American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN : 2320-0936
Volume-9, Issue-10, pp-98-107
www.ajer.org
Research Paper Open Access

Artificial Intelligence techniques for predicting the Critical Properties of Oil

Amer Badr BinMerdhah,Salem O. Baarimah,and Mazen A. Muherei
Petroleum Engineering Department, Hadhramout University-Hadhramout-Yemen

ABSTRACT:*Physical properties of pure components of oil such as critical compressibility, critical volume, critical temperature, critical pressure, molecular weight, specific gravity and standard boiling point are very important in compositional reservoir simulation. Perfectly, these properties should be obtained from actual laboratory measurements on samples collected from the bottom of the wellbore or at the surface. Quite often, however, these measurements are either not available, or very costly to obtain. For these reasons, there is a need for a quick and reliable method for predicting the physical properties of these components.*

This study presents both back propagation network and fuzzy logic techniques for predicting critical compressibility, critical temperature, and critical pressure. The models were developed using 120 data sets collected from different published sources. These data were divided into two groups: the first was used to train the Artificial Intelligence models and the second was used to test the models to evaluate their accuracy and trend stability.

Using the average percent relative error, average absolute percent relative error, minimum and maximum absolute percent relative error, root mean square error, and the correlation coefficient as criteria to evaluate the performance and accuracy of the new models. The present models provide predictions of the critical compressibility, critical temperature, and critical pressure with correlation coefficient of one for all models.

KEYWORDS*:Critical compressibility, critical temperature, and critical pressure, backpropagation network, fuzzy logic model.*

Date of Submission: 06-10-2020 Date of acceptance: 19-10-2020

I. INTRODUCTION

Recently, Artificial Intelligence techniques such as artificial neural network, fuzzy logic technique, and functional networks were used comprehensively in most of petroleum engineering applications such as in drilling engineering, reservoir engineering production engineering, petrophysics, rock mechanics and exploration [1]-[8].

Physical properties of pure oil reservoir componentsare very important in compositional reservoir simulation. A compositional reservoir simulator is used to model the complex compositional changes and phase behavior that occur in retrograde gas-condensate reservoirs during production. The compositional model gives increased accuracy by utilizing a more realistic description of the fluid. The compositional simulation models assume that reservoir fluid properties are dependent not only upon the reservoir temperature and pressure but also on the composition of the reservoir fluid which changes during production, either by depletion or by gas injection[9]-[12].

Totally, these properties should be obtained from actual laboratory measurements such as Constant Composition Expansion (CCE) and Constant Volume Depletion (CVD) on samples collected from the bottom of the wellbore or at the surface. Hence, engineers have to use empirically derived correlations such as an equation of state, linear, non-linear, multiple regressionscorrelations, [13]-[18]. So far, researchers did not utilize Artificial Intelligence for predicting these very important the critical properties of pure oil reservoir components.

This study presents both back propagation network (BPN) and fuzzy logic (FL) techniques for predicting the very important the critical properties of pure oil reservoir components include critical compressibility (Zc), critical temperature (Tc), and critical pressure (Pc) using 120 data sets collected from different crude samples. These data were divided into two subsets: the first one (84 sets) was used to train the

Artificial Intelligence models, the second group (36 sets) was used to test the models to evaluate their accuracy and trend stability.

II. ARTIFICIAL INTELLIGENCE OVERVIEW

Artificial Neural Network

An ANN model is a computer model that attempts to mimic simple biological learning processes and simulate specific functions based on the working of the human nervous system. It is an adaptive, parallel information processing system, which can develop associations, transformations or mappings between objects or data. The fundamental building block for neural networks is the single-input neuron as shown in Fig. 1. In addition, the simple neuron can be extended to handle inputs that are vectors. A neuron with a single R-element input vector as shown in Fig. 2.

