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Forecasting Oil Formation Volume Factor for API Gravity Ranges Using Artificial Neural Network

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Abstract

The Oil Formation Volume Factor (FVF) parameter is a very important fluid property in reservoir engineering computations. Ideally, this property should be obtained from actual measurements. Quite often, this measurement is either not available, or very costly to obtain. In such cases, empirically derived correlations are used in the prediction of this property. This work centers on building an artificial neural network (ANN) model to predict oil formation volume factor for the different API gravity ranges. The new models were developed using combination of 448 published data from the Middle East, Malaysia, Africa, North Sea, Mediterranean basin, Gulf of Persian fields and 1389 data set collected from the Niger Delta Region of Nigeria. The data have been divided into the following four different API gravity classes: heavy oils for API≤21, medium oils for 21<API≤26, blend oils for 26<API≤35 and light oils for API>35. The data set was randomly divided into three parts of which, 60% was used for training, 20% for validation, and 20% for testing for each particular API grade. Both quantitative and qualitative assessments were employed to evaluate the accuracy of the models to the existing empirical correlations. The ANN models outperformed the existing empirical correlations by the statistical parameters used with the best rank and better performance plots.

Key words: Oil formation volume factor; Artificial neural network; Back propagation; Statistical analysis; API gravity ranges

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INTRODUCTION

An accurate knowledge of Pressure-Volume-Temperature (PVT) properties is essential in reservoir and production engineering calculations. Estimation of reserves, determination of oil reservoir performance, recovery efficiency, production optimization and design of production systems are some of the areas which require precise determination of a fluid's physical properties at different conditions of pressure and temperature. Ideally, the physical properties of the reservoir fluids are determined experimentally in the laboratory. However, due to economical and/or technical reasons, quite often this information cannot be obtained from laboratory measured values. In this case, PVT properties must be estimated from empirically derived correlations. The correlations were developed using linear and non-linear regression or graphical techniques. The correlations are accurate within the range of data that were used to develop them (Osman *et al*., 2001). Among those PVT properties is the Oil Formation Volume factor (FVF), which is defined as the volume of reservoir oil that would be occupied by one stock tank barrel oil plus any dissolved gas at the bubble point pressure and reservoir temperature. Precise prediction of oil FVF is very important in reservoir and production computations.

Several correlations have been proposed for determining crude oil FVF such as Standing (1946), Glaso

(1980), Al-Marhoun (1988), Petrosky and Farshad (1993), Omar and Todds (1993), and Ikiensikimama (2009). In order to find relationship between the input and output data driven from accelerated experimentations, a powerful method than traditional modeling is necessary. A new predictive tool was developed in this study to estimate the oil formation volume factor for different API gravity grade using artificial neural networks (ANNs). ANN is an especially efficient algorithm to approximate any function with finite number of discontinuities by learning the relationships between input and output vectors (Hagan *et al.*, 1996 and Demuth *et al.*, 2009). These algorithms can learn from the experiments, and also are fault tolerant in the sense that they are able to handle noisy and incomplete data. The ANNs are able to deal with non-linear problems, and once trained can perform prediction and generalization at high speed (Sozen, *et al.*, 2004). They have been used to solve complex problems that are difficult for conventional approaches, such as control, optimization, pattern recognition, classification, properties and desired that the difference between the predicted and observed (actual) outputs be as small as possible (Hagan *et al.*, 1996).

The theory that inspires neural network systems is drawn from many disciplines: primarily from neuroscience; engineering, and computer science; secondarily from psychology, mathematics, and physics. These sciences are working toward the common goal of building intelligent system (Shokir, *et al.*, 2004, Buscema, 2002). Artificial neural network initially grew from the full understanding of some ideas and aspects about how biological systems work, especially the human brain. Neural systems are typically organized in layers. Layers are made up of a number of interconnected nodes (artificial neurons), which contain activation functions. Patterns are presented to the network via the input layer, which communicates to one or more hidden layers where the actual processing is done through a system of fully or partially weighted connections (Figure 1). The hidden layers then linked to the output layer. Neural network contains some sort of learning rule that modifies the weights of the connections according to the input patterns (Kay, 2001).The advantage of ANN over the conventional correlations is that, neural networks have large degrees of freedom for fitting parameters, and thus, capture the systems' non-linearity better than regression methods. They are also superior to the regression models in that they could be further trained and refined when additional data become available and hence improve their prediction accuracy. On the other hand, it is impossible to make any further change in a linear or non linear regression model as soon as a model development is over (Deng, 2007; Gharbi and Elsharkawy, 1997; Moghadassi *et al.*, 2009; Omole *et al.*, 2009).

