Artificial Intelligence Techniques for Predicting the Reservoir Fluid Properties of Crude Oil Systems

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Abstract- Reservoir fluid properties PVT such as oil bubble point pressure, oil formation volume factor, solution gas-oil ratio, gas formation volume factor, and gas and oil viscosities are very important in reservoir engineering computations. 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 the need for a quick and reliable method for predicting the reservoir fluid properties. Recently, Artificial Intelligence (AI) techniques were used comprehensively for this task. This study presents back propagation network (BPN), radial basis functions networks (RBF) and fuzzy logic (FL) techniques for predicting the formation volume factor, bubble point pressure, solution gas-oil ratio, the oil gravity, and the gas specific gravity. These models were developed using 760 data sets collected from published sources. Statistical analysis was performed to see which of these techniques are more reliable and accurate method for predicting the reservoir fluid properties. The new fuzzy logic (FL) models outperform all the previous artificial neural network models and the most common published empirical correlations. The present models provide predictions of the formation volume factor, bubble point pressure, solution gas-oil ratio, the oil gravity and the gas specific gravity with correlation coefficient of 0.9995, 0.9995, 0.9990, 0.9791 and 0.9782, respectively.

Keywords: *Reservoir fluid properties PVT, reservoir temperature, propagation network, fuzzy logic techniques*

1. INTRODUCTION

Recently, Artificial Intelligence techniques were used comprehensively in most of petroleum engineering applications, for example, drilling engineering, reservoir engineering production engineering, petrophysics, rock mechanics and exploration [1, 2, 3 and 4]. Artificial Intelligence techniques have also been used to predict the reservoir fluid properties. These properties include formation volume factor, isothermal compressibility, the solution gas-oil ratio, the gas specific gravity, the oil specific gravity, density, and viscosity.

Accurate reservoir fluid properties PVT such as oil bubble point pressure, oil formation volume factor, solution gas-oil ratio, gas formation volume factor, and gas and oil viscosities are very important in reservoir engineering computations and a requirement for all types of petroleum calculations such as determination of initial hydrocarbons in place, optimum production schemes, ultimate hydrocarbon recovery, design of fluid handling equipment, and reservoir volumetric estimates.

Totally, 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 the need for a quick and reliable method for predicting the reservoir fluid properties. Hence, engineers have to use empirically derived correlations such as an equation of state (EOS), linear, non-linear, multiple regressions correlations [5, 6, 7, and 8]. Recently, researchers utilized Artificial Intelligence models are used for this task. Some examples of AI models are artificial neural network, support vector machines, fuzzy logic technique, and functional networks.

This study covered back propagation network, radial basis functions networks and fuzzy logic techniques for predicting the very important reservoir fluid properties include the formation volume factor, bubble point pressure, solution gas-oil ratio, oil gravity and the gas specific gravity using 760 data sets collected from different crude samples. These data were divided into three groups. The first one (532 sets) was used to train the AI models, the second group (114 sets) was used to cross-validate the relationships established during the training process and, the last group (114 sets) was used to test the models to evaluate their accuracy and trend stability.

2. LITERATURE REVIEW

A good number of previous work has discussed various applications of AI in petroleum engineering references. So far, only few publications are available in literature for AI applications in predicting PVT properties because these PVT are particularly difficult to study due to the composition and phase changes of light components that occur during the reservoir depletion reference and are either not available, or very costly to obtain.

Gharbi [9] presented correlations for the bubble-point pressure and the oil formation volume factor as a function of the solution gas-oil ratio, the gas specific gravity, the oil specific gravity, and the temperature by using neural-network-based models. They used 498 data sets of different crude-oil and gas mixtures from the Middle East region. They obtained more accurate models for the prediction of PVT properties of Middle East crude oils than existing PVT correlations with correlation coefficient of 0.962 for bubble-point pressure and 0.979 for oil formation volume factor.