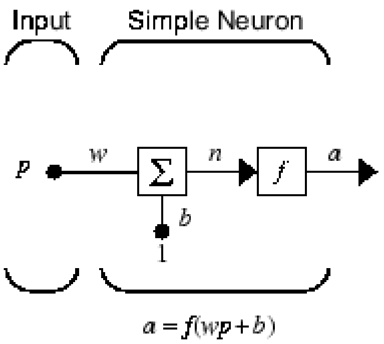

Fig. 1. Single-input neuron [19]

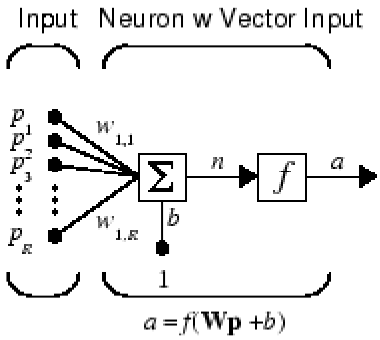

Fig. 2. Vectors-inputs neuron [19]

Three distinct functional operations that take place in this example neuron. First, the scalar input (P) is multiplied by the scalar weight (W) to form the product (WP), again (a) scalar. Second, the weighted input (WP) is added to the scalar bias (b) to form the net input n. In this case, the bias can be viewed as shifting the function (f) to the left by an amount b. The bias is much like a weight, except that it has a constant input of 1. Finally, the net input is passed through the transfer function (f), which produces the scalar output (a). The names given to these three functions are: the weight function, the net input function, and the transfer function. Many transfer functions are included in the Neural Network Toolbox software. Two of the most commonly used functions are shown below. Log-sigmoid transfer function generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity as shown in Fig. 3. While linear output neurons are used for function fitting problems. The linear transfer function purlin is shown in Fig. 4.

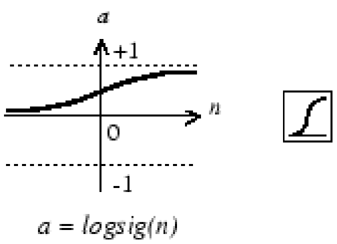

Fig. 3. Log-sigmoid transfer function [19]

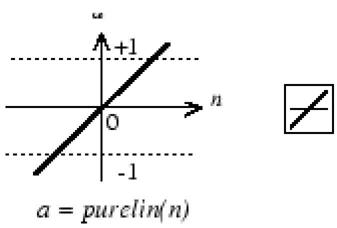

Fig. 4. linear transfer function[19]

Back propagation network (BPN) often has one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear relationships between input and output vectors. The linear output layer is most often used for function fitting (or nonlinear regression) problems. Fig. 5 shows back propagation network with sigmoid and linear transfer functions.

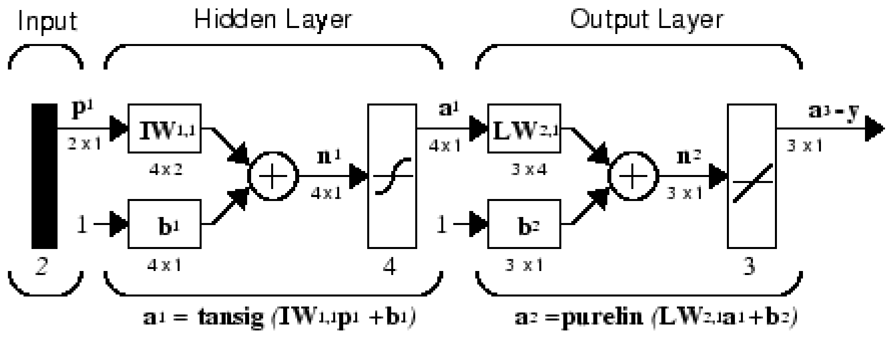

Fig. 5. Architecture of back propagation network [19]

Fuzzy Logic Technique

Fuzzy logic model or FL-model has two different meanings. In a narrow sense, fuzzy logic is a logical system, which is an extension of multivalued logic. However, in a wider sense fuzzy logic (FL) is almost synonymous with the theory of fuzzy sets, a theory that relates to classes of objects with unsharp boundaries in which membership is a matter of degree. The point of fuzzy logic is to map an input space to an output space, and the primary mechanism for doing this is a list of if-then statements called rules. All rules are evaluated in parallel, and the order of the rules is unimportant. The rules themselves are useful because they refer to variables and the adjectives that describe those variables. You have to define your system like rule base, membership functions and their number and shape manually. A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The input space is sometimes referred to as the universe of discourse, a fancy name for a simple concept. There are different kinds of membership functions for example, triangular membership function(trimf), trapezoidal membership function(trapmf), Gaussian membership function(gaussmf and gauss2mf),and generalized bell membership function(gbellmf) as shown in Fig. 6 and Fig. 7 .

