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Predict the Crude Oil Density, Gas Specific Gravity and Molecular WeightUsing Artificial Intelligence

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ABSTRACT: *Reservoir fluid properties such as crude oil viscosity, oil formation volume factor, bubble point pressure, solution gas oil ratio, gas formation volume factor, isothermal compressibility and crude oil density are very important in reservoir engineering computations. An accurate description of reservoir fluid properties of crude oils is necessary for solving many of reservoir engineering and surface operational problems. Most of the empirical Pressure-Volume-Temperature (PVT) correlations for any type of crude oil are functions of commonly available field data. The derived PVT correlations for crude oil are function of bubble point pressure, solution gas oil ratio, specific oil gravity, specific gas gravity, and temperature. Till date, no specific correlation has been developed for estimating PVT properties of crude oil using its chemical composition.*
This study presents radial basis functions networks (RBF) and fuzzy logic (FL) techniques for predicting the crude oil density, gas specific gravity and the molecular weight of a gas mixture using chemical composition of crude oil. The presented models here were established using 1500 data points, collected from mainly unpublished sources. Statistical analysis was conducted to see which of the Artificial Intelligence techniques (AI) were more reliable and accurate for predicting the reservoir fluid properties. The new radial basis functions networks (RBF) models outperformed most of the fuzzy logic (FL) models. The presented models provide good estimation for crude oil density, gas specific gravity and the molecular weight of a gas mixture with correlation coefficient (R^2) of 0.989, 0.997 and 0.998, respectively.
KEYWORDS*Artificial intelligence, crudeoil, gasspecific gravity, molecularweight, radial basis functions networks (RBF) and fuzzy logic*(*FL).*

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I. INTRODUCTION

Reservoir fluid properties are physical properties required for controlling the oil's flow through porous media and pipes. They are used comprehensively for the petroleum engineering applications in areas like drilling, reservoir and production engineering. Near accurate prediction of reservoir fluid properties is very critical for any of the reservoir related computations and is a major requirement for certain calculations, like, determination of initial hydrocarbons in place, optimum production schemes, ultimate hydrocarbon recovery, designing of any fluid handling equipment, and further for implementation of any enhanced oil recovery methods in future. Perfectly, reservoir fluid 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. Therefore, the concept of numerical correlation equations has been proposed to the petroleum industry to alleviate all difficulties in reservoir fluid properties determination and to predict reservoir fluid properties of reservoir oil. Recently, new techniques such as artificial intelligence (AI) techniques and expert software were used comprehensively for this task.

Recently, artificial intelligence (AI) techniques such as artificial neural network (ANN), fuzzy logic (FL), and functional networks (FN) are being widely used for most of the petroleum engineering applications suchasestimation of reservoir fluid properties [1] and [2], prediction of choke size in volatile and black oil reservoirs [3],calculation of oil and gas properties [4],estimation IPR for vertical oil well in solution gas derive reservoirs[5], and calculation of inflow performance relationship of a gas field using [6] . A

artificialintelligenceprovides functions which make modeling complex nonlinear systems easy as compared to a closed-form equation modeling. It possesses the learning ability from the given input data and further adapt to the input's environment. Also, it considers any weak assumptions regarding the physical phenomena which in turn affects for the generation of the input data [7]. A good number of past works discussed about different applications of AI for the advancement of petroleum engineering field. However, only limited publications were available in the literature regarding AI applications towards predicting PVT properties such as prediction of oil PVT properties [8]-[11], prediction of oil formation volume factor [12], estimation of bubble point pressure [13]-[14], and prediction of crude oil viscosity [15].

II. DATA ACQUISITION

For this study, 1500 data sets were collected from different conventional PVT reports which derived PVT from the differential liberation process for various reservoirs. Each data set consisted of methane (C_1), ethane (C_2), propane (C_3), i-butane (i-C_4), n-butane (n-C_4), i-pentane (i-C_5), n-pentane (n-C_5), hexane (C_6), heptane-plus (C_{7+}), molecular weight (Mw), gas specific gravity (γ_g), crude oil density (ρ_o), bubble point pressure (Pb), oil formation volume factor ($\beta o\ at$Pb), solution gas oil ratio ($Rs\ at$Pb), and reservoir temperature (T). Statistical distribution like maximum (Max), minimum (Min), mean, range, and standard deviation (SD) of the input data are presented in Table 1.