Osman [10] developed new correlations for predicting the formation volume factor at the bubble point pressure. The model was developed using 803 published data from the Middle East, Malaysia, Colombia, and Gulf of Mexico fields based on Artificial Neural Networks (ANN). They concluded that, the developed model provides better predictions and higher accuracy than the published empirical correlations with an absolute average percent error of 1.789%, and correlation coefficient of 0.988.

Al-Marhoun [11] used Artificial Neural Networks (ANN) to predict the bubble point pressure and, the formation volume factor at the bubble point pressure for Saudi Crude Oils. The models were developed using 283 data sets collected from Saudi reservoirs. The presented model provides predictions of the formation volume factor at the bubble point pressure with an absolute average percent error of 0.5116%, standard deviation of 0.6626 and correlation coefficient of 0.9989.

Osman [12] performed a expansive study on PVT properties of oil field brines correlation based on 1040 published data sets by using neural-network-based models. They developed two new models to predict different brine properties. The first model predicts brine density, formation volume factor (FVF), and isothermal compressibility as a function of pressure, temperature and salinity. The second model is developed to predict brine viscosity as a function of temperature and salinity.

El-Sebakhy [13] presented a new computational intelligence modeling scheme based on the support vector machines SVR scheme to predict both bubble point pressure and oil formation volume factor. They used solution gas-oil ratio, reservoir temperature, oil gravity, and gas relative density as input variables based on 782 published data sets. This model achieved the lowest absolute percent relative error, lowest minimum error, lowest maximum error, lowest root mean square error, and the highest correlation coefficient among other correlations for the used three distinct data sets (Standing, Glaso , Al-Marhoun and ANN System).

Hajizadeh [14] used the genetic algorithms technology to predict the reservoir fluid viscosity. The model was developed using 89 data sets collected from different crude samples. These data include pressure, temperature, reservoir fluid gas oil ratio and oil density, and the output parameter is fluid viscosity. They concluded that, the genetic algorithms model for prediction of the reservoir fluid viscosity can predict the output target viscosity data with a good accuracy(R) value for testing data is 0.99742. Also, Hajizadeh [14] introduced a new application of fuzzy logic and neural networks in petroleum engineering to predict the reservoir fluid viscosity. This model was developed using 89 data sets collected from different crude oil samples. The proposed fuzzy model predicted the average error of 0.16529 centipoises and R value of 0.999314.

Shokir [15] evaluated two new models for estimating the density and viscosity of pure hydrocarbon gases and hydrocarbon gas mixtures containing high amounts of pentane, plus small concentrations of non-hydrocarbon components using fuzzy logic approach. The fuzzy models were derived from 5,350 measurements of density and viscosity of various pure gases and gas mixtures. He obtained more accurate models for the prediction of density and viscosity of pure hydrocarbon gases and hydrocarbon gas mixtures with the lowest average absolute error (2.37%) among all tested gas density correlations and with the lowest average absolute error (2.37%) among all tested gas density correlations.

Oloso [16] demonstrated two new models for estimating the viscosity and solution gas/oil ratio (GOR). Artificial Neural Networks (ANN) and two of its advances; Support Vector Regression (SVR) and Functional Networks (FN), have been developed to evaluate these two models. They used three categories of data sets namely, data sets X, Y and Z. Data set X contains 99 points consists of the hydrocarbon and non-hydrocarbon components, and some other properties of the crude oil while data sets Y and Z have 1705 and 841 data points respectively. The data set Y consists of the viscosity-pressure measurements to generate the viscosity curves, whereas data set Z consists of solution GOR-pressure measurements. They concluded that SVR and FN give better performances than the conventional ANN technique.

Al-Nasser [17] developed a new gas viscosity correlations using Artificial Neural Networks. This model was used 5600 data points in which at least viscosity and density were measured directly at the same temperature and pressure.

Ikiensikimama [18] evaluated a new oil formation volume factor using Artificial Neural Networks based on 802 data sets from the Middle East, Malaysia, Colombia, and Gulf of Mexico fields. Of the 802 data points, 482 were used to train the ANN models, the remaining 160 to cross-validate the relationships established during the training process and 160 to test the model to evaluate its accuracy and trend stability. The developed model provides better higher accuracy than the published empirical correlations with an absolute average percent error of 1.19%, and correlation coefficient of 0.968.