Many investigators recognized that the neural network can serve the petroleum industry to create a more accurate PVT model (Al-Morhoun and Osman, 2002; Gharbi and Elsharkawy, 1997; Moghadassi *et al.*, 2009; Omole *et al.*, 2009). Few studies were carried out to model PVT properties using neural networks. Gharbi and Elsharkawy (1997) published neural network models for estimating bubble point pressure and oil formation volume factor for Middle East crude oils. They used two hidden layers neural networks to model each property separately. The bubble point pressure model had eight neurons in the first layer and four neurons in the second. The formation volume factor model had six neurons in both layers. Both models were trained using 498 data sets collected from the literature and unpublished sources. The models were tested by other 22 data points from the Middle East. The results showed improvement over the conventional correlation methods with reduction in the average error for the bubble point pressure oil formation volume factor.

Gharbi and Elsharkawy (1997) presented another neural network model for estimating bubble point pressure and oil formation volume factor for universal use. They used three-layer neural network model to predict the two properties. They developed the model using 5200 data sets collected from all over the world representing 350 different crude oils. Another set of data consisting of 234 data sets was used for verifying the results of the model. The reported results for the universal model showed less improvement than the Middle East neural model over the conventional correlations. The bubble point pressure average error was lower than that of the conventional correlations for both training and test data. The oil formation volume factor on the other hand was better than conventional correlations in terms of correlation coefficient. The average error for the neural network model is similar to conventional correlations for training data and higher for test data than the best performing conventional correlation.

Elsharkawy (1998) presented a new technique to model the behavior of crude oil and natural gas systems using a radial basis function neural network model (RBFNM). The model can predict oil formation volume factor, solution gas-oil ratio, oil viscosity, saturated oil density, under-saturated oil compressibility, and evolved gas gravity. He used differential PVT data of ninety samples for training and another ten novel samples for testing the model. Input data to the RBFNM were reservoir pressure, temperature, stock tank oil gravity, and separator gas gravity. Accuracy of the model in predicting the solution gas oil ratio, oil formation volume factor, oil viscosity, oil density, undersaturated oil compressibility and evolved gas gravity was compared for training and testing samples to all published correlations. The comparison shows that the proposed model is much more accurate than these correlations in predicting the properties of the oils. The behavior of the model in capturing the physical trend of the PVT data was also checked against experimentally measured PVT properties of the test samples. He concluded that although, the model was developed for specific crude oil and gas system, the idea of using neural network to model behavior of reservoir fluid can be extended to other crude oil and gas systems as a substitute to PVT correlations that were developed by conventional regression techniques.

Recently, Osman *et al.* (2001) used artificial neural network technique in the field of PVT in order to estimate the formation volume factor at the bubble point pressure. Their model was developed using 803 published data gathered from Malaysia, Middle East, Gulf of Mexico, and Colombia. They designed a three layer network; the input layer has four neurons covering the input data of gas-oil ratio, API gravity, relative gas density, and reservoir temperature; one hidden layer with five neurons and a single neuron for the formation volume factor in the output layer. This model showed a higher accuracy than the empirical correlations with an absolute average percent error of 1.789%, a standard deviation of 2.2053% and correlation coefficient of 0.988.

Shokir *et al.* (2004) published a work based on neural network using Matlab 7.5 to predict both bubble point pressure, and oil formation volume factor with the aid of two separated networks. The data used was a set of 160 measured data points collected from the Middle East region; 140 points were used for training, and 20 for testing. The network performed better than empirical correlation with average relative error percent of 0.030704 and correlation coefficient of 0.9981.