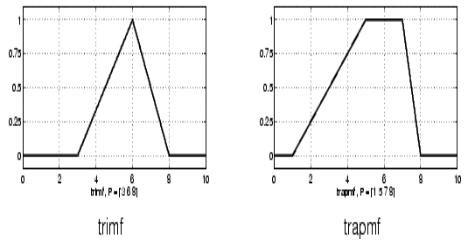

Fig. 6. Triangular and trapezoidal membership functions [19]

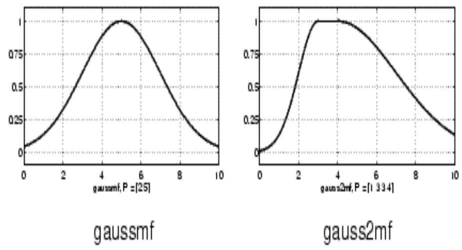

Fig. 7. Gaussian membership functions [19]

III. PHYSICAL PROPERTIES OVERVIEW

In this study, critical compressibility (Zc), critical temperature (Tc), and critical pressure (Pc) were predicted. These correlations are basically based on the following assumption:-

1- That critical compressibility (Zc) is a strong function of the critical volume (Vc), critical temperature (Tc), critical pressure (Pc),and molecular weight (Mw) [17].

Zc = f (Vc, Tc, Pc, Mw)

$$Z_c = \frac{V_c * P_c * M_w}{10.732 * T_C}$$

2- The critical temperature (Tc) is a strong function of the critical volume (Vc), critical compressibility (Zc), critical pressure (Pc), and molecular weight (Mw) [17].

Tc = f (Vc, Zc, Pc, Mw)

$$T_c = \frac{V_c * P_c * M_w}{10.732 * Z_C}$$

3- The critical pressure (Pc) is a strong function of the critical volume (Vc), critical compressibility (Zc), critical temperature (Tc), and molecular weight (Mw) [17].

Pc = f (Vc, Zc, Tc, Mw)

$$P_c = \frac{10.732 * T_c * Z_c}{V_c * M_w}$$

IV. DATA ACQUISITION AND ANALYSIS

A total of 120 data sets used for this study were collected from published sources as follows: 92 from Naji [17]and 28 Orangi [18]. Each data set contains critical compressibility (Zc), critical volume (Vc), critical temperature (Tc), critical pressure (Pc), and molecular weight (Mw) as shown in Table 1. Out of the 120 data points, 84 were used to train the model and 36 to test the model to evaluate its accuracy and generalization capability.

Table 1- Statistical descriptions of the training data

	Min	Max	Mean	Range	Mid-Ran.	Variation	St. Dev.	Skew.
Zc	0.1783	0.288	0.244	0.11	0.233	0.001	0.027	-0.691
Tc	227.16	1790	1336	1563	1009	155268	394	-0.0958
Pc	73.2	1071.3	257	998	572	38692	197	2
Vc	0.0626	26.755	2	27	13	15	4	4
MW	16.04	703.36	309	687	360	37624	194	0.176

Development of Artificial Intelligence (AI) Models

In this study, back propagation network (BPN) model was used to predict the critical compressibility (Zc), critical temperature (Tc), and critical pressure (Pc).

Critical Compressibility (Zc) Model

For the critical compressibility (Zc) model, we used (BPN) with structure 4-10-5-1. The first layer consists of four neurons representing the input values of the critical volume (Vc), critical temperature (Tc), critical pressure (Pc), and molecular weight (Mw). The second (hidden) layer consists of ten neurons and the third (hidden) layer consists of five neurons. The fourth layer contains one neuron representing the output predicted value of the critical compressibility (Zc).

Critical Temperature (Tc) Model

Critical Temperature (Tc) model was developed using (BPN) with structure 4- 11-1. The first layer consists of four neurons representing the input values of the critical volume (Vc), critical compressibility (Zc), critical pressure (Pc), and molecular weight (Mw). The second (hidden) layer consists of eleven neurons. The third layer contains one neuron representing the output predicted value of the critical temperature (Tc)

Critical Pressure (Pc) Model

Critical Pressure (Pc) Model was predicted using (BPN) with structure 4-10-5-1. The first layer consists of four neurons representing the input values of the critical volume (Vc), critical compressibility (Zc), critical temperature (Tc), and molecular weight (Mw). The second (hidden) layer consists of ten neurons and the third (hidden) layer consists of five neurons. The fourth layer contains one neuron representing the output predicted value of the critical pressure (Pc). For all the above models tangent sigmoid transfer function and linear transfer function training optimization were used.