3. RESEARCH METHODOLOGY

To achieve this work, back propagation network, radial basis functions networks, and fuzzy logic techniques were used for predicting the formation volume factor, bubble point pressure, solution gas-oil ratio, the oil gravity and the gas specific gravity

3.1 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 is able to develop associations, transformations or mappings between objects or data.

3.2 Radial Basis Functions Networks (RBF)

A radial basis function network is an artificial neural network that uses radial basis functions as activation functions. RBF networks have a number of advantages over BPN. First, they can model any non-linear function using a single hidden layer, which removes some design-decisions about numbers of layers. Second, the simple linear transformation in the output layer can be optimized fully using traditional linear modeling techniques, which are fast and do not suffer from problems such as local minimum which plague BPN training techniques. RBF networks can therefore be trained extremely quickly (i.e. orders of magnitude faster than BPN). In MATLAB there are different types of a radial basis function network such as:

1. newrb - Design a radial basis network.
2. newrbe - Design an exact radial basis network.
3. Newgrnn - Design a generalized regression neural network.
4. newpnn - Design a probabilistic neural network.

3.3 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 is almost synonymous with the theory of fuzzy sets, a theory which 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 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).

3.4 Data Acquisition and Analysis

Totally, the 760 data sets used for this work were collected from published sources as follows: Katz [19] (53), Glaso[6] (41), Vazquez and Beggs[7] (254), Al-Marhoun[8] (160), Omar and Todd1[20] (93) Ghetto[21] (137), and Gharbi and Elsharkawy[22] (22). Each data set contains formation volume factor, bubble point pressure, total solution gas oil ratio, average gas gravity, oil gravity, and reservoir temperature. Of the 760 data points, 532 were used to train the model, 114 to cross-validate the relationships established during the training process and 114 to test the model to evaluate its accuracy and generalization capability. Statistical descriptions of the training and testing data are given in Table 1 and 2.

Table - 1: Statistical descriptions of the training data

	Min	Max	Mean	Range	Mid-Ran.	Variation	St. Dev.	Skew.
Bob	1.028	2.588	1.32341	1.56	1.808	0.053	0.231	1.413
Bpp	126	7127	1790.93	7001	3626.5	1326072	1152	0.878
Rs	9	2637	536.121	2628	1323	179352	423	1.228
γg	0.589	1.367	0.904	0.778	0.978	0.025	0.159	0.830
API	15.3	59.5	36.071	44.2	37.4	53.6	7.324	-0.015
Tf	74	294	171.486	220	184	2446	49	0.092

Table - 2: Statistical descriptions of the testing data

	Min	Max	Mean	Range	Mid-Ran.	Variation	St. Dev.	Skew.
Bob	1.032	2.126	1.324	1.094	1.579	0.051	0.225	1.094
Bpp	130	4620	1812.11	4490	2375	1312921	1146	0.140
Rs	26	1850	568.4	1824	938	178735	423	0.714
γg	0.589	1.367	0.952	0.778	0.978	0.027	0.165	0.698
API	19.4	51.7	33.195	32.3	35.55	41	6.4	0.237
Tf	74	271	158.671	197	172.5	2062.04	45.4	0.203

3.5 Development of Artificial Intelligence (AI) Models

In this study presents back propagation network, radial basis functions networks and fuzzy logic models were used to predict the formation volume factor, bubble point pressure, solution gas-oil ratio, oil gravity and the gas specific gravity.

For the formation volume factor model, we used with structure 4-11-5-1. The first layer consists of four neurons representing the input values of the solution gas-oil ratio, the reservoir temperature, the gas specific gravity, and the oil gravity. The second (hidden) layer consists of eleven neurons and the third (hidden) layer consists of five neurons. The fourth layer contains one neuron representing the output predicted value of the formation volume factor.