Table 1. Statistical description for chemical compositions of crude oil data sets

Property	Min	Max	Mean	Range	SD
C_1	0.05	59.93	18.87	59.88	12.38
C_2	0.09	14.09	6.94	14.00	2.95
C_3	0.27	12.2	6.52	11.93	1.69
i-C_4	0.01	4.85	1.17	4.84	0.43
n-C_4	0.33	8.56	4.07	8.23	0.89
i-C_5	0.43	5.38	1.71	4.95	0.49
n-C_5	0.85	8.3	2.79	7.45	0.75
C_6	0.95	10.39	4.23	9.44	1.38
C_{7+}	18.5	86.1	49.79	67.60	14.61
Mw	165	508	284.89	343.00	52.92
γ_g	0.799	1.02	0.909	0.221	0.17
ρ_o	39.75	60.2	49.975	20.45	7.50
Pb	149	6010	3079.5	5861	1100
βo atPb	1.04	2.13	1.585	1.09	0.23
RsatPb	1	1679	840	1678	389.40
T	100	340	187.53	240.00	34.35

III. RESEARCH METHODOLOGY

The presented study was conducted using both radial basis functions networks (RBF) and fuzzy logic (FL) techniques for predicting the crude oil density, gas specific gravity and the molecular weight of a gas mixture. Statistical error analysis such as an average absolute percent relative error (AAPRE), standard deviation error (SD) and thecorrelation coefficient(R^2) were used towards evaluating the performance and accuracy of the new crude oil density, gas specific gravity and the molecular weight models.

For radial basis functions networks (RBF), newrbe - Design an exact radial basis network was used for developing the radial basis functions networks (RBF) models. The fact of FL is to plan an input data to an output value, and the key mechanism for achievement this is rules. All rules are assessed in parallel, and the order of the rules is insignificant.In order to obtain an accurate output results, a membership function was used. A membership is a curve that describes in what way each point in the input space is plotted to a membership value (or degree of membership) between 0 and 1. Triangular, trapezoidal, gaussian, and generalized bell are different kinds of membership functions. To improve the FL model, An adaptive neuro fuzzy inference system (ANFIS) was used.

The main task for ANFIS to learn the rules and membership functions from data and learned a relationship between inputs and outputs. Grid Partitioning and Subtractive Clustering are two important versions based on the training algorithm of the ANFIS hybrid model were used to optimize the fuzzy model. crude oil density, gas specific gravity and the molecular weight of a gas mixture models were established using the following structure:

1. Number of training (epoch) = 180
2. Clustering radius (radii) = 0.12

IV. RESULTS AND DISCUSSION

After the training of neural networks, the models were further tested and evaluated. For this, the last data group with 400 data sets was used which was not witnessed by the neural network while training. Fig.1 and 2 represent the accuracy of the measured versus the predicted crude oil density values for the radial basis functions model while training and testing, respectively. For the new fuzzy logic crude oil density model, the measured versus predicted crude oil density values correlation for training and testing, respectively were considered as shown in fig. 3 and 4.

Fig.5 and 6 display the performance of the measured against the predicted gas specific gravity values using radial basis functions model during training and testing, respectively. Fig. 7 and 8 demonstrate the performance of the measured against the predicted gas specific gravity values using fuzzy logic model during training and testing, respectively. Fig. 9 and 10 illustrate the performance of the measured against the predicted molecular weight values using radial basis functions model for training and testing, respectively. For the new fuzzy logic molecular weight model, the measured versus predicted molecular weight values correlation for training and testing, respectively were considered as shown in fig. 11 and 12.