For the fuzzy logic (FL) model we used Subtractive Clustering (SC) and Grid Partitioning techniques. For Clustering a radius of 0.1 was selected. For grid partitioning, a triangular (trimf) membership function was used after checking the model for over-fitting for all the above models.

Evaluation Criteria

To compare the performance and accuracy of the new model, statistical error analysis is performed. The statistical parameters used for comparison are: minimum and maximum absolute percent error, average percent relative error, average absolute percent relative error, root mean square and the correlation coefficient. Equations for those parameters are given below:

1. Average Percent Relative Error:
It is the measure of the relative deviation from the experimental data, defined by:

$$E_a = \frac{1}{n} * \sum_{i}^{N} [E_i]$$

Where Ei is the relative deviation of an estimated value from an experimental value

$$E_i = \left[\frac{V_{exp} - V_{est}}{V_{exp}}\right] * 100 \, , i = 1,2,3 \ldots ..n$$

2. Average Absolute Percent Relative Error:
It measures the relative absolute deviation from the experimental values, defined by:

$$E_{aa} = \frac{1}{n} * \sum_{i}^{n} [E_i]$$

1- Maximum and minimum and absolute percent relative error
To define the range of error for each correlation, the calculated absolute percent relative error values are scanned to determine the maximum and minimum values. They are defined by:

$$E_{min} = \max_{i=1}^{n} \lfloor Ei \rfloor$$

$$E_{min} = \min_{i=1}^{n} \lfloor Ei \rfloor$$

5. The Correlation coefficient:
It represents the degree of success in reducing the standard deviation by regression analysis, defined by:

$$R = \sqrt{1 - \sum_{i=1}^{n} [V_{exp} - V_{est}] / \sum_{i=1}^{n} [V_{exp} - \bar{V}]}$$

$$\bar{V} = \frac{1}{n} * \sum_{i}^{n} [V_{exp}]$$

V. RESULTS AND DISCUSSION

After training the neural networks, the models become ready for testing and evaluation. To perform this, the last data group (37 data sets), which was not seen by the neural network during training, was used.

Table 2 shows the comparison of evaluation criteria such as maximum absolute percent relative error, minimum absolute percent relative error, average absolute percent relative error, average percent relative error, standard deviation, and correlation coefficient, respectively of the results for critical compressibility (Zc), critical temperature (Tc), and critical pressure (Pc) correlations, respectively by using back propagation network.

Fig. 8 and 9 show the plots of the predicted versus experimental critical compressibility (Zc) values correlations for training and testing, respectively using back propagation network (BPN). The predicted versus experimental critical compressibility values correlations for training and testing, respectively using the fuzzy logic (FL) model were considered as shown in Fig. 10 and 11.

Fig. 12 and 13 illustrate the plots of the measured versus estimated critical temperature (Tc) values correlations for training and testing, respectively using back propagation network (BPN). While Fig. 14 and15 demonstrate the same for critical temperature, values predicted by fuzzy logic (FL) model.

Fig. 16 and17 demonstrate the same for critical pressure (Pc) values. At the same time as Fig. 18 and 19, explains the same for critical pressure values predicted by fuzzy logic (FL) model.

As can be observed from Table2, the (FL) proposed model achieved the lowest maximum error(0.0296 %), the lowest absolute percent relative error (0.0052%), and the lowest standard deviation(0.0086%) and showed high accuracy in predicting the critical compressibility (Zc) values (correlation coefficient is 1).

The Same observation can be obtained from same Table for critical temperature (Tc) correlations, the (FL) predicted model also achieved the lowest maximum error(0.0296 %), the lowest absolute percent relative error (0.0052%), and the lowest standard deviation(0.0086%) and illustrated high accuracy in predicting the critical temperature (Tc) values (correlation coefficient is 1).

For critical pressure (Pc) modles as can be concluded from the results shown in Table1, the lowest maximum error(0.0934%), the lowest absolute percent relative error (0.0176%), and the lowest standard deviation(0.0316%) and showed high accuracy in predicting the critical temperature (Tc) values (correlation coefficient is 1).

