Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 37:118–126, 2015

ISSN: 1556-7036 print/1556-7230 online
DOI: 10.1080/15567036.2011.578111

Taylor & Francis
Taylor & Francis Group

Application of Artificial Neural Networks (ANNs) to Predict the Rich Amine Concentration in Gas Sweetening Processing Units

O. Rahmanpour,[1] M. H. Zargari,[2] and M. A. Ghayyem[1]

[1]*Gas Engineering Department, Petroleum University of Technology, Ahwaz, Iran*
[2]*Petroleum Engineering Department, Petroleum University of Technology, Ahwaz, Iran*

Gas sweetening is a fundamental step in gas treatment processes. Acid gas loading in alkanolamine solutions is one of the most important and commonly used parameters for monitoring the performance of gas treating units, and therefore should be closely monitored to prevent operational problems, such as excessive energy consumption and corrosion in units. In this article, a new method based an artificial neural network for prediction of rich amine concentration is presented. H_2S, H_2O, and CO_2 mole fractions in sour gas and H_2S, H_2O, and CO_2 diethanolamine mole fractions in lean amine by their flow rates have been input variables of the network and have been set as network output. To check the artificial neural network model, the samples have been divided into three groups. Among the 130 data set, 92 data have been implemented to find the best artificial neural network structure as train data (group 1). Nineteen data have been used to check generalization capability of the trained artificial neural network named validation data (group 2) and 19 data have been used to test optimized network as test data (group 3). The results of this study include the calculation of R value and mean squared error between the experimental data and artificial neural network predictions that show good accuracy of this type of modeling.

Keywords: alkanolamine solution, ANN modeling, gas treatment processes, prediction

INTRODUCTION

The flow diagram shown by Figure 1 illustrates the arrangement of the equipment needed for the amine process. In gas sweetening units, acid gases (H_2S and CO_2) are chemically absorbed from a gas using aqueous alkanolamine solutions, to product a "sweet gas." The solvent is regenerated in a desorption column and the purified (or "lean") solvent is recycled to the absorption column (Patil et al., 2006). Acid gas loading in alkanolamine solutions is one of the most important and commonly used parameters for monitoring the performance of gas treating units. Loading errors can have serious consequences. For example, if lean loadings are actually lower than measured, then excessive solvent circulation and energy consumption may be the result, unbeknownst to

Address correspondence to O. Rahmanpour, Gas Engineering Department, Petroleum University of Technology, Ahwaz, Iran. E-mail: orahmanpour@gmail.com

Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/ueso.

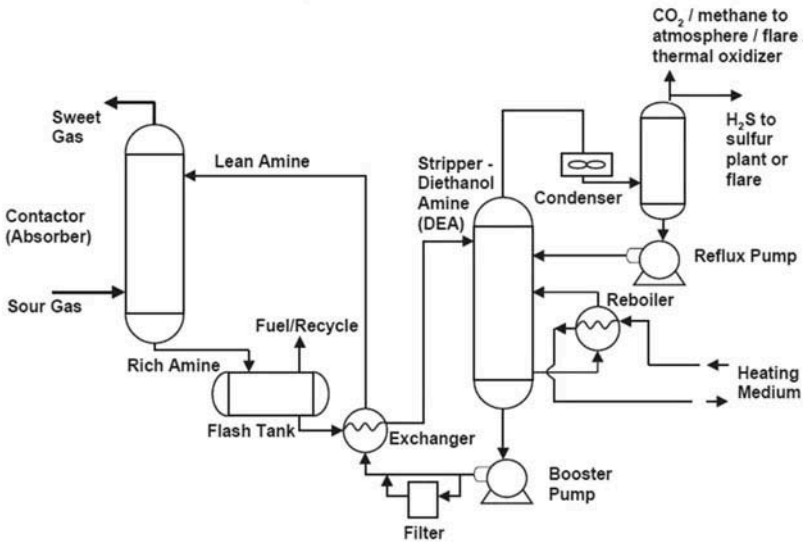

FIGURE 1 A typical amine process diagram.

operations. If the real loadings are actually higher than measured, then either treating objectives may not be met at all or, far worse, corrosion will spiral into the unmanageable. Today's world energy needs demand greater reliability and better efficiency of hydrocarbon treating units (Nathan and Ralph, 2009). Most operating companies usually exceed design inlet gas flow rates with higher concentration of acid gas components; therefore, their analyses are somewhat unrealistic and perhaps overly optimistic. Note that the larger the unit, the greater the need for optimization. The weekly amine analysis is most informative as most amine problems are triggered by contaminated solutions. Amine concentration should be closely monitored to prevent operational problems (Abedinzadegan, 2008). Increasing awareness of the corrosion and safety implications associated with elevated rich amine loading has led many operating companies to establish internal guidelines or standards that set hard limits to operations. While this addresses the safety and reliability issues, it should be recognized that one consequence is leaving some profit on the table (Nathan and Ralph, 2009).

