Journal of Engg. Research Vol. 11 No.(1B) pp.362-373 DOI:10.36909/jer.12229

Evaluates A PVT Correlation to Estimate Dead Oil Viscosity for Libyan Crudes Using 104 Samples from Different Reservoirs

Mohammed A. Samba[*, ****], Li Yiqiang[*], Wannees A. Alkhyyali[**], Yousef A. Altaher[**] and Fiki Hidayat[***]

[*] *Petroleum Engineering Institute, China University of Petroleum-Beijing CUP, China.*

[**] *Department of Oil and Gas Engineering Department, Sebha University, Libya.*

[***] *Department of Petroleum Engineering, Faculty of Engineering, Universitas Islam Riau, Pekanbaru, Indonesia.*

, ** Corresponding Author: Mohammed_samba@yahoo.com*

Submitted: 23-11-2020

Revised: 05-08-2021

Accmitted: 14-08-2021

ABSTRACT

Viscosity is defined as the resistance of the fluid to flow. It plays a very significant role in most oil and gas engineering applications. The measured viscosity for any crude oil at surface condition is called by the dead oil viscosity, where the dead oil viscosity is a function in any correlation to calculate the viscosity of the crude oil. Thus, the dead oil viscosity is important in most applications related to the petroleum engineering. Accordingly, a new mathematical and artificial neural network (ANN) dead oil viscosity correlations were developed for Libyan crudes and compared with renowned dead oil viscosity correlations using 104 samples from different reservoirs. The evaluation in this study has been done by statistical and graphical error analysis. The results shown that the ANN model has proven to be a useful tool for predicting where the ANN model has given the best result with low error AAD was 14.40509 % and $R^{\wedge 2}$ was 95.91%. The ANN model and mathematical model gave the lowest error when they compared with different empirical correlations.

Keywords: Dead oil viscosity; Mathematical model; ANN; Dead oil; Viscosity model.

INTRODUCTION

Viscosity of dead oil is a significant property necessary by experts in almost all periods of producing recovers. The viscosity value is essential before applying any plan for any production procedures such as an input parameter into a simulation to obtain accurate performance prediction. In addition to that, it is considered to be one of the main factors that effect on the selection of the EOR method. Therefore, in general, viscosity is measured through laboratory apparatuses in the lab as long as oil samples and laboratory apparatuses are available.

In some cases, laboratory measurements cannot be carried out either due to the lack of oil samples or for economic reasons. Empirical correlations can be used if the laboratory measurement is not possible (Naseri, A., Nikazar, M., & Dehghani 2005) . Various dead oil viscosity correlations have been developed around the entire world. Some of those correlations are useful and equipped with an essential part of the most of petroleum engineering studies. Some of the familiar dead oil viscosity correlations around the world are the correlations of Beal (1946), Beggs & Robinson (1975), Glaso (1980), Egbogah & Ng (1990), Labedi (1992) and Petrosky Jr & Farshad (1995).

Beal's Correlation

From 655 values for dead-oil viscosity above 100°F, Beal (1946) developed a graphical correlation for determining the viscosity of the dead oil as a function of temperature and the API gravity. The mathematical relationship as follows:

$$\mu od = (0.32 + \frac{1.8(10^7)}{API^{4.53}})(\frac{360}{T - 200})^a \quad (1)$$

$$a = 10^{(0.43+\frac{8.33}{API})} \quad (1.1)$$

Where

μ_{od}: viscosity of the dead oil as measured at 14.7 psia , cp

T: temperature, F°

Beggs and Robinson Correlation

Beggs & Robinson (1975) developed an empirical correlation for determining the viscosity of the dead oil. The correlation originated from analyzing 460 dead oil viscosity measurements. The proposed relationship is mathematically expressed as follows:

