intelligence Methodologies in the Prediction of the Dirty Amine Flow Rate of a Gas Sweetening Absorption Column, Petroleum Science and Technology, 32:5, 527-534, DOI: 10.1080/10916466.2011.582067

To link to this article: http://dx.doi.org/10.1080/10916466.2011.582067

Petroleum Science and Technology, 32:527–534, 2014

ISSN: 1091-6466 print / 1532-2459 online
DOI: 10.1080/10916466.2011.582067

An Investigation of Artificial Intelligence Methodologies in the Prediction of the Dirty Amine Flow Rate of a Gas Sweetening Absorption Column

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Adaptive neuro-fuzzy and artificial neural networks (ANN) were used for the prediction of dirty amine flow rate of a refinery adsorption column. Gas flow rate and gas pressure were the experimental inputs and dirty amine flow rate was selected as output. Recursive least square and error back propagation algorithm have been applied for training adaptive neuro-fuzzy system and multi layer perceptron neural network. Comparison of prediction errors showed that both models predict dirty amine flow rate with high accuracy and results are in good agreement with the experimental data; nonetheless the neuro-fuzzy model predicted this system better than ANN.

Keywords: Adaptive neuro-fuzzy system, amine process, artificial neural network, gas sweetening plant, natural gas

1. INTRODUCTION

Natural gas well streams often contain hydrogen sulfide (H_2S) and carbon dioxide (CO_2). Hydrogen sulfide is a common reduced sulfur compound found in several industrial waste gases (Panchariya et al., 2004). H_2S must be removed from natural gas because it is a toxic, poisonous, and extremely corrosive component. It can also cause catalyst poisoning in the refinery process. Most treating processes that remove H_2S will also remove CO_2. CO_2 is corrosive and has no heating value. Also, carbon dioxide removal may be required for the gas entering to cryogenic plants to prevent solidification of the CO_2.

There are many treating processes available for removal of H_2S from natural gas including: chemical solvents, physical solvents, adsorption hybrid solvents, and physical separation (Fortuny et al., 2008). Absorption in alkanolamine-based solvents is one of the most commonly used processes for the removal of H_2S and CO_2. This process consists of the exothermic reaction of acidic components with an alkanolamine absorption liquid in a gas/liquid column (Huttenhuis et al., 2007).

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Alkanolamines, such as monoethanolamine (MEA), diethanolamine (DEA), di-2-propanolamine (DIPA), and N-methyldiethanolamine (MDEA), are commonly used. These amine mixtures have been called a variety of names including formulated amines and MDEA based amines (Zhang et al., 2008). MDEA has been attended lately and is desirable for broader application because of its excellent properties.

Often knowledge base precise modeling methods are not suitable for complex systems due to lack of precise knowledge about these systems, nonlinear behavior and time varying characteristics of them. This limitation introduce tendency to modeling complex systems based on intelligent methods such as neural networks and fuzzy modeling. The neural network has been applied for the design of wellhead chokes in gas condensate production (Zarenezhad and Aminian, 2011). Sadrzadeh et al. (2009) applied a neuro-fuzzy model coupled with a mathematical model for prediction of zinc ions separation from wastewater using electro dialysis. Evgueniy and Libing (2007) applied adaptive neuro-fuzzy interface system to predict solid oxide fuel cell performance in residential micro generation installation. In addition, the flow rate of dirty amine of an adsorption column in the Khangiran gas refinery was predicted using neural network and genetic algorithm by Seqatoleslami et al. (2010). Comparisons of artificial neural network (ANN) and neuro-fuzzy models have been performed recently to delineate the best model for the prediction of parameters. Xiaobin and Hongjing (2008) compared ANN and neuro-fuzzy models to predict the flow fields and temperature distributions due to natural convection in a triangular enclosure. Singh et al. (2006) applied neuro-fuzzy and ANN model for the prediction of Cadmium removal.

The purpose of this study was to compare neuro-fuzzy and ANN models to predict the flow rate of dirty amine of an adsorption column in the Khangiran gas refinery in Iran. The other aim of this work was also to enhance the accuracy of the absorption column modeling technique, verifying the performance and its validity.