Table2- Statistical analysis of the results critical compressibility (Zc), critical temperature (Tc), and critical pressure (Pc)

		EMax	EMin	Eaa	Ea	Estd	R
Zc	BPN	3.0443	0.0097	0.6622	0.0812	0.8788	0.9973
Zc	FL	0.0296	1.13E-005	0.0052	0.0012	0.0086	1
Tc	BPN	2.6410	0.0034	0.2550	-0.0313	0.4964	0.9999
Tc	FL	0.0296	1.13E-005	0.0052	0.0012	0.0086	1
Pc	BPN	4.6470	0.0003	0.4102	0.0984	0.7432	0.9999
Pc	FL	0.0934	3.10E-006	0.0176	4.79E-004	0.0316	1

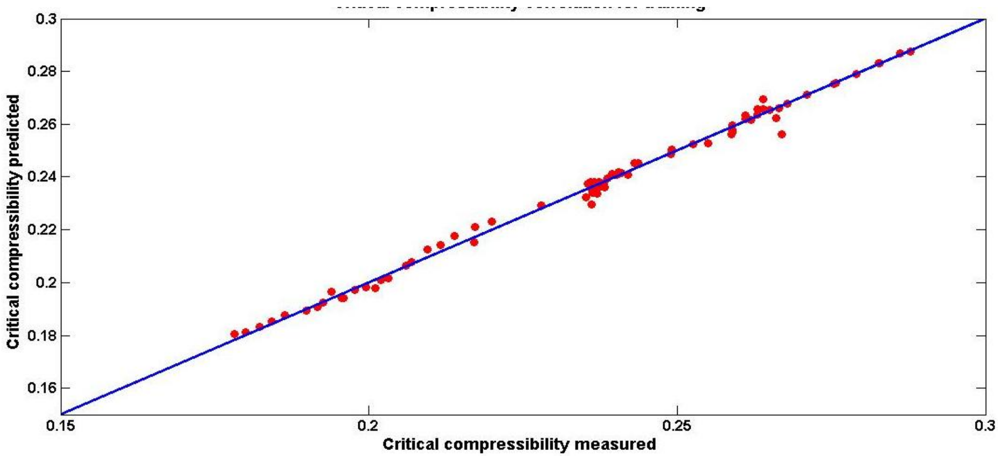

Fig. 8. Critical compressibility (Zc) model for training data by using (BPN)

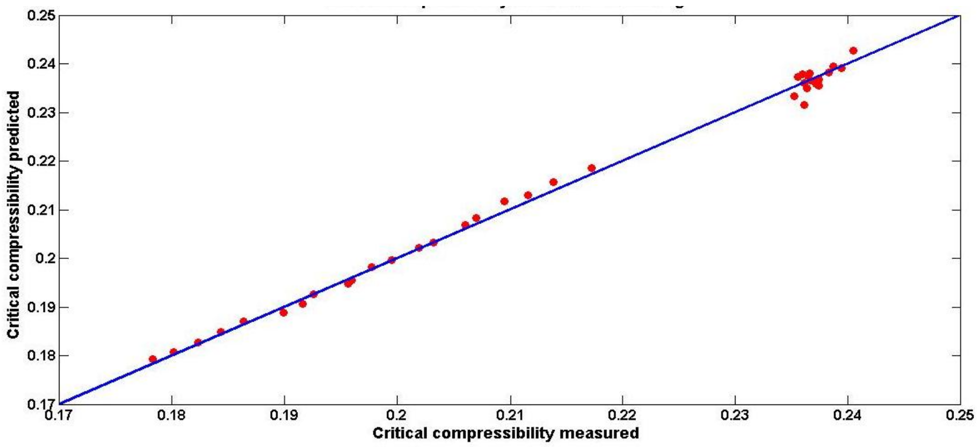

Fig. 9. Critical compressibility (Zc) model for testing data by using (BPN)

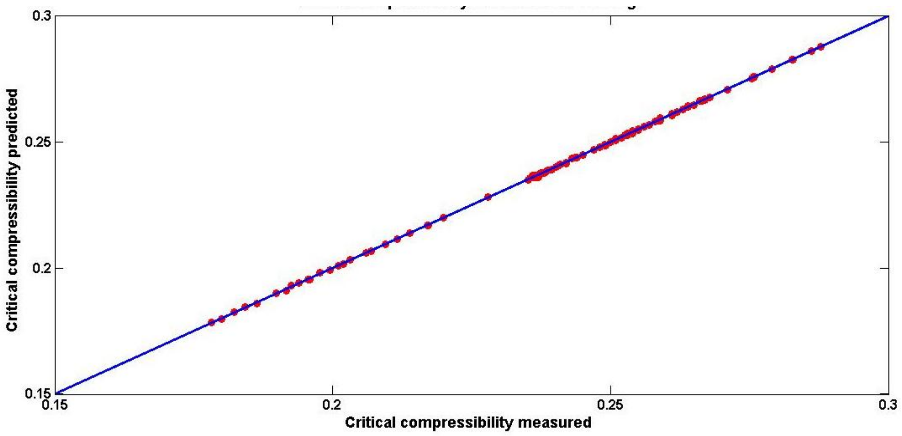

Fig. 10. Critical compressibility (Zc) model for training data by using (FL)