$$\mu od = 10^X - 1 \quad (2)$$

Where

$$X = 10^{(3.0324-0.02023\times API)} \times T^{-1.163} \quad (2.1)$$

Glaso's Correlation

Glaso (1980) proposed a generalized mathematical relationship for computing the dead oil viscosity. The relationship was developed from experimental measurements on 26 crude oil samples. The proposed relationship is mathematically expressed as follows:

$$\mu od = (3.141 \times 10^{10}) \times Y \quad (3)$$

Where

$$Y = T^{-3.444}(log\ API)^{(10.313\times(log\ T)-36.447)} \quad (3.1)$$

Egbogah-Jacks (without pour point) Correlation

Egbogah & Ng (1990) were used to generate a range of data between 10 and 20 °API oil density and 50 to 200°F of reservoir temperature. The proposed relationship is mathematically expressed as follows:

$$\mu od = 10^{10(-1.7095+A+(-1.12943+B))\times log(C)} - 1 \quad (4)$$

Where

$$A = \left(\frac{389.45}{API+131.5}\right) \quad (4.1)$$

$$B = \left(\frac{135.585}{API+131.5}\right) \quad (4.2)$$

$$C = (T - 32) \times \frac{5}{9}) \quad (4.3)$$

Labedi Correlation

Labedi (1992) also developed the dead oil viscosity correlation in the range of 0.66 to 4.79 centipoise, oil density ranges from 32.2° to 48.0°API, and temperature covering the range from 38 to 152 C° using 91 data points. The proposed relationship is mathematically expressed as follows:

$$\mu od = \frac{10^{9.224}}{API^{4.7018} \times T^{0.6789}} \quad (5)$$

Petrosky and Farshad Correlation

Petrosky Jr & Farshad (1995) developed a dead oil viscosity correlation for oil mixtures ranging from 16 - 45 °API. The proposed relationship is mathematically expressed as follows:

$$\mu od = 2.3511 \times 10^{7} \times T^{-2.10255} \times Y \quad (6)$$

Where

$$Y = (log\ API)^{(4.59388 \times ((log\ T) - 22.82792)}$$

The primary condition to use any empirical correlation is that the reservoir's data should be within the range data of the correlation (survey area). The differences between those correlations are between the number of samples and the survey area, where it should be taken into the account for any study. The properties of the crude oil in North Africa countries are different from the properties of the crude oil at Asian Countries. Thus, if the temperature criterion for correlation is between 100 and 250 C^0, this correlation is not valid for the reservoirs with a temperature higher than 250 C^0 and lower than 100 C^0. There are many familiar correlations except that which has mentioned in this paper. However, the correlations that have mentioned in this paper are valid to use them for Libyan crude oil based on the collected data that has been used in this paper.

Moreover, the mathematical model is still useful, but, at the same time, still gives a high error. It mostly happened when the predicted value is compared with the laboratory result (Elsharkawy & Alikhan, 1999). The values of dead oil viscosity are in the range of 0.1 to 6 centipoise. Accordingly, to predict a model for the dead oil viscosity parameter is different from other parameters such as gas oil ratio (GOR) and API Oil density due to the small value of the dead oil viscosity. For instance, if the difference between the predicted value and the original value is 0.2 and the original value of dead oil viscosity is 0.8, that means the error is 25 %. Conversely, when calculating the error for another parameter such as GOR, if the difference between the predicted value and the original value is 1000 and the original value of GOR is 15000 SCF/STB, the error is only 6.66 %. Thus, most published oil viscosity correlations that have been used this study have provided high error.

Hence, the ANN has been applied as a prediction tool for PVT properties correlation to reduce the error. Different types of algorithm such as Feedforward backpropagation with the Levenberg Marquardt training algorithm have been used to predict dead oil viscosity in previous studies (Samba & Syihab, n.d.). Where, many studies have maintained that ANNs can solve the PVT correlation problems in the oil and gas industry (Al-Marhoun and Osman 2002). Therefore, in recent studies researchers have utilized ANNs to predict more accurate PVT correlations (Al-Marhoun and Osman 2002; Boukadi et al. 1999; Gharbi and Elsharkawy 1997).