2. THEORETICAL ROUTINES

2.1 ANN

The feed-forward neural networks are the most popular architectures due to their structural flexibility, good representational capabilities and availability of a large number of training algorithms (Haykin, 1999). A multi layer perceptron (MLP) network is a kind of feed-forward neural network with different transfer functions which is probably the most popular ANN in engineering problems in the case of non-linear mapping and is called Universal Approximator. The network needs to be trained using a training algorithm such as back propagation in order to reduce the global error by adjusting the weights and biases of the neural network. An output of a three-layer MLP network is defined by Eq. (1) (Haykin, 1999; Khandekar et al., 2008).

$$\psi_k^2 = f^2\left(\sum_{J=1}^{S^1} w_{jk}^2 f^1\left(\sum_{i=1}^{R} w_{ij}^1 p_i + b_j^1\right) + b_k^2\right), k = 1 to S^2 \tag{1}$$

Where superscript 1 denotes the hidden layer and superscript 2 denotes the output layer. R, S^1, and S^2 illustrate the numbers of input, hidden, and output units, respectively. In addition, f, w_{ij} and b represent transfer function, synaptic weight parameter and bias, respectively. The input of the neuron consists of variables $x_1, x_2, \ldots x_p$ and a threshold (or bias) term. Each of these input values is multiplied by a weight w_i, after which the results are added with the bias term. On the result, a known activation function φ performs a prespecified (nonlinear) mathematical operation. In order to approximate function $\psi(x_1, x_2, \ldots x_p)$ where $(x_1, x_2, \ldots x_p)$ are R independent input variables, a three-layer perceptron network with R input neurons, S^1hidden neurons by tan-sigmoid transfer function, and one output neuron by linear transfer function were selected.

2.2 Neuro-Fuzzy

Fuzzy logic is a form of multivalued logic derived from fuzzy set theory that was initiated by Lotfi Zadeh in 1965 (Li-Xin, 1996). The main contribution of fuzzy logic is a methodology for description of linguistic variable in precise mathematical terms and computing in words.

2.2.2 Fuzzy system

Generally, the fuzzy logic system is divided into four sections: fuzzification, fuzzy rule base, fuzzy inference engine, and defuzzification. The fuzzifier fuzzifies real valued variables based on fuzzy membership functions of input space. The fuzzy rule base consists of fuzzy IF-THEN rules for which all other components of the system are used to implement. The other is fuzzy inference engine that combines fuzzy IF-THEN rules in the fuzzy rule base, based on fuzzy logic principles and generates fuzzy output. Finally the defuzzifier that transforms the fuzzy output into the crisp value in the output space (Li-Xin, 1996).

2.3 Neuro-Fuzzy Model Design

In this study we have designed a neuro-fuzzy model and tuned membership function parameters by the error back-propagation and recursive least square (RLS) algorithms in order to track given input-output pairs. Fuzzy rule base of the fuzzy system is consists of IF-THEN rules such as

IF x_1 is $A_1^{l_1}$and ... and $x_n$is $A_1^{l_1}$ THEN Y is $B^{l_1 l_2 \ldots l_n}$

Where $l_i = 1, 2, \ldots, N_i$, $i = 1, 2, \ldots n$, and $B^{l_1 l_2 \ldots l_n}$ is any fuzzy membership function centered at $\bar{y}^{l_1 l_2 \ldots l_n}$.

If a product inference engine, singleton fuzzifier and center average defuzzifier would be selected for the fuzzy system, and the final input-output function of the system can be indicated by Eq. 3:

$$f(x) = \frac{\sum_{l_1=1}^{N_1} \cdots \sum_{l_n=1}^{N_n} \bar{y}^{l_1 \ldots l_n} \left[\prod_{i=1}^{n} \mu_{A_i^{li}}(x_i)\right]}{\sum_{l_1=1}^{N_1} \cdots \sum_{l_n=1}^{N_n} \left[\prod_{i=1}^{n} \mu_{A_i^{li}}(x_i)\right]} \tag{3}$$

Where $\mu_{A_i^{li}}(x_i)$ is membership degree of x_i in $A_i^{l_i}$ triangular membership function and N_i is the number of fuzzy membership functions in each input dimension (Li-Xin, 1996). The structure of neuro-fuzzy model is shown in Figure 1.

3. EXPERIMENTAL

In this work the prototype refinery is located in the SARAKHS gas field, onshore Iran. The total number of data's acquired at the time of this study was added up to 132 data that have been collected during one year. The entire absorption column's data obtained from this gas refinery were inlet flow rate of gas (Q_{gas}), inlet pressure of gas (P_{gas}) and dirty amine flow rate (Q_{amine}). mean squared error (MSE), normalized mean squared error (NMSE), mean absolute error (MAE), and R^2 (coefficient of determination) were used for evaluation of the models according to (Bera and Ghosh, 2005).