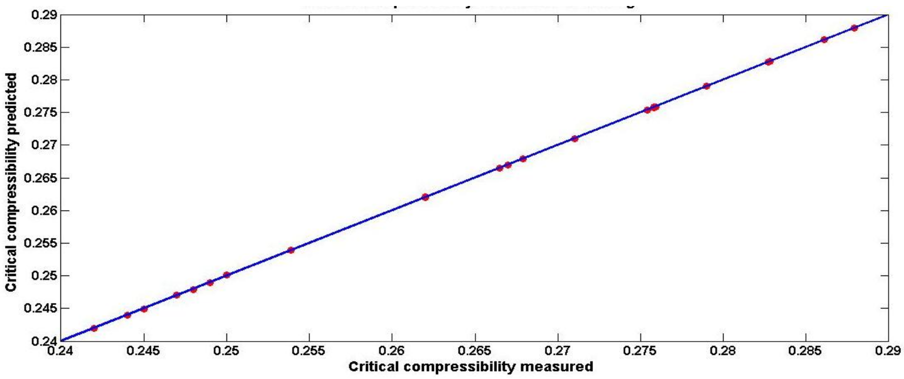

Fig. 11. Critical compressibility (Zc) model for testing data by using (FL)

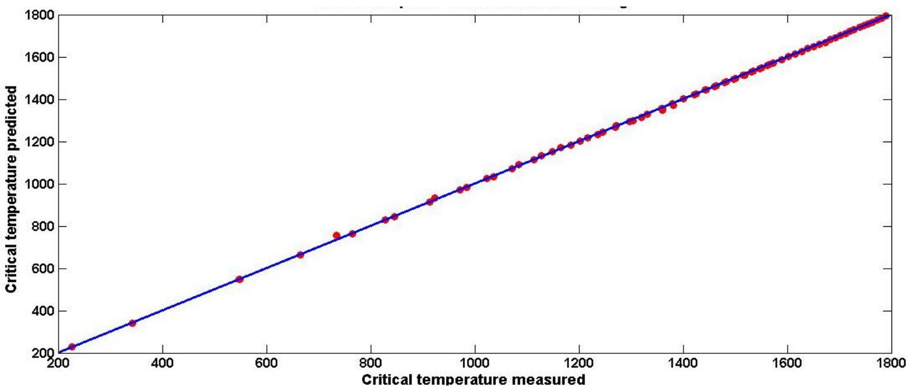

Fig. 12. Critical temperature (Tc) model for training data by using (BPN)

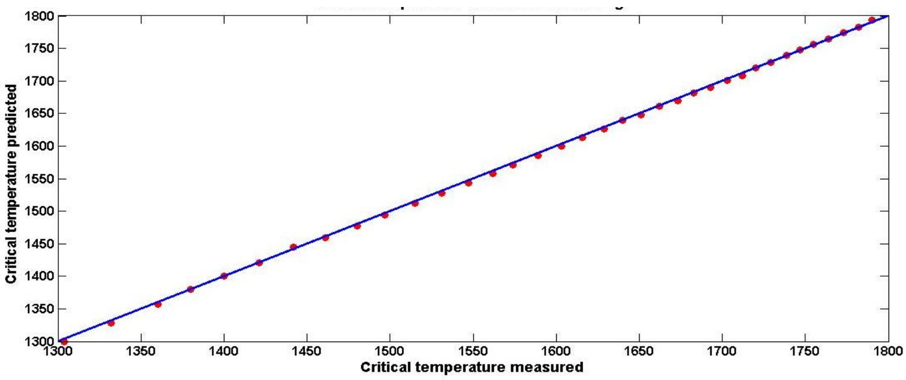

Fig. 13. Critical temperature (Tc) model for testing data by using (BPN)