Moghadassi *et al.* (2009) presented an Artificial Neural Network (ANN) for estimation of PVT properties of compounds. The data set was collected from Perry's Chemical Engineers' Handbook. Different training schemes for the back propagation learning algorithm; Scaled Conjugate Gradient (SCG), Levenberg-Marquardt (LM) and Resilient back Propagation (RP) methods were used. The accuracy and trend stability of the trained networks were tested. The LM algorithm with sixty neurons in the hidden layer proved to be the best suitable algorithm with the minimum Mean Square Error (MSE) of 0.000606. ANN is one of the best estimating method with high performance used in forecasting the PVT properties.

The API gravity reliability analysis is used to assess the reliability of grouping correlations accuracy according to oil gravity. Particularly, since the density of oil is a fundamental characteristic as it reflects the chemical composition of crudes on which all the fluid main properties depend Ikiensikimama and Ogboja (2009). De-ghetto *et al.*, (1994) showed that the samples belonging to the same group (class) are physically and chemically more comparable than samples from different groupings. For this reason, this study is centered on developing a ANN model for predicting oil FVF of different API gravity grade, using published data from the Middle East, Malaysia, Africa and the Niger Delta Region of Nigeria. Depending on their API gravity, crude species have been classified as light, blend, medium and heavy. The light crude has API gravity above 35^{o}, the blend is between 26^{o}, and 35^{o}, medium is between 21^{o} and 26^{o} while the heavy has API gravity less than or equal to 21^{o}. This work will also, evaluate and compare the accuracy of the ANN model to those of the existing empirical correlations.

1. DATA ACQUISITION AND ANALYSIS

Data used for this work were collected from published sources and Niger-Delta region of Nigeria. The Niger-Delta data set was validated and it was assumed that the published data was validated by the authors. After the validation of the Niger-Delta data and the combination of the published data, 1837 data sets were gotten. The data set comprises: 93 data set from Omar-Todd (1993), 195 data set from De- ghetto *et al.*, (1994), 160 data set from Al-Marhoun (1988) and 1389 data set from Niger-Delta. Each data set contains reservoir temperature, oil gravity, total solution gas oil ratio, average gas gravity, and oil formation volume factor. The data set used in the development of oil FVF ANN for the various API gravity grade are as follows: 129 for the heavy crude oil, 256 for the medium crude oil, 303 for the blend crude oil and 1149 for the light crude oil. Of the various API gravity grade data points, 60% were used to train the ANN models, the remaining 20% to cross-validate the relationships established during the training process and 20% to test the model to evaluate its accuracy and trend stability. The description of training and test data for the different API gravity grade are given in Tables 1 and 2 respectively.

Table 1
Summary of the Maximum and Minimum Values of Training Data for Oil Formation Volume Factor Neural Network

API Type	Range	T (^{o}F)	^{o}API	Y_g (air=1)	R_s (scf/stb)	FVF (bbl/stb)
Heavy	Max.	250.0	21.00	1.517	500.23	1.3080
	Min.	123.0	6.00	0.560	7.00	1.0130
Medium	Max.	275.0	26.00	1.356	640.00	1.3930
	Min.	80.5	31.31	0.531	8.61	1.0165
Blend	Max.	262.2	34.79	1.367	1256.95	1.6710
	Min.	80.0	26.70	0.562	26.00	1.0390
Light	Max.	341.0	56.80	1.789	3299.00	3.6708
	Min.	80.0	35.15	0.599	47.30	1.0390

Table 2
Summary of Maximum and Minimum Values of Test Data for Oil Formation Volume Factor Neural Network

API Type	Range	T (^{o}F)	^{o}API	Y_g (air=1)	R_s (scf/stb)	FVF (bbl/stb)
Heavy	Max.	250.0	20.98	1.429	596.67	1.3020
	Min.	123.0	6.50	0.560	30.00	1.0440
Medium	Max.	276.8	25.55	1.356	396.41	1.2760
	Min.	100.0	21.90	0.561	29.00	1.0165
Blend	Max.	218.0	34.79	1.228	775.00	1.3720
	Min.	100.0	26.70	0.565	42.20	1.0470
Light	Max.	303.0	53.20	1.290	2881.00	3.0030
	Min.	74.0	35.10	0.501	36.30	1.0820