The amine reboiler provides the heat input to an amine stripper, which reverses the chemical reactions and drives off the acid gases. The reboiler duty should be maintained as low as possible, but must be adequate to regenerate the amine solution sufficiently to meet the sweet gas requirements and to ensure that the CO_2 loadings in the reboiler do not cause excessive corrosion. Higher reboiler duties do not reduce circulation rates to any degree and just consume energy (Bullin, 2003). Consequently, the rich amine properties are used to reduce the reboiler duty, if rich amine flow rates are to be high in the striper section, the reboiler duty should be increased.

GAS SWEETENING PLANTS PROBLEMS

There are many problems in gas sweetening units; some of these problems are due to lack of sufficient information process conditions. These problems can be predicted with an artificial

neural network (ANN) model. Some of the problems that are caused by rich amine conditions are listed below:

- Gas is not sweet:
  - Acid gas loading is too low.
  - Rich amine flow rate is too low (foaming).
- Dirty, degraded amine:
  - Too high rich amine acid gas loading (especially CO_2).
- Excessive energy consumption:
  - Rich amine flow rate is too high.
  - Rich amine concentration is too low.
- Excessive corrosion:
  - Rich amine concentration is too high.

Applying an ANN to a system needs sufficient input and output data instead of a mathematical equation. ANN can be trained using input and output data to adapt to the system. Also, ANN can be used to deal with the problems with incomplete and imprecise input data (Akcayol and Cinar, 2005). In this study, an ANN is used for prediction of the rich amine and sweet gas concentrations in a gas sweetening processing unit. The results of this study include the calculation R value and mean squared error (MSE) that have shown good accuracy of this type of modeling.

ARTIFICIAL NEURAL NETWORKS THEORY

Nowadays, there is a new field of computational science that integrates the different methods of problem solving that cannot be so easily described without an algorithmic traditional focus. These methods, in one way or another, have their origin in the emulation, more or less intelligent of the behavior of the biological systems. It is a new way of computing denominated artificial intelligence, which through different methods is capable of managing the imprecision and uncertainties that appear when trying to solve problems related to the real world, offering a strong solution and easy implementation. One of those techniques is known as artificial neural networks (ANN) (Gasca, 2006).

An ANN is an abstract simulation of a real nervous system and its study corresponds to a growing interdisciplinary field, which considers the systems as *adaptive, distributed*, and mostly *nonlinear*, three of the elements found in the real applications.

The problems, which were normally solved through classical statistical methods, such as discriminant analysis, logistic regression, Bayes analysis, multiple regression, and a time-series model, are being tackled by ANNs. It is, therefore, time to recognize ANN as a powerful tool for data analysis (Kumar Jha, 2004). The ANNs are used in many important engineering and scientific applications; some of these are signal enhancement, noise cancellation, pattern classification, system identification, prediction, and control. Besides, they are used in many commercial products, such as modems, image processing and recognition systems, speech recognition, and bio-medical instrumentation, among others (Gasca, 2006).

Most of the neural network applications in the oil and gas industry are based on supervised training algorithms. During a supervised training process, both input and output are presented to the network to permit learning on a feedback basis. A specific architecture, topology, and training algorithm are selected and the network is trained until it converges. During the training process,

neural network tries to converge to an internal representation of the system behavior. Although by definition neural nets are model-free function approximates.

Neural networks have shown great potential for generating accurate analysis and results from large historical databases, the kind of data that engineers may not consider valuable or relevant in conventional modeling and analysis processes. Neural networks should be used in cases where mathematical modeling is not a practical option. This may be due to the fact that all of the parameters involved in a particular process are not known and/or the inter-relation of the parameters is too complicated for mathematical modeling of the system (Mohaghegh, 2000). ANNs are able to process data fast and also provide easy means of applying an already built model to a new system (Zargari et al., 2010). And ANNs can be composed of different numbers of neurons. In chemical applications, the sizes of ANNs (i.e., the number of neurons) are ranging from tens of thousands to as little as less than ten. The neurons in ANNs can all be put into one layer or two, three, or even more layers of neurons can be formed (Zupan, 1994).