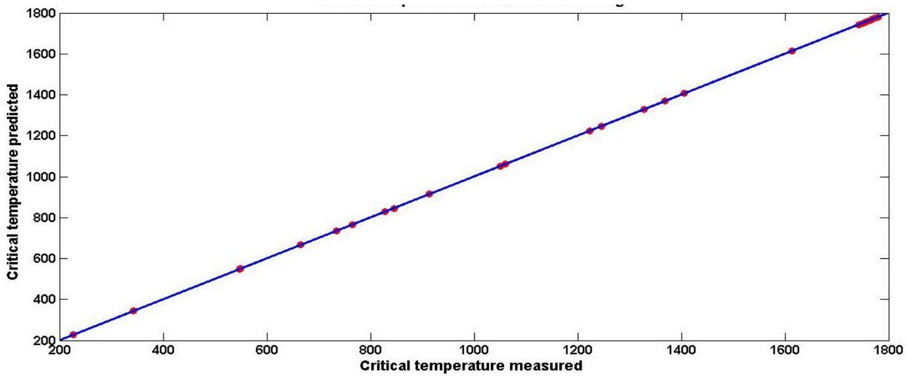

Fig. 14. Critical temperature (Tc) model for training data by using (FL)

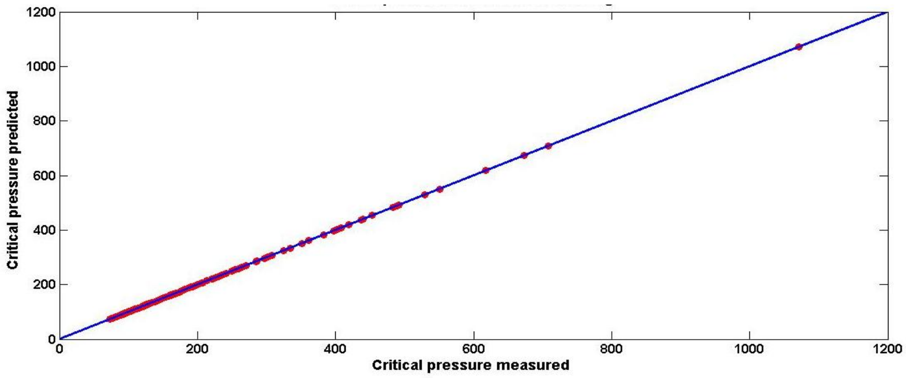

Fig. 15. Critical temperature (Tc) model for testing data by using (FL)

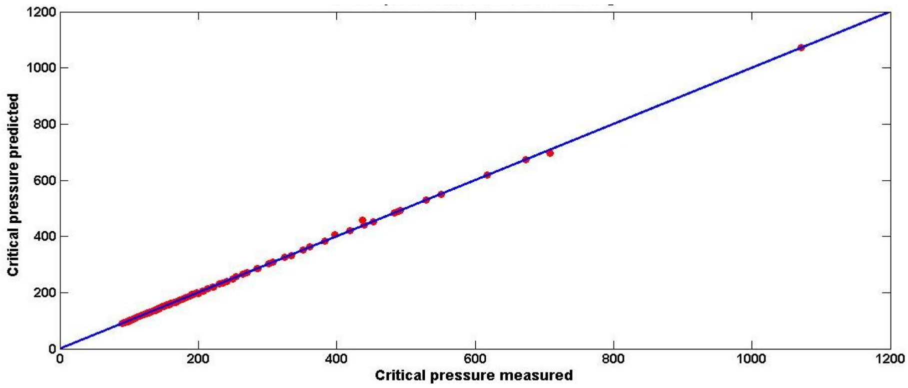

Fig. 16. Critical pressure (Pc) model for training data by using (BPN)

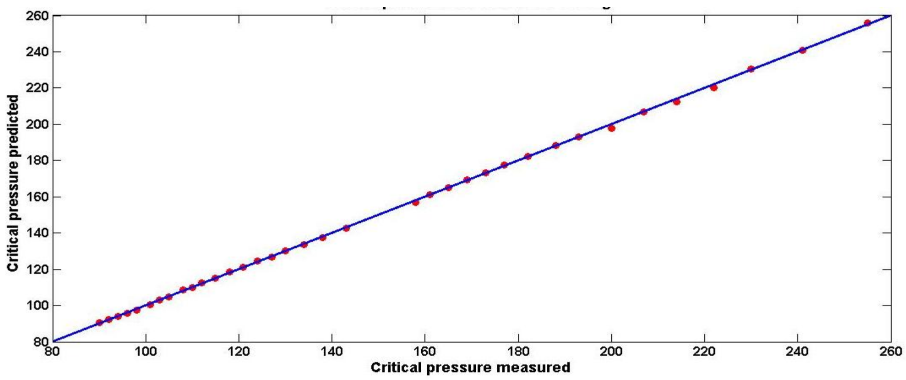

Fig. 17. Critical pressure (Pc) model for testing data by using (BPN)