2. NEURAL NETWORK ARCHITECTURE

Matlab (7.5 version) neural network module was used to build the network using back-propagation algorithm with the Levenberg-Marquardt procedure for the optimization procedure Matlab (2004). Back propagation Neural Network (BPNN) is a multi-layered network, and information flows from the input to the output through at least one hidden/middle layer. Each layer contains neurons that are connected to all neurons in the neighboring layers (Figure 1). The connections have numerical values (weights) associated with them. During the training phase, the weights are adjusted according to the generalized delta rule. Training is completed when the network is able to predict the given output. A three layers network was used in this work. A Levenberg- Marquardt algorithm was used to train the three-layer network. The first layer consists of four neurons representing the input values of reservoir temperature, solution gas oil ratio, gas specific gravity and API oil gravity. The second layer consists of hidden neurons, and the third layer contains one neuron representing the output values of the oil formation volume factor. The data were divided into two groups: training group and testing group. The training group is further split into two groups: the first was used to train the network; the second set was used to test the error during the training, this is called cross validation. Cross validation gives the ability to monitor the general performance of the network and prevent the network from over fitting the training data. In a BPNN, the input activity is transmitted forward while the error is propagated backwards. The neurons in the BPNN use a transfer function that is sigmoid or S shaped. A key feature of the sigmoid function is that it has a minimum value of 0 and a maximum value of 1 and is differentiable everywhere with a positive slope. The derivative of the transfer function is required to calculate the error that is back propagated and it is also easy to calculate.

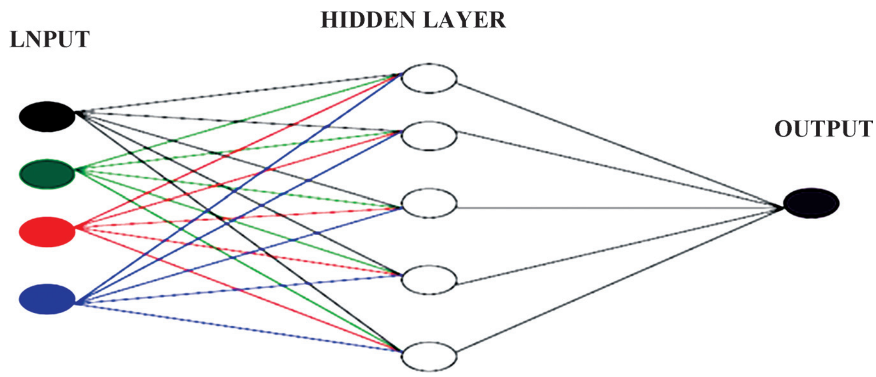

Figure 1
Schematic of an Artificial Neural Network with One-Hidden Layer

3. MODELING TECHNIQUE

Matlab (7.5 version) neural network module was used to build the network using back-propagation algorithm with the Levenberg-Marquardt procedure for the optimization procedure (Matlab, 2004). Six steps were adopted in building this Artifical Neural network.

STEP 1: Defining a Problem: This is to arrange a set of P input vectors and T output vectors as columns into first and second matrix in the Matlab work space as follows:

(P) Input = [GOR data; T data; API data; Y_g data]; (T) Targets = [FVF data]

STEP 2: Opening the Neural Network Fitting Tool: The Neural Network Fitting tool can be invoke by this command 'nftool'.

STEP 3: Setting Network Size: This is to set the number of neuron in the network's hidden layer.

STEP 4: Train The Network to Fit the Input and Target: The network uses the default Levenberg-Marquardt algorithm for training. The application randomly divides input vectors and target vectors into three sets as follows; 60% are used for training, 20% are used to validate that the network is generalizing and to stop training before overfitting, the last 20% are used as a completely independent test of network generalization.

4. QUANTITATIVE AND QUALITATIVE SCREENING

To compare the performance and accuracy of the new model to other empirical correlations, two forms of analysis were performed which include quantitative and qualitative. For quantitative screening method, statistical error analysis was used. The statistical parameters used for the assessment were percent mean relative error (E_r), percent mean absolute error (E_a), percent standard deviation relative (S_r), percent standard deviation absolute (S_a) and correlation coefficient (R).