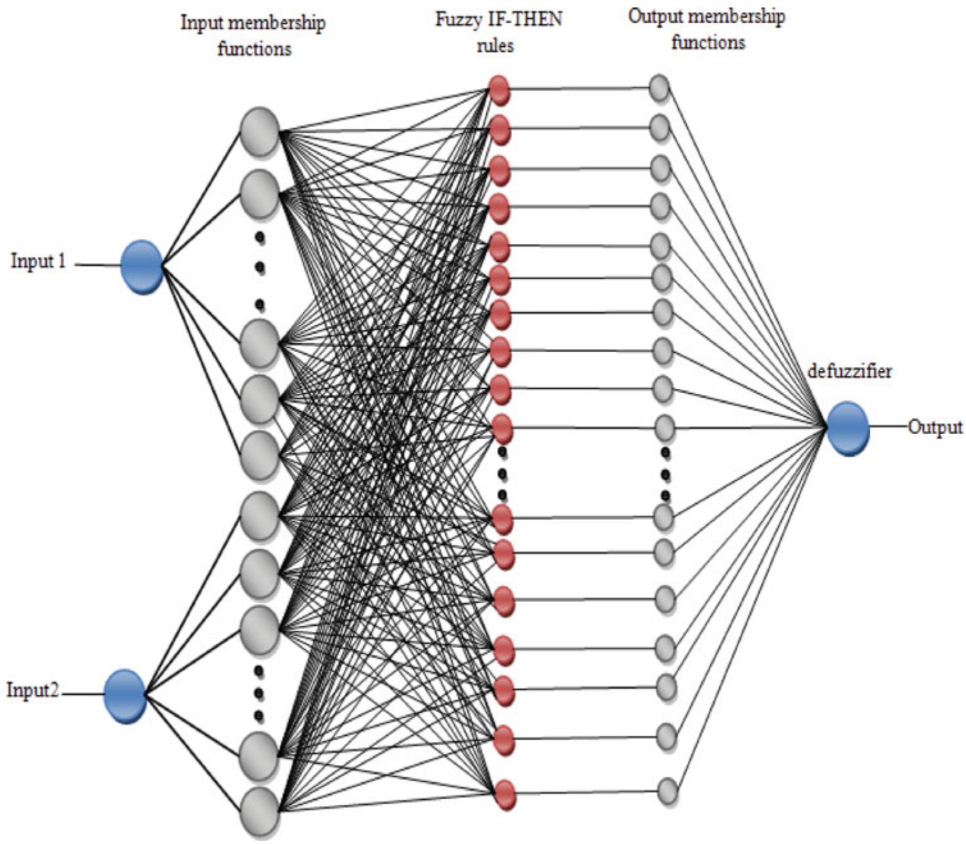

FIGURE 1 Structure of neuro-fuzzy model.

4. RESULTS AND DISCUSSION

4.1 Data Set and Descriptor Generation

The database to be introduced to the neural network was broken down into three groups: training, cross-validation, and verification. In neuro-fuzzy model the 100 input-output pairs of the database is used for training and 32 input-output pairs for testing of model After modeling, the outputs are collected and reports are then generated showing the testing results.

4.2 Simulation Results

4.2.1. ANN result

The optimal number of neurons of two hidden layers network for dirty amine flow rate was obtained using trial and error method. The training results of the ANN on the validation data showed the lowest MSE when the number of hidden neurons was 16. It was found that 2-16-16-1 architecture is the best model in terms of MSE, which means 2-16-16 and one neuron in input, hidden, and output layers, respectively. With this architecture R^2 of test set was 0.859.