Tables 2, 3 and 4 represent the achieved an average absolute percent relative error (AAPRE), standard deviation error (SD), andcorrelation coefficient(R^2) for the predicted radial basis functions and fuzzy logic crude oil density, gas specific gravity and the molecular weight models during training and testing, respectively. From Table 2, it can be seen that radial basis functions crude oil density proposed model attained the lowest an average absolute percent relative error (AAPRE) of 0.080%, and the lowest standard deviation error (SD) of 0.629% and further showed higher accuracy towards predicting crude oil density values (R^2 = 0.989) as compared to the fuzzy logic proposed models.

From Table 3, it can be observed that for gas specific gravity correlations, the radial basis functions predicted model achieved the lowest an average absolute percent relative error (AAPRE) of 0.043 % and the lowest standard deviation error (SD) of 0.292% and also showed a higher accuracy while predicting gas specific gravity values (R^2 = 0.997) as compared to the fuzzy logic proposed models. For molecular weight models, as can be seen from the results shown in Table 4, the radial basis functions predicted model accomplished the lowest an average absolute percent relative error (AAPRE) of 0.222%, and the lowest standard deviation error (SD) of 1.276% and also showed higher accuracy towards predicting molecular weight values (R^2 = 0.998) as related to the fuzzy logic proposed models.