The purpose of this study is to develop a new ANN model and mathematical model for Libyan crude oil viscosity. Then we test the model's performance using the most common published oil viscosity correlations for the selected Libyan crude oil and then compared with the experimental viscosities data collected from the fields. As mentioned previously, the statistical analysis is the criterion presented for the evaluation in this paper.

METHODOLOGY

To train and test the ANN and mathematical model, sufficient and accurate data should be collected. Different field data was used to provide required data for neural networks and mathematical model.

Collect and Prepare the Data

One hundred and four samples have been collected from different Libyan fields and different locations (east, west, south, and middle) as shown in the Figure 1. The data was validated before running any purpose. The variation of inputs and outputs for ANN and mathematical models are provided. Data variation range is shown in Table 1.

Table 1. Data Variation Range

PVT Property	Minimum	Maximum
Stock tank-oil gravity (API)	24.97	52

Reservoir temperature (F)	104	303.1
Viscosity at atmospheric pressure	0.176	5.79

Figure 1. Map of Different Data Locations

Calculating the Dead Oil Viscosity by Using Different Dead Oil Viscosity Correlations

In this case, a dead oil viscosity for different crude oil of Libyan fields was calculated using different dead oil viscosity correlations. The crude oil API gravity and the reservoir temperature are the main parameters that affect the dead oil viscosity for all the correlations. The correlations that were used in this study are: Beal, Glaso, Egbogah-Jacks (without pour point), Beggs-Robinson, Petrosky & Farshad and Labedi. The correlation with a low error was choose as the best correlation. Finally, the results were compared with mathematical model and ANN model that was built.

Generating a Mathematical Model

In this case, a mathematical model was obtained using a regression function in Excel. The regression was including the same data provided from the experimental PVT reports that have been used in this study. All the values have been converted to a logarithmic form to get the exponent equation (less error) rather than a linear equation. The regression function in Excel was used to obtain the relationship between the input and the output. The mathematical model was included two inputs (reservoir temperature and oil API gravity) and one output (the dead-oil viscosity).

Build ANN Model

Training and testing the ANN were carried out by MATLAB. The backpropagation algorithm was utilized to train the expert system using the data obtained from fields. The MATLAB software was used to understand the ANN. 100 % of the data were used in the training of the neural network as well as the same data were used to validate the system, because total samples of samples (104) still consider low to train the ANN. The ANN expert system's goal is to have the capacity to predict an output; the maximum target between the collected outputs and expect system output is 15%. Furthermore, the data should be checked to ensure good quality and sufficient in the values.

Input and Output Data

As mentioned, the program input data are further differentiated into three (training set, validation set and applied set). The Building of ANN model was included two inputs (reservoir temperature and oil API gravity) as shown in most international correlations that has mentioned previously and one goal was for outputs (only the dead oil viscosity).

Prediction of the Dead Oil Viscosity

To investigates and evaluate the performance of the considered dead oil viscosity models, we used the error % absolute deviation (AD) and percent absolute average deviation (% AAD). It defined as follows:

$$AD\% = \frac{|\mu^{exp} - \mu^{cal}|}{\mu^{exp}} \times 100 \quad (7)$$

$$\mathrm{AAD\%} = \frac{1}{\mathrm{n}} \sum_{i=1}^{n} \frac{|\mu\mathrm{od}^{\mathrm{exp}} - \mu\mathrm{od}^{\mathrm{cal}}|}{\mu\mathrm{od}^{\mathrm{exp}}} \times 100 \quad (8)$$

where

n = number of experimental points.

μ^{exp} = the experimental viscosity.

μ^{cal} = the calculated viscosity.

The error square % AAD indicates how close the calculated values are to experimental values.