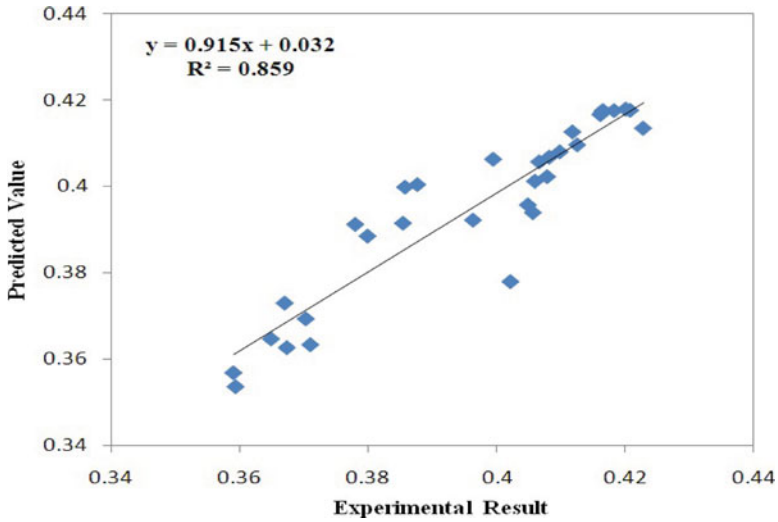

FIGURE 2 Predicted values versus experimental results of dirty amine flow rate in ANN test set.

4.2.2 Neuro-fuzzy model

In neuro-fuzzy model, we applied the same input-output pairs as ANN to peruse the performance of these two models. The best choice for the number of membership function for dirty amine flow rate prediction was seven, which were selected by trial and error. Using this number of membership function showed good agreement between experimental and predicted values of adaptive neuro-fuzzy model. The coefficients of determination of train and test were 0.952 and 0.964, respectively.

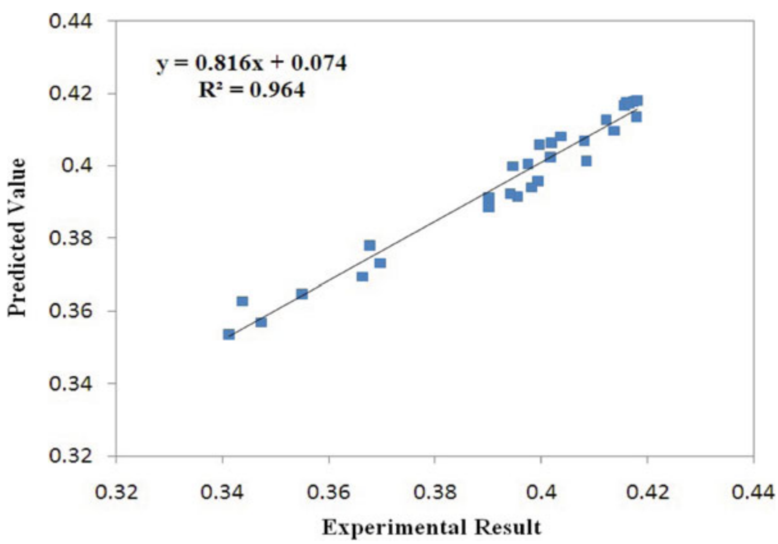

FIGURE 3 Predicted values versus experimental results of dirty amine flow rate in adaptive neuro-fuzzy test set.