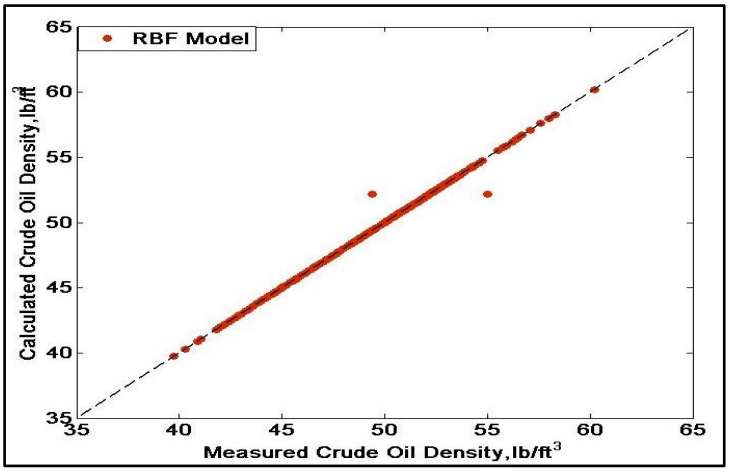

Fig. 1. Accuracy of RBF crude oil density model for training

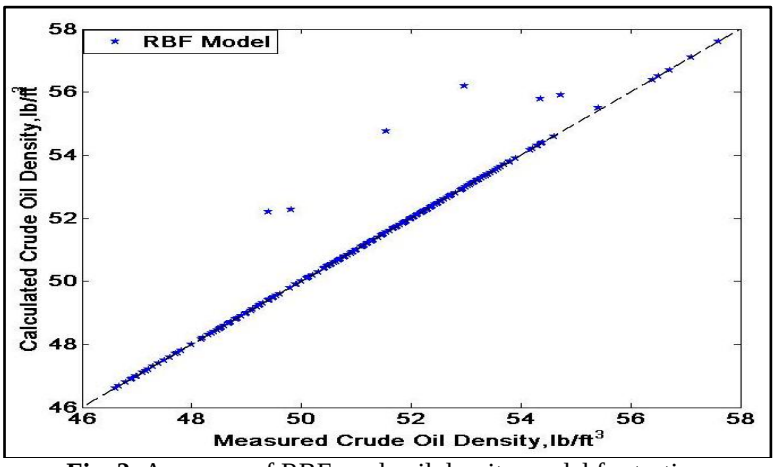

Fig. 2. Accuracy of RBF crude oil density model for testing

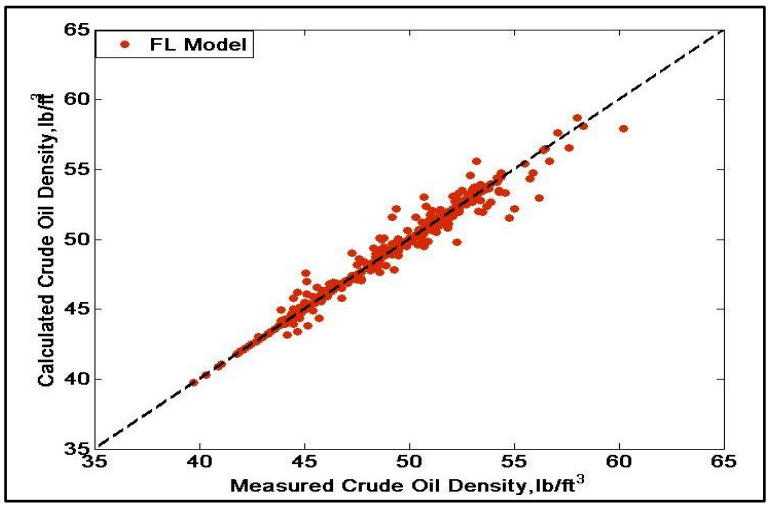

Fig. 3. Accuracy of FL crude oil density model for training

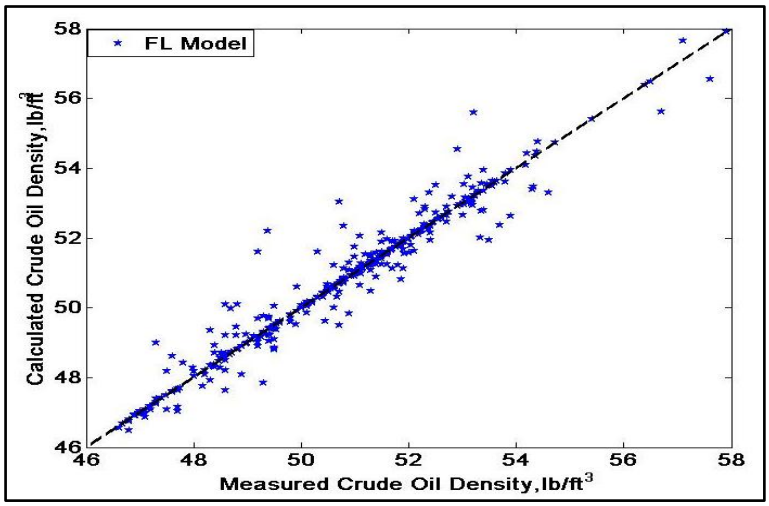

Fig. 4. Accuracy of FL crude oil density model for testing

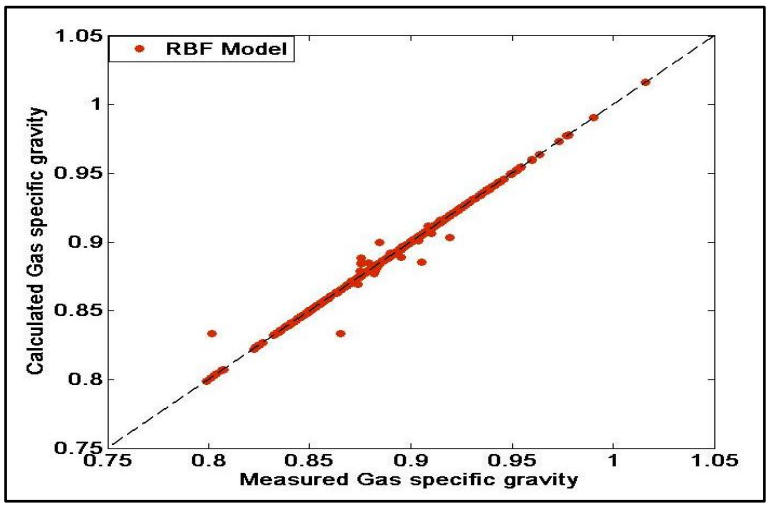

Fig. 5. Accuracy of RBF gas specific gravity model fortraining

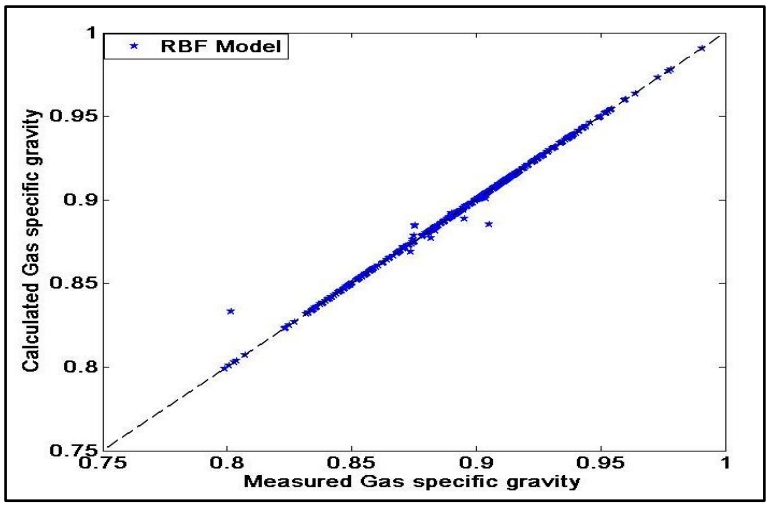

Fig. 6. Accuracy of RBF gas specific gravity models for testing

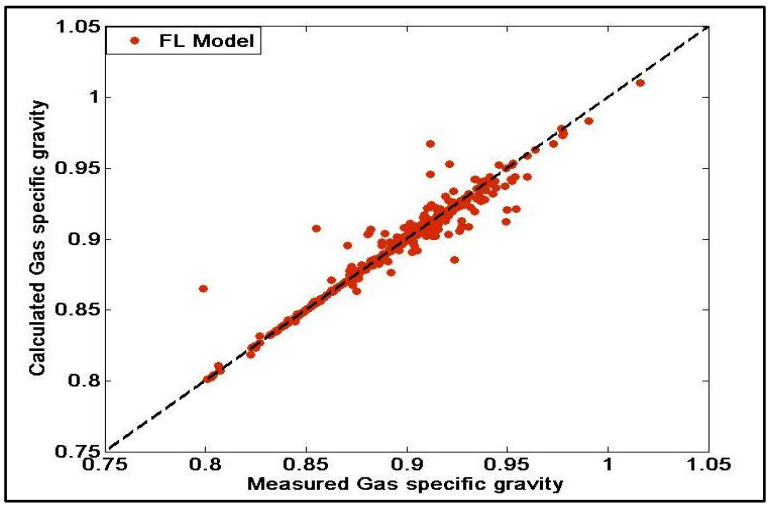

Fig. 7. Accuracy of FL gas specific gravity model for training

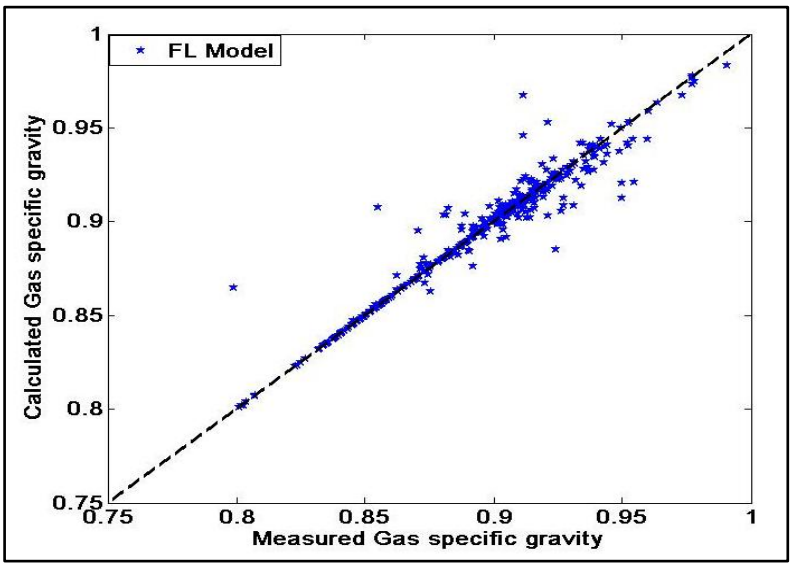

Fig. 8. Accuracy of FL gas specific gravity model for training

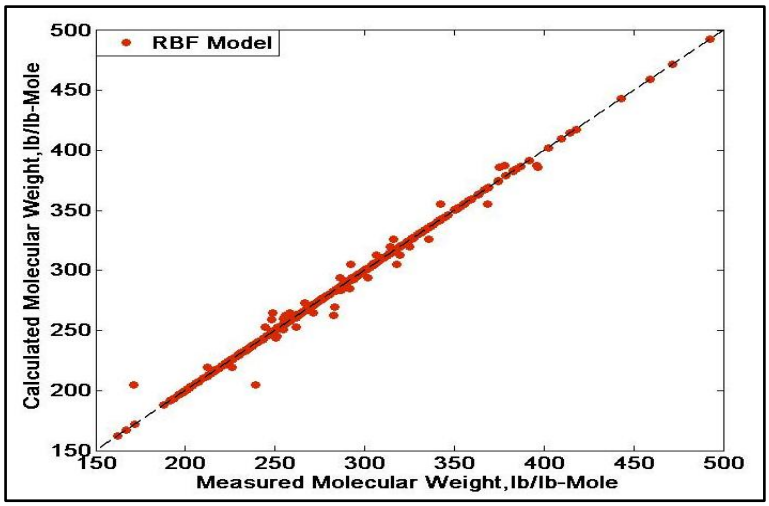