RICH AMINE CONCENTRATION PREDICTION BASED ON ANN

The purpose of this section is to develop a neural network model that can be used to predict rich amine concentration for gas sweetening units. Since sour gas and lean amine data are available from one of the gas sweetening units, the idea of finding a relation between these data and rich amine concentration data passes the mind. Input sets used for the modeling system include:

- CO_2 concentration in sour gas
- H_2S concentration in sour gas
- H_2O concentration in sour gas
- Flow rate in sour gas (M_{sour})
- CO_2 concentration in lean amine

TABLE 1
Network Design for Rich Amine Concentration (a), Results of Networks with 15 Hidden Neurons for Rich Amine Concentration Prediction (b)

(a)

Training algorithm	Levenberg-Marquardt as (TRAINLM)
Performance function	MSE (Mean Squared Error)
Number of layers	2
Neurons for input layer	15
Activation function	TANSIG (Tan-sigmoid)

(b)

		Train		*Validate*		*Test*	
	Number of Input	*MSE*	*R*	*MSE*	*R*	*MSE*	*R*
CO_2	9	7.20×10^{-6}	0.99	2.10×10^{-5}	0.99	1.22×10^{-4}	0.99
H_2O	9	3.30×10^{-5}	0.99	1.01×10^{-5}	0.99	1.59×10^{-4}	0.99
H_2S	9	2.81×10^{-3}	0.99	5.69×10^{-3}	0.99	3.14×10^{-3}	0.99
DEA	9	3.85×10^{-3}	0.98	6.64×10^{-4}	0.99	9.35×10^{-4}	0.96

- H_2S concentration in lean amine
- H_2O concentration in lean amine
- DEA concentration in lean amine
- Flow rate in lean amine (M_{lean})

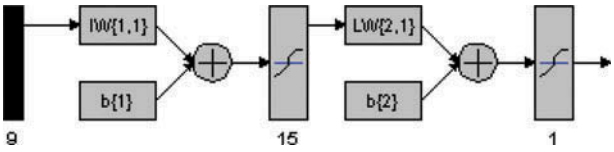

FIGURE 2 Structure of selected network for prediction of rich amine concentration.