Bubble point pressure models developed using with structure 4-11-22-1. The first layer consists of four neurons representing the input values of the solution gas-oil ratio, the reservoir temperature, the gas specific gravity, and the oil gravity. The second (hidden) layer consists of eleven neurons and the third (hidden) layer consists of twenty two neurons. The fourth layer contains one neuron representing the output predicted value of the bubble point pressure.

Solution gas-oil ratio models predicted using with structure 4-11-15-1. The first layer consists of four neurons representing the input values of the bubble point pressure, the reservoir temperature, the gas specific gravity, and the oil gravity. The second (hidden) layer consists of eleven neurons and the third (hidden) layer consists of fifteen neurons. The fourth layer contains one neuron representing the output predicted value of the solution gas-oil ratio.

For oil gravity models, the (BPN) with structure 4-11-22-1 was used. The first layer consists of four neurons representing the input values of the bubble point pressure, the reservoir temperature, the gas specific gravity, and the solution gas-oil ratio. The second (hidden) layer consists of eleven neurons and the third (hidden) layer consists of twenty two neurons. The fourth layer contains one neuron representing the output predicted value of the oil gravity.

To predict the gas specific gravity models, we used with structure 4-11-20-1. The first layer consists of four neurons representing the input values of the bubble point pressure, the reservoir temperature, the oil gravity, and the solution gas-oil ratio. The second (hidden) layer consists of eleven neurons and the third (hidden) layer consists of twenty neurons. The fourth layer contains one neuron representing the output predicted value of the gas specific gravity. For all above models tangent sigmoid transfer function and linear transfer function training optimization were used. For radial basis functions networks (RBF) we used design an exact radial basis network (newrbe) with radbas transfer function.

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

3.6 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 Eiis the relative deviation of an estimated value from an experimental value

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

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

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

3. 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:

$$E_{min} = \underset{i=1}{\overset{n}{max}} [Ei]$$

$$E_{min} = \underset{i=1}{\overset{n}{min}} [Ei]$$

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

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

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

4. RESULTS AND DISCUSSION

After training the neural networks, the models become ready for testing and evaluation. To perform this, the last data group (228 data sets), which was not seen by the neural network during training, was used.

Table 3 through 7 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 formation volume factor, bubble point pressure, solution gas-oil ratio, oil gravity, gas specific gravity correlations, respectively by using back propagation network, radial basis functions networks, and fuzzy logic techniques.

As can be observed from Table 3, fuzzy logic proposed model achieved the lowest maximum error(4.208%), the lowest absolute percent relative error (0.210%), and the lowest standard deviation (0.593%) and showed high accuracy in predicting the formation volume factor values (correlation coefficient is 0.9995) than the (BPN) and (RBF) proposed models. Also, the fuzzy logic model outperforms all the empirical correlations and the artificial neural network models.

Same observation can be obtained from Table 4 for bubble point pressure correlations, the fuzzy logic predicted model also achieved the lowest maximum error(46.066%), the lowest absolute percent relative error (1.897%), and the lowest standard deviation (4.849%) and showed high accuracy in predicting the bubble point pressure values (correlation coefficient is 0.9995) than the (BPN) and (RBF) proposed models.

For solution gas-oil ratio models as can be concluded from the results shown in Table 5, the (FL) predicted model achieved the lowest maximum error(33.407%), the lowest absolute percent relative error (2.688%), and the lowest standard deviation (5.310%) and showed high accuracy in predicting the solution gas-oil ratio values (correlation coefficient is 0.9990) than the (BPN) and (RBF) proposed models.

Oil gravity correlations show that, the (FL) predicted model achieved the lowest maximum error(19.027%), the lowest absolute percent relative error (2.303%), and the lowest standard deviation(3.945%) and showed high accuracy in predicting the oil gravity values (correlation coefficient is 0.9761) than the (BPN) and (RBF) proposed models as can be concluded from the results shown in Table 6.

For gas specific gravity models as can be concluded from the results shown in Table7, the (FL) predicted model achieved the lowest maximum error (14.937%), the lowest absolute percent relative error (1.999%), and the lowest standard deviation(3.297%) and showed high accuracy in predicting the gas specific gravity values (correlation coefficient is 0.9782) than the (BPN) and (RBF) proposed models.