Fig. 9. Accuracy of RBF molecular weight model for training

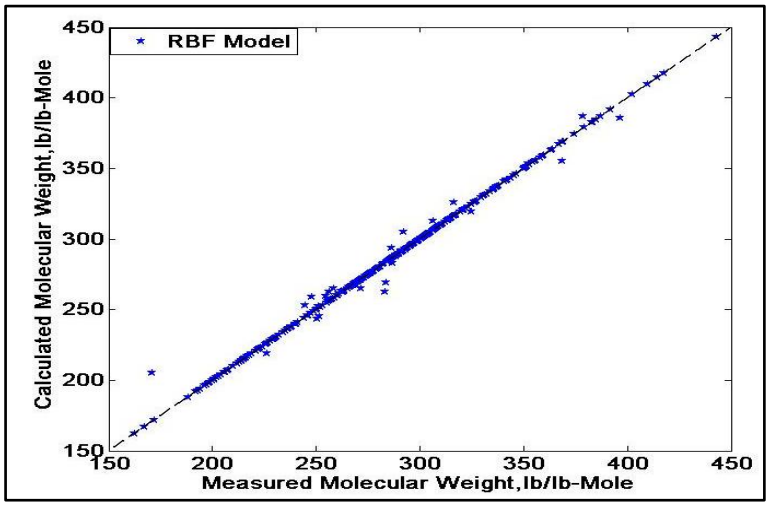

Fig. 10. Accuracy of RBFmolecular weight model for testing

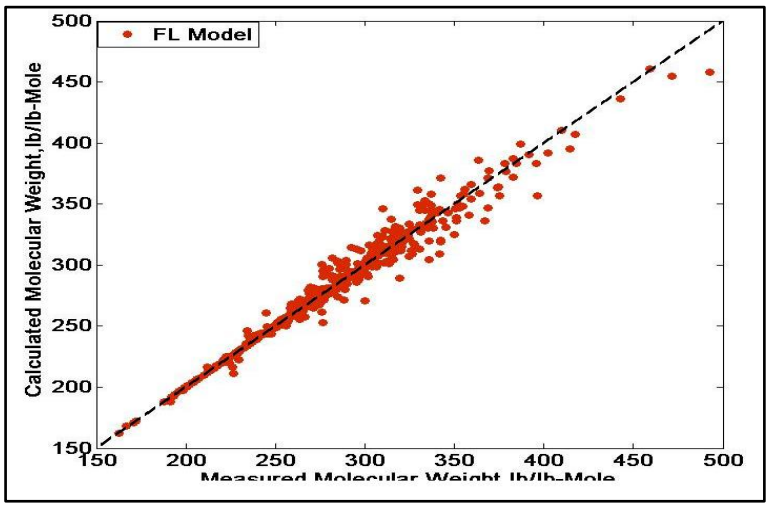

Fig. 11. Accuracy of FL molecular weight model for training

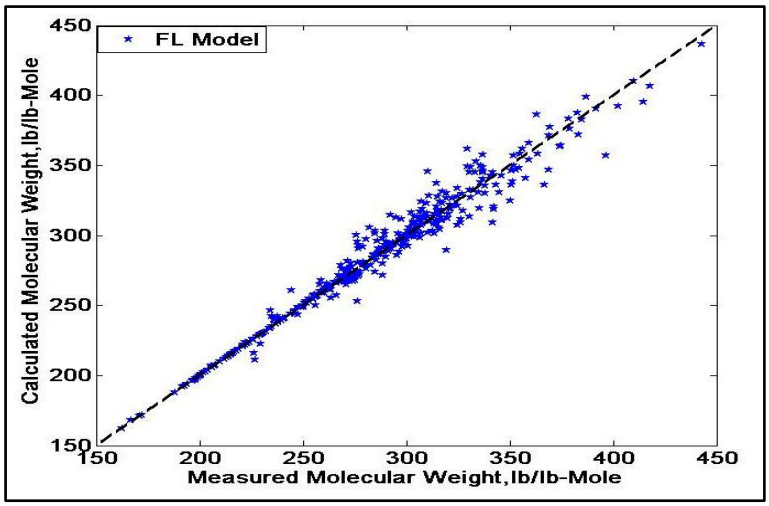

Fig. 12. Accuracy of FL molecular weight model for testing

Table 2-Statistical Analysis of crude oil density models by using RBF and FL techniques

Model	Type	Region	AAPRE%	SD%	R^2
Crude oil density	RBF	Training	0.020	0.327	0.999
		Testing	0.080	0.629	0.989
Crude oil density	FL	Training	0.485	1.055	0.988
		Testing	0.442	0.902	0.976

Table 3-Statistical Analysis of gas specific gravity models by using RBF and FL technique

Model	Type	Region	AAPRE%	SD%	R^2
Gas specific gravity	RBF	Training	0.030	0.247	0.998
		Testing	0.043	0.292	0.997
Gas specific gravity	FL	Training	0.292	0.777	0.976