For correlation comparison, a new approach of combining all the statistical parameters mentioned above (E_r, E_a, S_r, S_a and R) into a single comparable parameter called Rank was used as given by Ikiensikimama (2009). A brief description of the method follows. The use of multiple combinations of statistical parameters in selecting the best correlation can be modeled as a constraint optimization problem with the function formulated as;

$$Min\ Z_i = \sum_{i=1}^{m} S_{ij} q_{ij} \quad (1)$$

Subject to

$$\sum_{i=j}^{n} S_{ij} \quad (2)$$

With $0 \leq S_{ij} \leq 1$ (3)

Where $S_{i,j}$ is the strength of the statistical parameter j of correlation i and q_{ij}, the statistical parameter j corresponding to correlation ij = E_r, E_a, …. R^1 ,where R^1 = (1-R) and Z_i is the rank, RK (or weight) of the desired correlation. The optimization model outlined in equations 1 to 3 was adopted in a sensitivity analysis to obtain acceptable parameter strengths. The final acceptable parameter strengths so obtained for the quantitative screening are 0.4 for E_a, 0.2 for R, 0.15 for S_a, 0.15 for S_r, and 0.1 for E_r. Finally, equation 1 was used for the ranking. The correlation with the lowest rank was selected as the best correlation for that fluid property. It is necessary to mention that minimum values were expected to be best for all other statistical parameters adopted in this work except R, where a maximum value of 1 was expected. Since the optimization model (Equations 1 to 3) is of the minimizing sense a minimum value corresponding to R must be used. This minimum value was obtained in the form (1-R). This means the correlation that has the highest correlation coefficient (R) would have the minimum value in the form (1-R). In this form the parameter strength was also implemented to 1-R as a multiplier. Ranking of correlations was therefore made after the correlation had been evaluated against the available database. For qualitative screening, performance plots were used. The performance plot is a graph of the predicted versus measured properties with a 45^o reference line to readily ascertain the correlation's fitness and accuracy. A perfect correlation would plot as a straight line with a slope of 45^o.

5. RESULTS AND DISCUSSION

The trained ANN models were tested with 20% of training data (test data) points that were not previously used during training and validation. These data were randomly selected by the MATLAB tool to test the accuracy and stability of the model. The performance of the ANN model was compared with field data and the predictions from other empirical correlations such as Standing (1947), Glaso (1980), Obomanu and Okpobiri (1987), Al-Marhoun (1988), Petrosky and Farshad (1993), Omar and Todd (1993), Al-mehaideb (1994), and Ikiensikimama (2009). These predictive correlations were carefully selected, having been developed specifically for the prediction of oil FVF and some of which were recommended for the estimation of oil FVF for API gravity range.

The results of the assessment as presented in Figures 2-5 gives statistical accuracies for all the oil FVF correlations examined using different API gravity range. From these figures the ANN model ranked best. The results of the evaluations (as shown in Figure 2) give the statistical accuracies and the rankings for all the oil FVF for Heavy crude oil correlations assessed. ANN achieves the highest correlation coefficient (R) of 0. 9941, the lowest absolute relative error (E_a) of 0.533 with the best rank of 0.391,while other rank values range between 0.8261 for Omar and Todd (1993) been the second best, and 3.3982 for Obomanu and Okpobiri (1987) correlation which took the last position.

Figure 3 shows a comparison of the statistical parameter and the ranking for all the oil FVF for Medium crude oil that were studied. The ANN emerges as the best correlation having the first ranking position of 0.7590 to be compared to other correlations evaluated. Omar and Todds (1993) took the second position with the rank value of 0.9001 while Obomanu and Okpobiri (1987) took the last position on the ranking list. Omar and Todds (1993) and Al- Marhoun (1988) were among the oil FVF correlations recommended to be best in estimating oil FVF in the API gravity ranges of API≤21, 21<API≤26 and 26<API≤35 which agree with the study conducted by Ikiensikimama and Ogboja (2009). The result obtained for each group are believed to be very significant as it is plausible that sample belonging to the same group are physically and chemically more comparable than samples from different groupings De-Ghetto *et al.* (1994).

Figures 4 and 5 also illustrated the statistical analyses and the ranking for Blend and Light crude oil. The blend crude oil ANN model has the best rank value of 0.6136 while that for the light crude is 2.0417. It should be noted that the ANN model outperforms other empirical correlations despite the fact that the ANN model did not see the testing data during training. On the other hand, some of these data sets were already used in developing the other empirical correlations. The higher accuracy of the predicted results indicates that the neural network was successfully trained. Also, these results demonstrated the efficiency of the training algorithm.