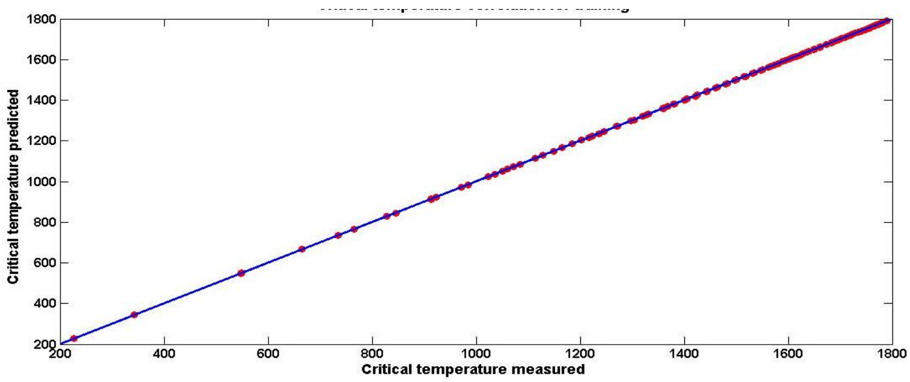

Fig. 18. Critical pressure (Pc) model for training data by using (FL)

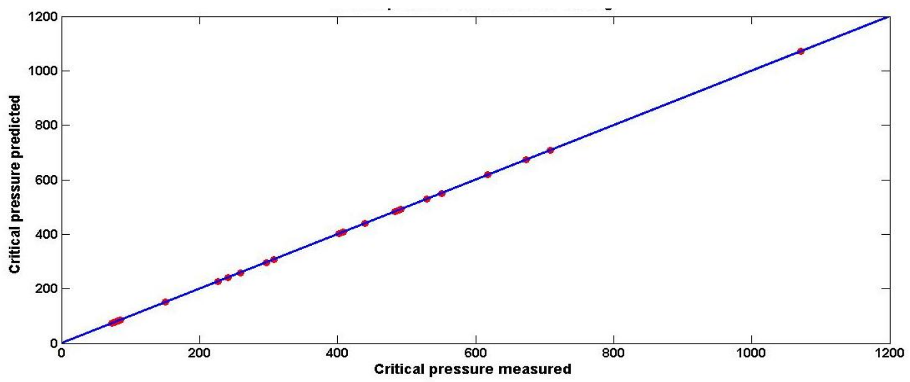

Fig. 19. Critical pressure (Pc) model for testing data by using (FL)

VI. CONCLUSIONS

Based on the analysis of the results obtained in this study, the following conclusions can be made:-

In this study, both back propagation network (BPN) and fuzzy logic (FL) models were used to predict critical compressibility (Zc), critical temperature (Tc), and critical pressure (Pc).

For gas critical compressibility (Zc), critical temperature (Tc), and critical pressure (Pc) models, this is the first an attempt that was made to obtain these models using back propagation network (BPN).

The new fuzzy logic (FL) models outperform all the artificial neural network models.

The results show that the developed (FL) critical compressibility (Zc) model provides better predictions and higher accuracy. The present model provides prediction of the critical compressibility (Zc) with correlation coefficient of 1.

The developed developed (FL) critical temperature (Tc) model provides prediction of the critical temperature (Tc) with correlation coefficient of 1.

The critical pressure (Pc) model provides prediction of the critical pressure (Pc) with correlation coefficient of 1.

Nomenclature
Zc = Critical compressibility
Vc = Critical volume
Tc = Critical temperature
Pc = Critical pressure
Mw = Molecular weight
γg= Specific gravity
Tb = Normal boiling point
CCE = Constant Composition Expansion
CVD = Constant Volume Depletion
Ea = Average percent relative error
Eaa = Average absolute percent relative error
EMax = Maximum absolute percent relative error
EMin = Minimum absolute percent relative error
Estd = Standard deviation error

R = Correlation coefficient
BPN = Back propagation network
FL = Fuzzy logic
Vexp = Experiment value
Vest = Measured value

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