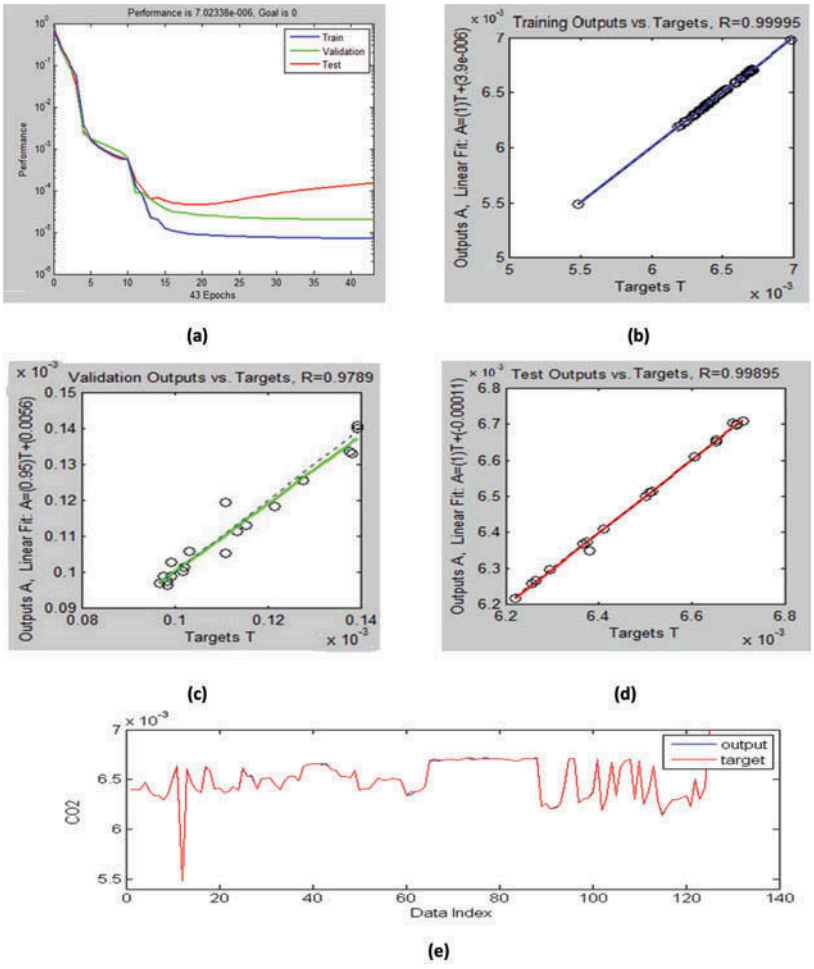

FIGURE 3 Performance of selected network for CO_2 (a), R value of train data for CO_2 (b), R value of validate data for CO_2 (c), R value of test data for CO_2 (d), and CO_2 concentration prediction with selected network (e).

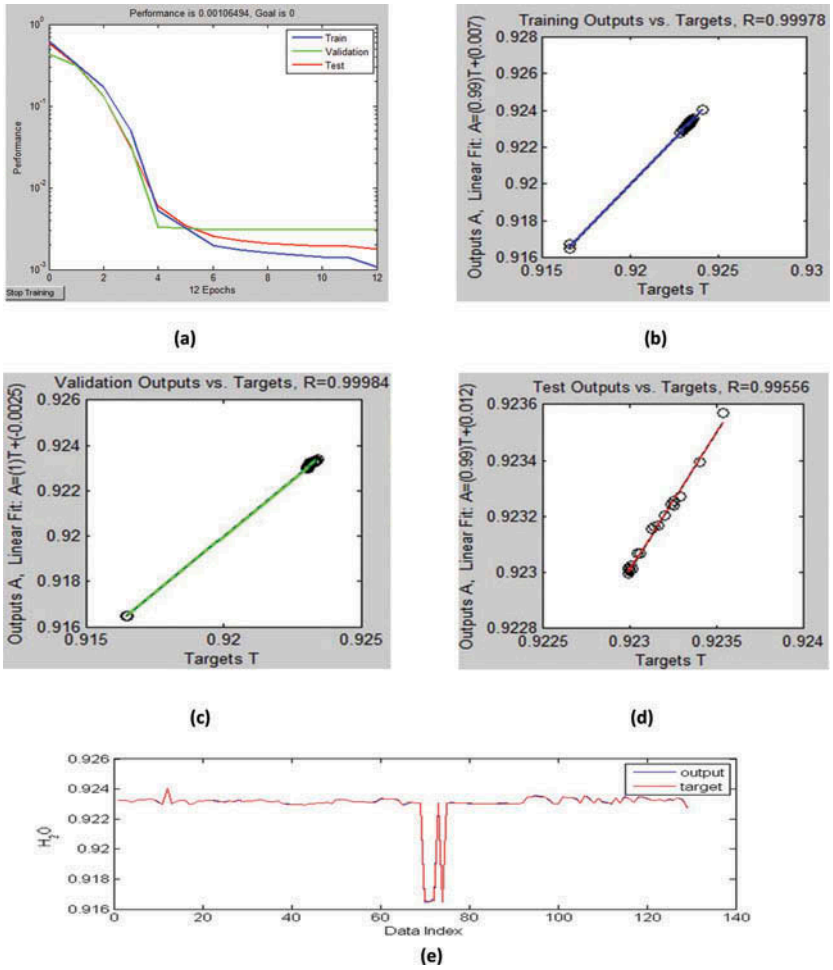

FIGURE 4 Performance of selected network for H_2O (a), *R* value of train data for H_2O (b), *R* value of validate data for H_2O (c), *R* value of test data for H_2O (d), and H_2O concentration prediction with selected network (e).

NETWORK DESIGN FOR RICH AMINE CONCENTRATION

The structure of constructed networks for rich amine concentration is reported in Table 1a and shown in Figure 2. Four networks are modeled to predict CO_2, H_2O, H_2S, and DEA concentration, with good accuracy regarding *R* value and mean squared error (MSE) as performance shown in Table 1b. These results are also presented in Figure 3 for CO_2, Figure 4 for H_2O, Figure 5 for H_2S, and Figure 6 for DEA.

CONCLUSIONS

The ultimate goal of amine sweetening is to produce specification quality product as economically as possible. This purpose can be reached by ANN.