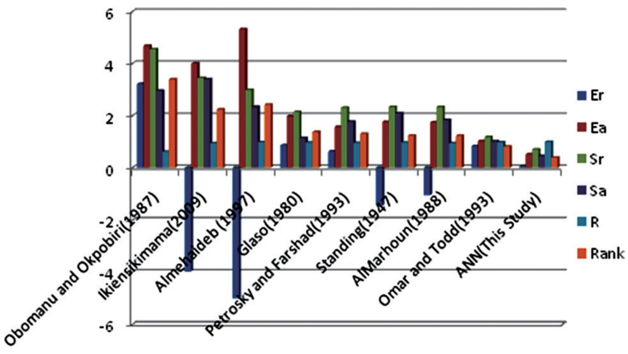

Figure 2
Comparison of the Statistical Accuracy for Heavy Crude

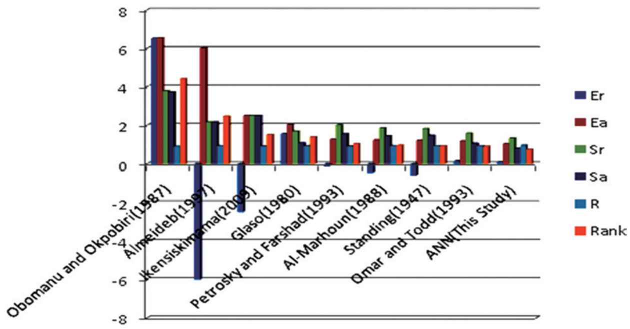

Figure 3
Comparison of the Statistical Accuracy for Medium Crude

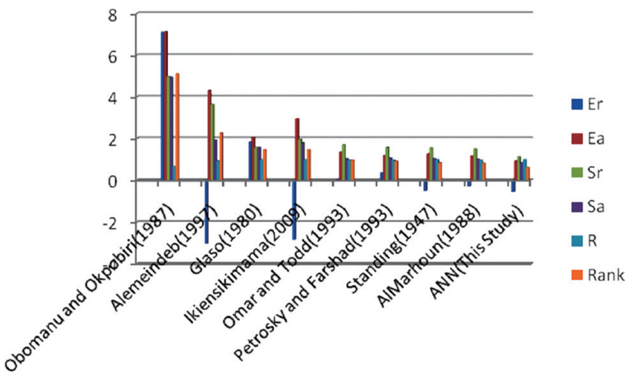

Figure 4
Comparison of the Statistical Accuracy for Blend Crude

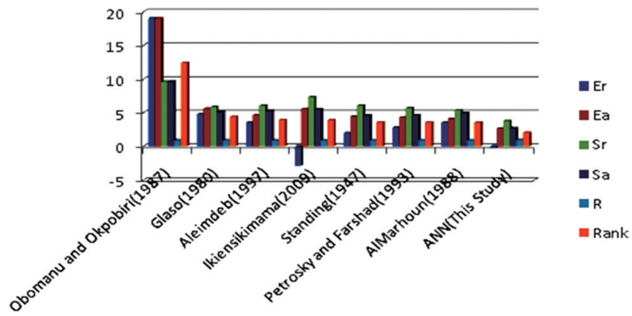

Figure 5
Comparison of the Statistical Accuracy for Light Crude

Figures 6-9 illustrated cross plots of the predicted versus experimental oil FVF values for Heavy, Medium, Blend and Light API gravity grade. A cross plot is graph of predicted versus measured properties with a 45^o reference line to readily ascertain the correlation's fitness and accuracy. Figures 6-9 show the most tight cloud of points around the 45º line indicating the excellent agreement between the experimental and the calculated data values. Again, this indicates the superior performance of the ANN model compared to other empirical correlations.