		Testing	0.379	0.907	0.971

Table 4-Statistical Analysis of molecular weight models by using RBF and FL technique

Model	Type	Region	AAPRE%	SD%	R^2
Molecular weight	RBF	Training	0.213	1.247	0.999
		Testing	0.222	1.276	0.998
Molecular weight	FL	Training	1.345	2.390	0.987
		Testing	1.624	2.670	0.986

V. CONCLUSION

Based on the results obtained for different reservoir fluid properties study, the following conclusions are made:

In this study, radial basis functions networks (RBF) and fuzzy logic (FL) techniques for predicting the crude oil density, gas specific gravity and the molecular weight of a gas mixture using chemical composition of crude oil with high accuracy.

The new radial basis functions crude oil density proposed model attained the lowest an average absolute percent relative error (AAPRE) of 0.080%, and the lowest standard deviation error (SD) of 0.629% and further showed higher accuracy towards predicting crude oil density values (R^2 = 0.989) as compared to the fuzzy logic proposed models.

For gas specific gravity correlations, the new radial basis functions predicted model achieved the lowest an average absolute percent relative error (AAPRE) of 0.043 % and the lowest standard deviation error (SD) of 0.292% and also showed a higher accuracy while predicting gas specific gravity values (R^2 = 0.997) as compared to the fuzzy logic proposed models.

For molecular weight models, the new radial basis functions predicted model accomplished the lowest an average absolute percent relative error (AAPRE) of 0.222%, and the lowest standard deviation error (SD) of 1.276% and also showed higher accuracy towards predicting molecular weight values (R^2 = 0.998) as related to the fuzzy logic proposed models.

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