Figures 1 and 2 show the plots of the predicted versus experimental formation volume factor values correlations for training and testing, respectively using fuzzy logic. The predicted versus experimental bubble point pressure values correlations for training and testing, respectively using fuzzy logic were considered as shown in Figures 3 and 4. Figures 5 and 6 illustrate the plots of the measured versus estimated solution gas-oil ratio values correlations for training and testing, respectively using fuzzy logic.

While Figures 7 and 8 demonstrate the same for oil gravity values predicted by fuzzy logic model. Figures 9 and 10 show these plots for the predicted gas specific gravity values correlations using fuzzy logic.

Table - 3: Statistical analysis of the results for formation volume factor correlations by using back propagation network, radial basis functions networks, and fuzzy logic techniques

		E_{Max}	E_{Min}	Eaa	Ea	Estd	R
Bob	BPN	6.4856	0.0044	0.8257	0.1304	1.1553	0.9977
Bob	RBF	5.9829	0.0003	0.2948	0.0415	0.6780	0.9993
Bob	FL	4.2086	2.32E-006	0.2107	0.0048	0.5938	0.9995

Table - 4: Statistical analysis of the results for bubble point pressure correlations by using back propagation network, radial basis functions networks, and fuzzy logic techniques

		E_{Max}	E_{Min}	Eaa	Ea	Estd	R
Bpp	BPN	132.9376	0.0048	8.8816	1.1238	16.2480	0.9926
Bpp	RBF	37.0370	0.0006	1.9797	0.3570	5.4500	0.9969
Bpp	FL	46.066	6.74E-005	1.897	0.1268	4.849	0.9995

Table - 5: Statistical analysis of the results for solution gas-oil ratio correlations by using back propagation network, radial basis functions networks, and fuzzy logic techniques

		E_{Max}	E_{Min}	Eaa	Ea	Estd	R
Rs	BPN	188.8399	0.0469	14.3770	2.7674	30.3288	0.9903
Rs	RBF	186.0215	0.005	2.8052	1.6245	17.6495	0.9953
Rs	FL	33.407	6.18E-004	2.6883	0.3849	5.3101	0.9990

Table - 6: Statistical analysis of the results for oil gravity correlations by using back propagation network, radial basis functions networks, and fuzzy logic techniques

		E_{Max}	E_{Min}	Eaa	Ea	Estd	R
API	BPN	43.275	0.024	5.1348	0.6751	7.8184	0.9296
API	RBF	38.1263	0.003	4.9373	0.1314	4.4378	0.9708
API	FL	19.0279	1.60E-004	2.303	0.0994	3.945	0.9761

Table - 7: Statistical analysis of the results for gas specific gravity correlations by using back propagation network (BPN), radial basis functions networks, and fuzzy logic techniques

		E_{Max}	E_{Min}	Eaa	Ea	Estd	R
γg	BPN	32.1189	0.0018	4.3758	0.541	6.7368	0.9128
γg	RBF	82.9745	1.88E-005	2.0325	0.2373	6.2351	0.9710
γg	FL	14.9378	5.65E-006	1.9992	.0417	3.2974	0.9782

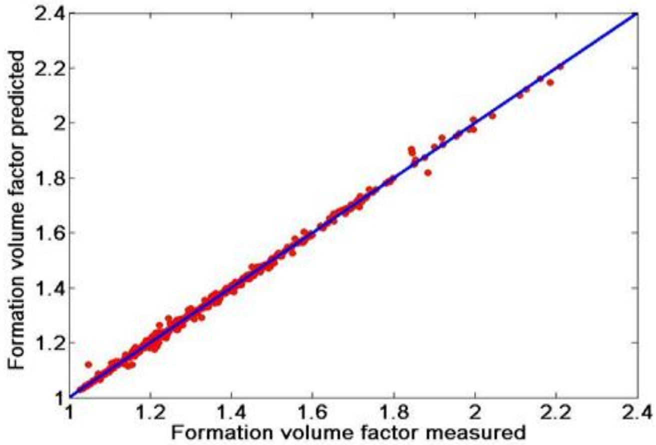

Fig. - 1: Formation volume factor correlation for training by using (FL)