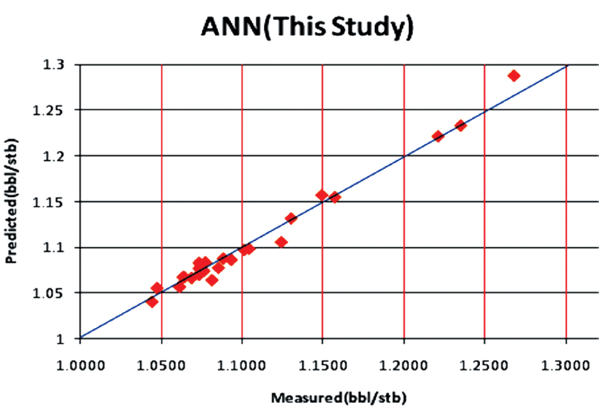

Figure 6
Cross Plot of ANN (This Study) Correlation for Heavy Crude

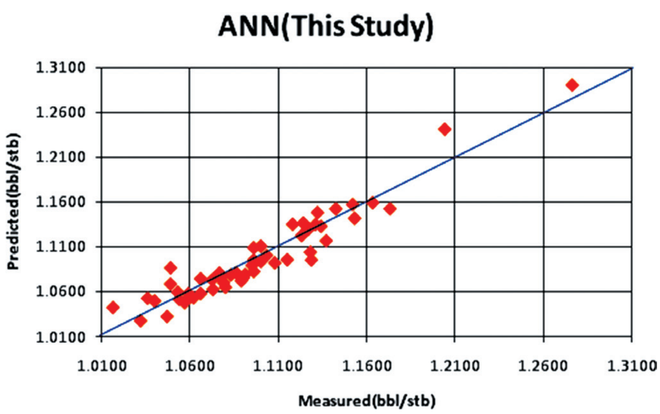

Figure 7
Cross Plot of ANN (This Study) Correlation for Medium Crude

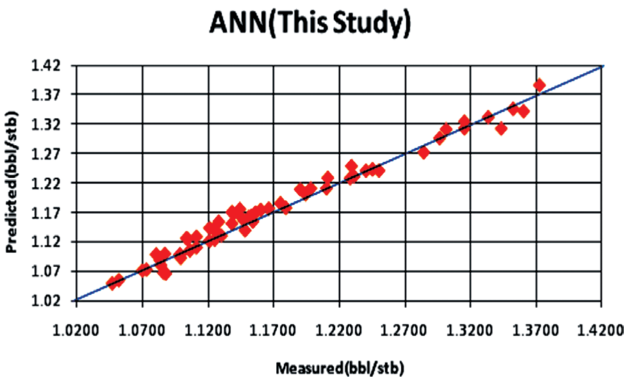

Figure 8
Cross Plot of ANN (This Study) Correlation for Blend Crude

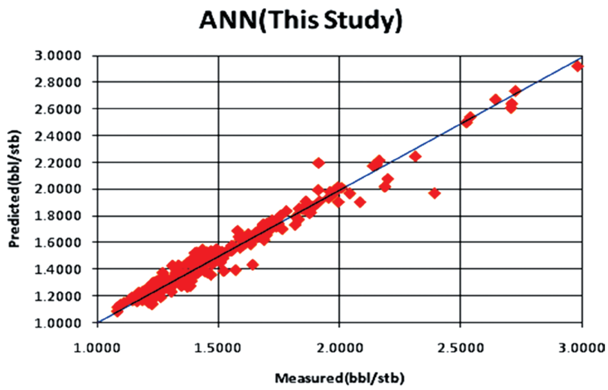

Figure 9
Cross Plot of ANN (This Study) Correlation for Light Crude

CONCLUSION

The newly developed artificial neural network model for predicting crude oil formation volume factor for various API gravity grade was found to be better than the empirical correlations. From the analysis made, the new ANN models outperformed the existing correlations in terms of the statistical parameters used. It also show the best ranks and better performance plots as compared to the existing empirical correlations for those regions where the data was used. For oil API gravity ranges, the following correlations are recommended: Heavy oils (API≤21), Omar and Todd (1993); Medium (21<API≤26), Omar and Todd (1993); Blend (26<API≤35), Al-Marhoun (1988); and light oils (API>35), Al-Marhoun (1988). Therefore, these correlations are recommended globally for the prediction of oil formation volume factor for oil API gravity ranges in the absence of ANN models, new or improved correlations.

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