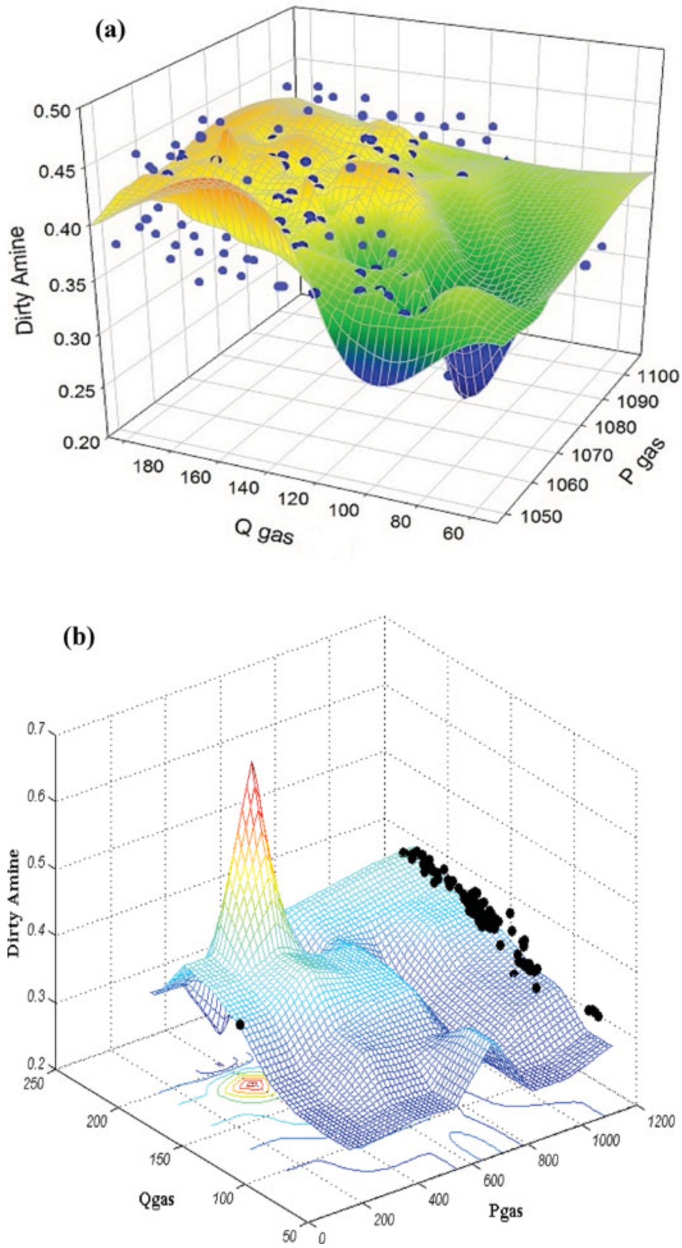

FIGURE 4 (a) Best fitted surfaces predicted with ANN model. (b) Best fitted surfaces predicted with adaptive neuro-fuzzy model.

4.3 Comparison of Neuro-Fuzzy and ANN Models

In Figures 2 and 3 predicted dirty amine flow rate using ANN and neuro-fuzzy models are plotted versus the experimental results for the test sets. A good agreement between predicted and

TABLE 1
Performance of Neuro-Fuzzy and ANN Model Test Sets

Performance	*Neuro-Fuzzy Model*	*ANN Model*
MSE	0.0000698	0.0178
NMSE	0.182592	0.6585
MAE	0.0054	0.1015
R^2	0.964	0.859

experimental values indicates the fitness of both models. However, neuro-fuzzy model shows better R^2 and of course better fitness of predicted and experimental values.

As it is illustrated in Table 1, different errors like MSE and MAE are thoroughly lower for neuro-fuzzy model in comparison with ANN model. It is confirmed by comparison of coefficient of determination which is 0.964 in neuro-fuzzy model and 0.859 in ANN model. All of these show the excellence of neuro-fuzzy model. The generalization performance of the best-fitted surfaces of ANN and neuro-fuzzy models are illustrated in Figures 4a and 4b. As it is demonstrated in Figure 4a, the experimental data of dirty amine flow rate does not fit on model surface properly and consequently ANN model does not fit the experimental data excellently. On the other hand, Figure 4b illustrates the surface created applying the neuro-fuzzy model of the predicted dirty amine.

Comparing the predicted dirty amine flow rate using neuro-fuzzy and ANN model with the experimental results in Figure 5 demonstrates that both two models follow the experimental results appropriately. Conclusively, it can be concluded that the neuro-fuzzy model is comparatively more accurate than the ANN model for the prediction of dirty amine flow rate according to different indexes of errors and coefficient of determination.

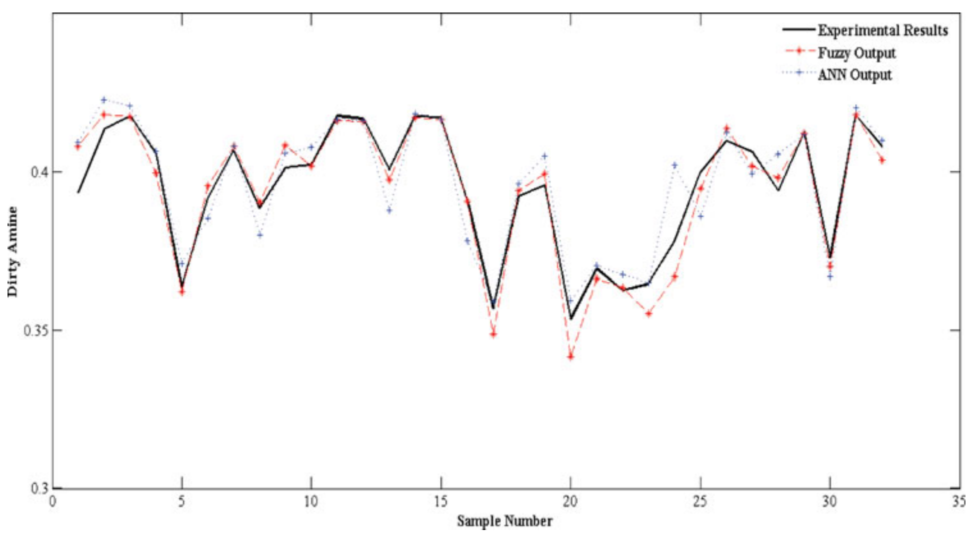

FIGURE 5 Comparison of neuro-fuzzy and ANN predictions together with experimental results of test sets.