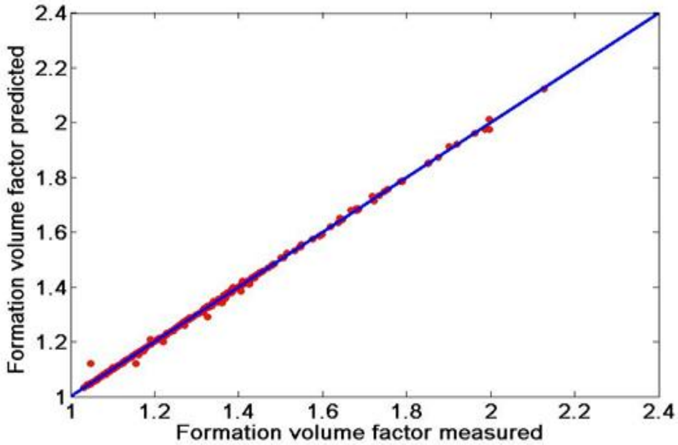

Fig. - 2: Formation volume factor correlation for testing by using (FL)

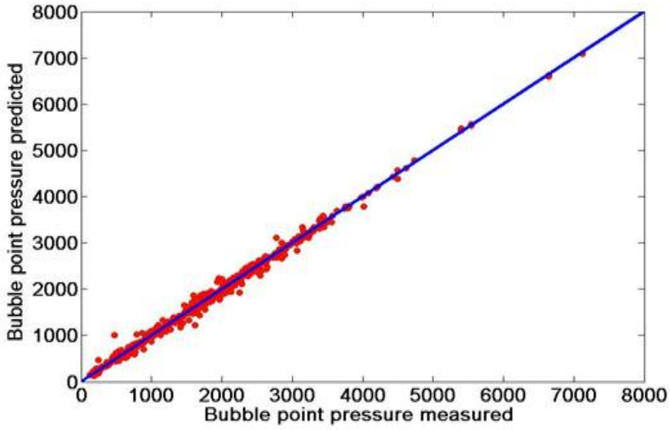

Fig. - 3: Bubble point pressure correlation for training by using (FL)

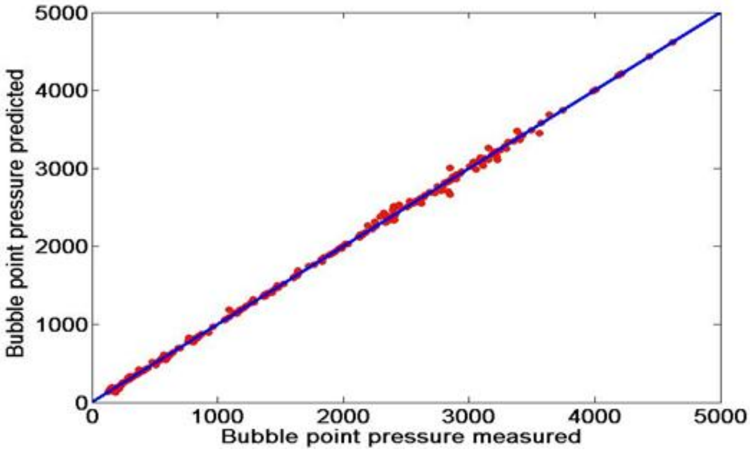

Fig. - 4: Bubble point pressure correlation for testing by using (FL)