RESULT & DISCUSSION

Prediction of Dead oil viscosity

The common method of evaluating correlations by most of researchers is to select a generally familiar correlation and adapt it to modify the data. Beal's, Beggs-Robinson, Glasø's, Egbogah-jacks, Labedi, and Petrosky & Farshad correlations for dead oil viscosity were evaluated using Libyan crude oil. The $\boldsymbol{AD\%}$ and **AAD**% were the primary statistical parameters used as comparative standards for testing the evaluated models. The statistical accuracy of dead oil viscosity for different correlations is shown in Table 2.

From Table 2, Beggs-Robinson's correlation outperforms the rest of correlations with the lowest average absolute error (AD %) 41.68 % and percent absolute average deviation (**AAD** %) is 0.0974% for dead oil viscosity.

Table 2. Statistical Analysis for different dead oil viscosity correlations

Correlation	$\boldsymbol{AD\%}$	$\boldsymbol{AAD\%}$
Beal's	46.46	0.1191
Beggs & Robinson	41.68	0.0974
Glaso's	46.92	0.1212
Egbogah-Jacks	61.15	0.1421
Labedi	64.89	0.0372
Petrosky & Farshad	44.88	0.109

The error diagrams for all used correlations are shown in Figure 2. Cross plot (Graphical analysis) of relative errors, which is a plot of the measured value versus experimental value, is used. A perfect correlation would plot a straight line with a slope of 45º as shown in Figure 3.