5. CONCLUSION

This research demonstrates a comparative analysis of the modeling approaches by an ANN and neuro-fuzzy model by manipulating the Khangiran gas refinery sweetening absorption column data. It should be mentioned that the models were evaluated for the first time using the experimental data. Neuro-fuzzy and ANN models were trained using inlet gas flow rate and inlet gas pressure and then optimum number of membership function and hidden layers were found. The results of the present study revealed that both neuro-fuzzy and ANN methods presented in this study show a good potential to model this complex, nonlinear, and multivariate problem. Comparing errors and also R^2 confirm that the neuro-fuzzy method is better than the ANN method, while the results obtained from ANN satisfactorily matched the experimental results. Nonetheless, neuro-fuzzy model presented here can be used for accurate prediction of output parameter of the absorption tower and other columns with similar characteristics.

ACKNOWLEDGMENTS

The authors would like to thank National Iranian Oil Company (NIOC) and National Iranian South Oil Field Company (NISOC) for financial support of this project.

REFERENCES

Bera, A. K., and Ghosh, A. (2005). Regression model for bearing capacity of a square footing on reinforced pond ash. *Geotextiles Geomembrane* 23:261–285.

Evgueniy, E., and Libing, Y. (2007). Application of adaptive neuro-fuzzy inference system techniques and artificial neural networks to predict solid oxide fuel cell performance in residential microgeneration installation. *J. Power Sources* 170:122–129.

Fortuny, M., Baeza, J. A., Gamisans, X., Casas, C., Lafuente, J., and Deshusses, M. A. (2008). Biological sweetening of energy gases mimics in biotrickling filters. *J. Chemosphere* 71:10–17.

Haykin, S. (1999). *Neural networks* (2nd ed.). New York, NY: Prentice-Hall.

Huttenhuis, P. J. G., Agrawal, N. J., Hogendoorn, J. A., and Versteeg, G. F. (2007). Gas solubility of H_2S and CO_2 in aqueous solutions of N-methyldiethanolamine. *J. Pet. Sci. Eng.* 55:122–134.

Khandekar, S., Joshi, Y. M., and Mehta, B. (2008). Thermal performance of closed two-phase thermosyphon using nano-fluid. *Int. J. Therm. Sci.* 47:659–667.

Li-Xin, W. (1996). *A course in fuzzy systems and control facsimile edition*. New York, NY: Prentice-Hall.

Panchariya, P. C., Palit, A. K., Popovic, D., and Sharma, A. L. (2004). Nonlinear system identification using Takagi-Sugeno type neuro-fuzzy model. Intelligent systems. *Proc. 2nd Int. IEEE Conf.* 76–81.

Sadrzadeh, M., Ghadimi, A., and Mohammadi, T. (2009). Coupling a mathematical and a fuzzy logic-based model for prediction of zinc ions separation from waste water using electro-dialysis. *Chem. Eng. J.* 151:262–274.

Seqatoleslami, N., Koolivand Salooki, M., and Mohamadi, N. (2011). Auto-design of neural network based GAs for manipulating the Khangiran gas refinery sweetening absorption column outputs. *Pet. Sci. Technol.* 29:1437–1448.

Singh, T. N., Singh, V. K., and Sinha, S. (2006). Prediction of cadmium removal using an artificial neural network and a neuro-fuzzy technique. *J. Mine Water Environ.* 25:214–219.

Xiaobin, H., and Hongjing, Q. (2008). A nonlinear system identification method based on fuzzy dynamical model and state-space neural network. *CCDC Conf.* 4738–4741.

Zarenezhad, B., and Aminian, A. (2011). Artificial neural network model for design of wellhead chokes in gas condensate production fields. *Pet. Sci. Technol.* 29:579–587.

Zhang, P., Shi, Y., Wei, J., Zhao, W., and Qing, Y. (2008). Regeneration of 2-amino-2-methyl-1-propanol used for carbon dioxide absorption. *J. Environ. Sci.* 20:39–44.