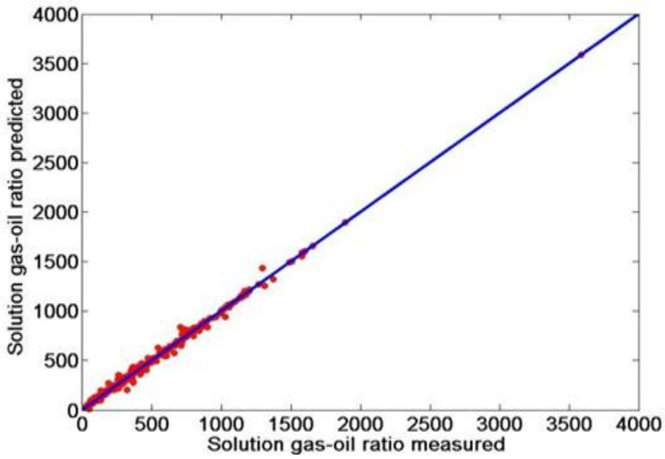

Fig. - 5: Solution gas-oil ratio correlation for training by using (FL)

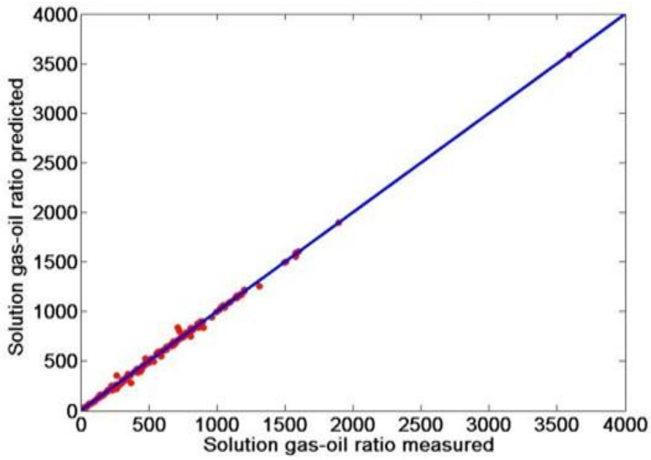

Fig. - 6: Solution gas-oil ratio correlation for testing by using (FL)

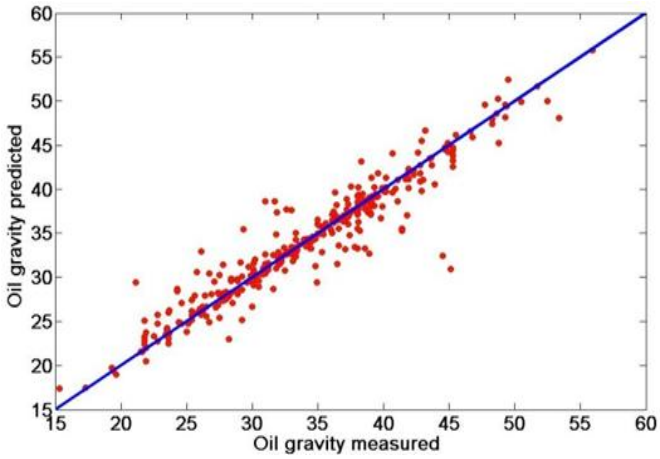

Fig.- 7: Oil gravity correlation for training by using (FL)

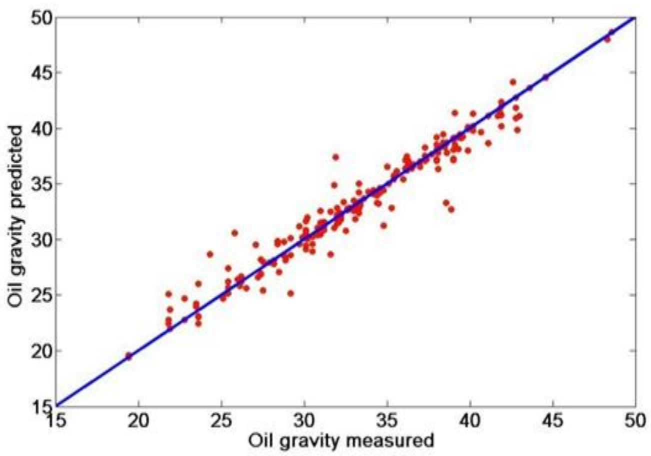

Fig. - 8: Oil gravity correlation for testing by using (FL)