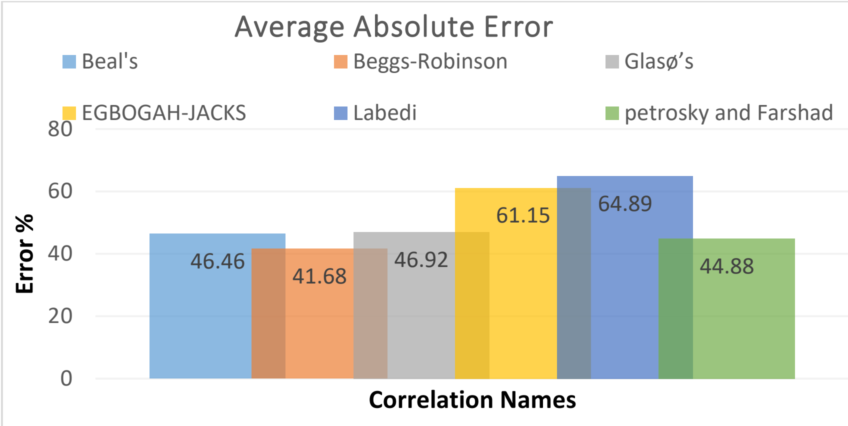

Figure 2. % Error diagram for dead oil viscosity

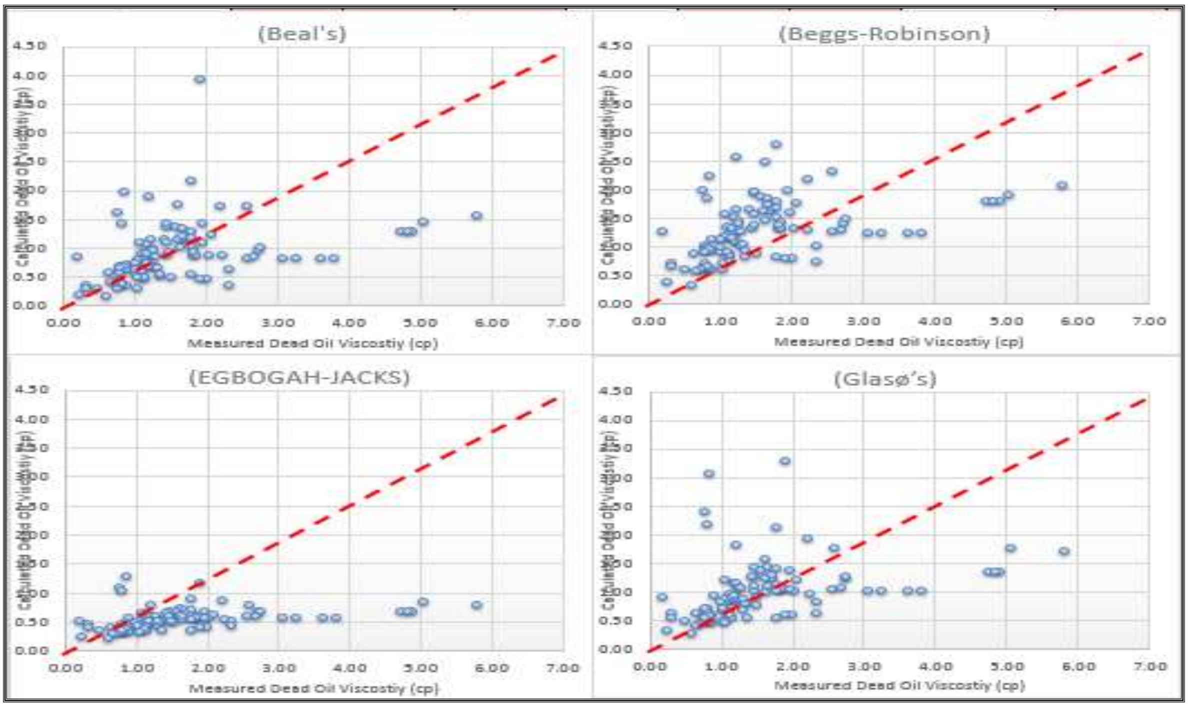

Figure 3. Cross Plot for Dead Oil Viscosity

Mathematical Correlation for Libyan Dead Oil Viscosity

Firstly, the linear equation was obtained, but the linear equation has given high error and unexpected value of standard error. Based on the linear equation, an exponent equation could be driven from the linear equation. The final form of the driven equation is as the following

$$\mu od = 10^{A} \times API^{B} \times T^{C}(°F) \times 0.77 \qquad (9)$$

where

A = **6.151266**

B = **-2.04028**

C = **-1.19421**

Statistical accuracy for the new develop correlation compared with Beggs & Robinson's correlation is presented in Table 3. From Table 3, it can be seen that a new mathematical correlation outperforms Beggs & Robinson's correlation with the lowest **AAD** 38.5% and **AAD is** 0.1452% for dead oil viscosity. In additional, the mathematical model has the lowest error when compared with different correlations as shown in the Figure 4. A Comparison of Cross plot for predicted μod^{exp} and measured μod^{cal} of mathematical correlations with Beggs & Robinson correlations is shown in Figure 5.

Table 3. Comparison between Best Correlation and New Mathematical Correlation

Correlation	$AD\%$	$AAD\%$
Beggs & Robinson	41.68	0.0974
New Mathematical Correlation	38.5	0.1452