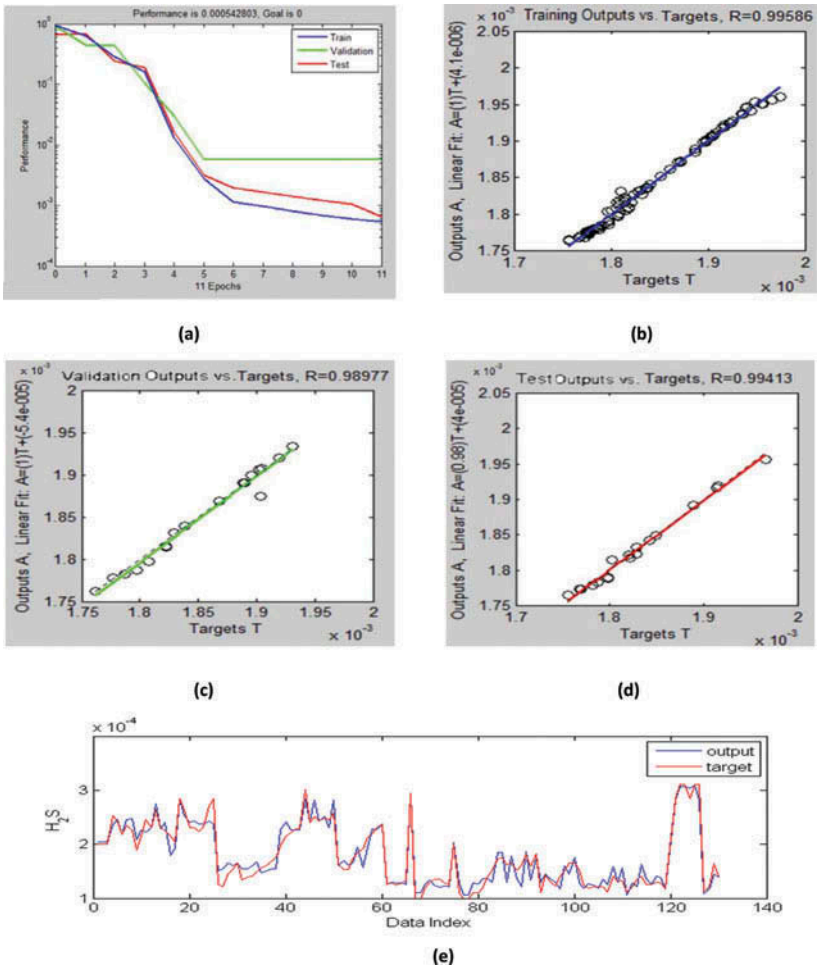

FIGURE 5 Performance of selected network for H_2S (a), *R* value of train data for H_2S (b), *R* value of validate data for H_2S (c), *R* value of test data for H_2S (d), and H_2S concentration prediction with selected network (e).

Based on the results of this work, the following conclusions are obtained:

1. By prediction of rich amine concentration before processing, time to determine the concentration can be saved.
2. ANNs show good accuracy of this type of modeling and can be used instead of measurement systems, for example, chromatography or other analytical techniques (saving cost).
3. Pre processing in gas sweetening units is one of the important tasks that can be reached by ANNs modeling.
4. Absorber column controlling can be simplified by these ANNs modeling.
5. Computational intelligence models, which result in the lowest error based on actual field data, are strongly proposed to solve intricate industrial problems, instead of empirical correlations and mechanistic models.
6. Rich amine concentration calculations and predictions can help to reach system equilibrium.
7. Rich amine properties are used to reduce the re-boiler duty and energy consumption.