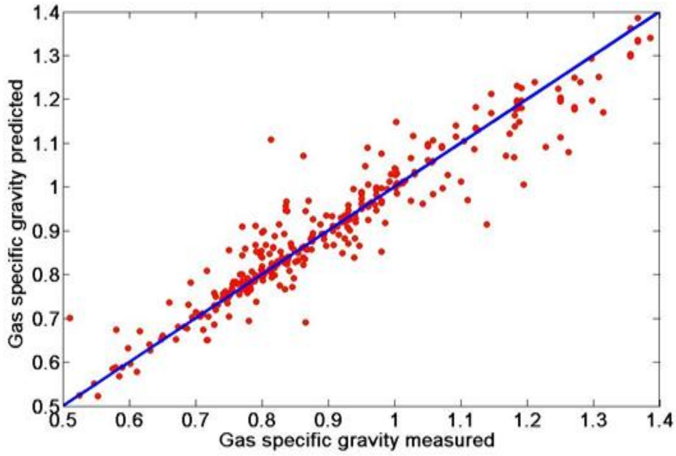

Fig. - 9: Gas specific gravity correlation for training by using (FL)

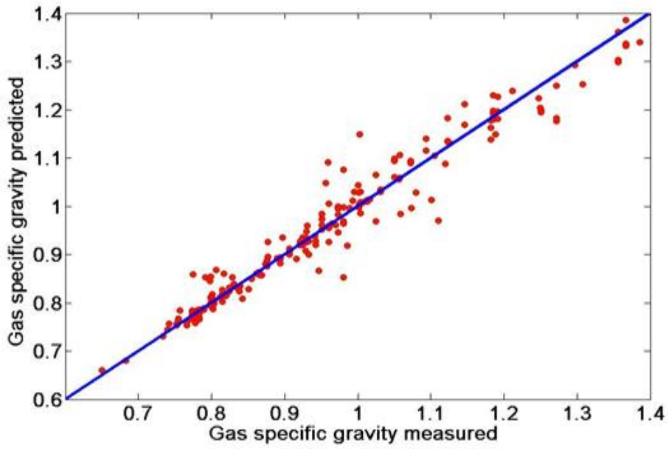

Fig. - 10: Gas specific gravity correlation for testing by using (FL)

5. CONCLUSIONS

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

- In this study, back propagation network, radial basis functions networks, and fuzzy logic techniques were used to predict five new models.
- Five new models were developed to predict the formation volume factor, bubble point pressure, solution gas-oil ratio, oil gravity, and the gas specific gravity.
- The new fuzzy logic models outperform all the artificial neural network models and the most common published empirical correlations.
- The results show that the developed formation volume factor model provides better predictions and higher

accuracy than all the empirical correlations and the artificial neural network models. The present model provides prediction of the formation volume factor at the bubble point pressure with correlation coefficient of 0.9995.

- The developed bubble point pressure model outperforms both the standard feedforward neural networks and the most common published empirical correlations. Thus, the developed (RBF) model has better, efficient, and reliable performance compared to the most published correlations. This present model provides prediction of the bubble point pressure with correlation coefficient of 0.9995.
- For of gas-oil ratio, oil gravity, and the gas specific gravity models this is the first an attempt that was made to obtain these models using fuzzy logic.
- These present models provide predictions of gas-oil ratio, oil gravity, and the gas specific gravity with correlation coefficient of 0.999, 0.9761, and 0.9782 respectively.

NOMENCLATURE

Bob = Formation volume factor at the bubble- point pressure, RB/STB
Bpp = Bubble- point pressure, psia
Rs = Solution gas oil ratio, SCF/STB
Tf = Reservoir temperature, degrees Fahrenheit
API = Oil density
γg = Gas relative density (air =1.0)
Ea = Average percent relative error
Eaa = Average absolute percent relative error
E_{Max} = Maximum absolute percent relative error
E_{Min} = Minimum absolute percent relative error
Estd = Standard deviation error
R = Correlation coefficient
BPN = Back propagation network
FL = Fuzzy logic
RBF = Radial basis functions networks
Vexp = Experiment value
Vest = Measured value

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