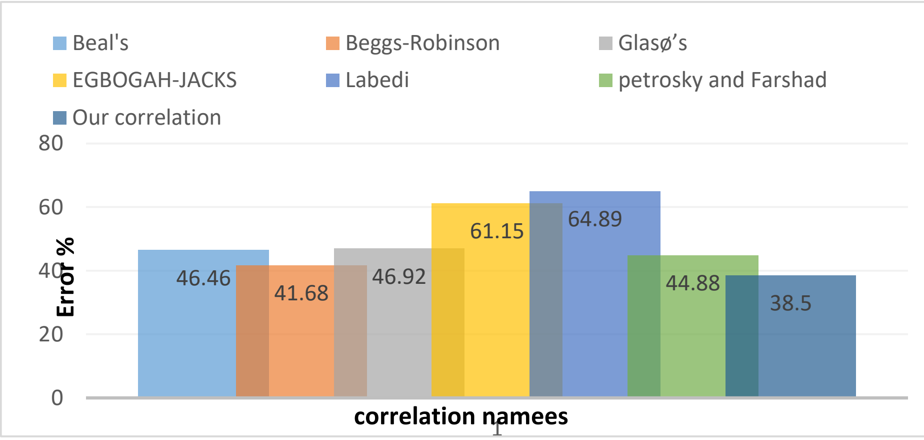

Figure 4. Comparison between Best Correlation and New Mathematical Correlation

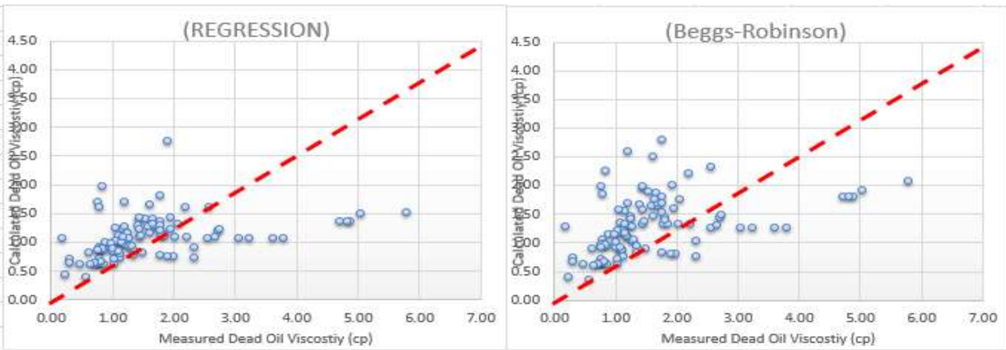

Figure 5. Comparison of Cross Plot for Predicted μod^{exp} And measured μod^{cal} of New Libyan Correlation with Beggs & Robinson Correlations

Viscosity -Temperature for All Measurements

As it shows in Figure 6, most of the calculation data showed the increase of the temperature leads to reduced dead oil viscosity. Some correlations, such as Beals and Beggs, have shown out of range calculation for some samples. Our new mathematical model has given consistent results for most of the samples compared to the other correlations.

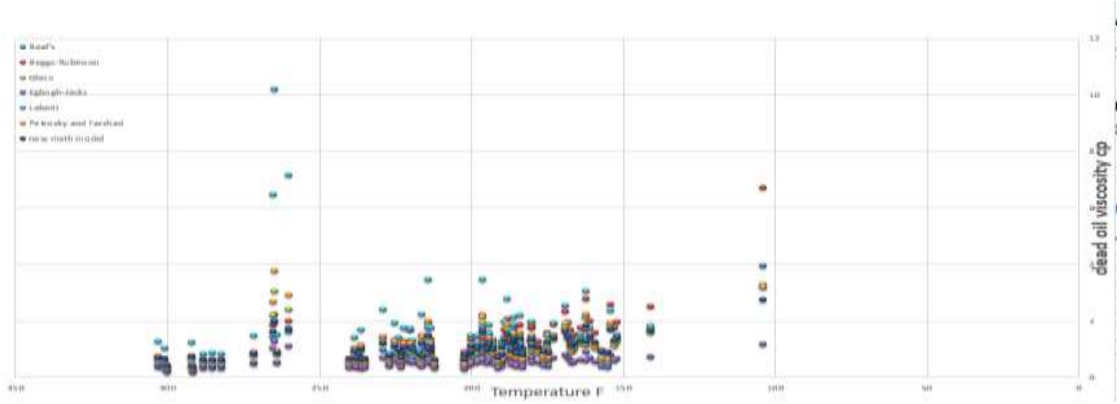

Figure 6. Viscosity-temperature dependency

Artificial Neural Network Result for µod Model

The backpropagation algorithm was utilized for training the expert system using the data obtained from PVT reports. The number of hidden layers plays an important factor in getting fewer inaccuracy by trial and error. Some researchers have recommended some correlations to predict the numbers and the members of the hidden layers, but those models are not accurate. The only way to get the lowest error during the ANN training is through trial-and-error method. After more trial and error and several adjustments, a final architecture was reached for all job patterns. The system contains a learning rate and momentum of 0.8. The best number of the hidden layer obtained is 3. The members (neurons) of the hidden layer are 25, 22 and 12, respectively, as shown in the Figure 7. These neurons are activated by sigmoid function; **this** architecture gave the smallest error for the ANN. The one and two hidden layers used to see if the new architecture could improve the final prediction. However, both of those layers have proven a higher error than three hidden layers. Generally, the ANN provided the best estimation of dead oil viscosity with a correlation coefficient of 95.91% and an average absolute relative error of 14.40%. A cross plot for predicting dead oil viscosity by the neural network is shown in Figure 8.