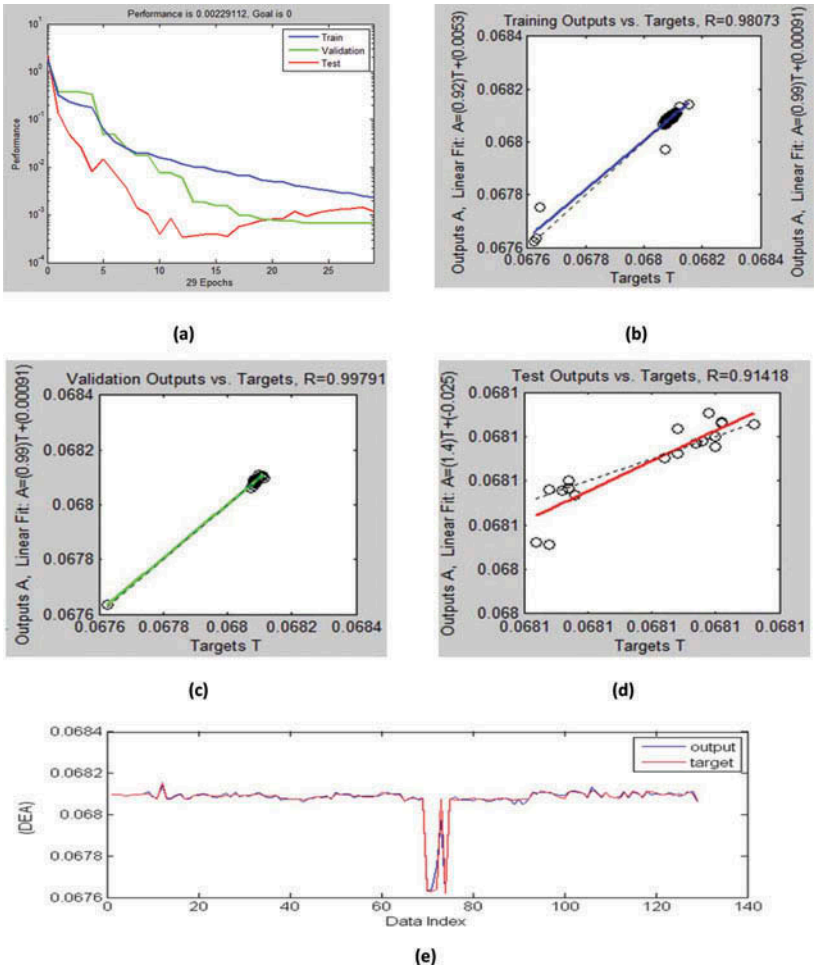

FIGURE 6 Performance of selected network for DEA (a), *R* value of train data for DEA (b), *R* value of validate data for DEA (c), *R* value of test data for DEA (d), and DEA concentration prediction with selected network (e).

RECOMMENDATIONS

1. Application of genetic algorithm in conjunction with ANNs may cause to have better results.
2. More error free data available for prediction cause to have better modeling.
3. More streams in gas sweetening units can be used to model in applicability of computational intelligence, for example, concentration of lean amine stream and concentration of sweet gas stream.
4. In the absorber section, relations can be found between concentration of rich amine and lean amine with ANN.

REFERENCES

Abedinzadegan, M. 2008. *Design and Operations of Natural Gas Sweetening Facilities*. Newfoundland, Canada: Faculty of Engineering and Applied Science, Memorial University of Newfoundland (MUN).

Akcayol, A., and Cinar, C. 2005. Artificial neural network based modeling of heated catalytic converter performance. *Appl. Therm. Eng*. 25:2341–2350.

Bullin, J. A. 2003. Why not optimize your amine sweetening unit. *GPA Europe Annual Conference*, Heidelberg, Germany, September 25–27.

Gasca, E. 2006. *Artificial Neural Networks*. Mexico: Instituto Tecnológico de Toluca.

Kumar Jha, G. 2004. *Artificial Neural Networks*. New Delhi, India: Indian Agricultural Research Institute–PUSA.

Mohaghegh, Sh. 2000. *Virtual intelligence applications in petroleum engineering: Part 1- Artificial neural networks. J. Petr. Tech., Distinguished Author Series* 64–73.

Nathan, A., and Ralph, H. 2009. Acid gas loading error analysis: Is the analysis full of error or is there error in the analysis? *Brimstone–STS Sulphur Symposium*, Vail, Colorado, September.

Patil, P., Malik, Z., and Jobson, M. 2006. *Prediction of CO_2 and H_2S Solubility in Aqueous MDEA Solution Using an Extended Kent and Eisenberg Model*. Manchester, UK: Centre for Process Integration, School of Chemical Engineering and Analytical Science, The University of Manchester (BK1064-ch47_R2_250706).

Rahmanpour, O., Zargari, M. H., Ghayyem, M. A. 2014. Lean amine concentration prediction based on computational intelligences as artificial neural networks (ANNs) in gas sweetening processing units. *Energ. Source. Part A* 36:2464–2473.

Zargari, H., Poordad, S., and Kharrat, R. 2010. *Porosity and permeability prediction based on computational intelligences as artificial neural networks (ANNs) and adaptive neuro-fuzzy inference systems (ANFIS) in southern carbonate reservoir of Iran*. Ahwaz, Iran: Petroleum University of Technology.

Zupan, J. 1994. *Introduction to Artificial Neural Network (ANN) Methods: What They Are and How to Use Them?*. Tarragona, Spain: Department of Chemistry, University Rovira i Virgili.