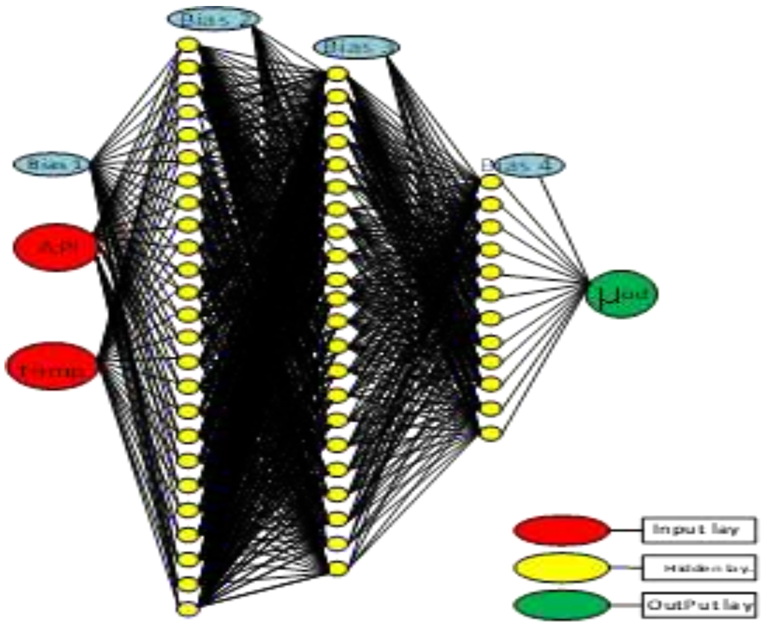

Figure 7. Neural Network Schematically

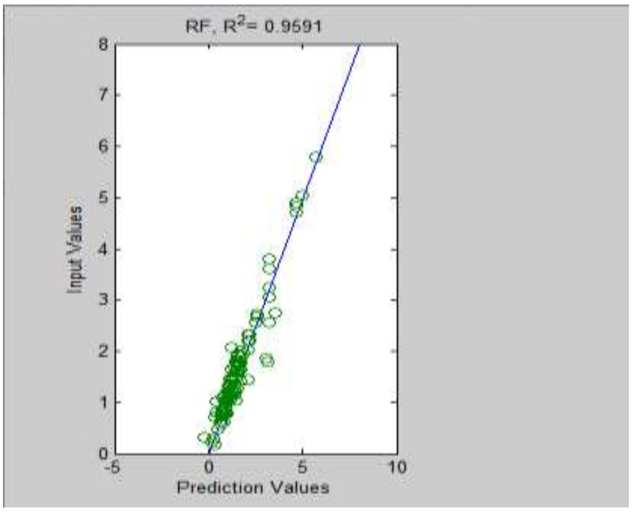

Figure 8. The Fit for The Validation Data

Figure 9 shows the performance plot for ANN, where the mean square error drops gradually. The blue line shows the training area, and the green line shows the validation area. The training stops when the validation area stops decreasing. The green circle on the green line means the value when the validation area stops decreasing. Therefore, the training also stops. The red line shows the test data indicating how is the neural network generates the new data. Also, Figure 10 shows some results of the validation data for the forward ANN developed for all the jobs. They all use three hidden layers in the architecture with 25, 22 and 12 neurons, respectively, and a learning rate and momentum of 0.8.

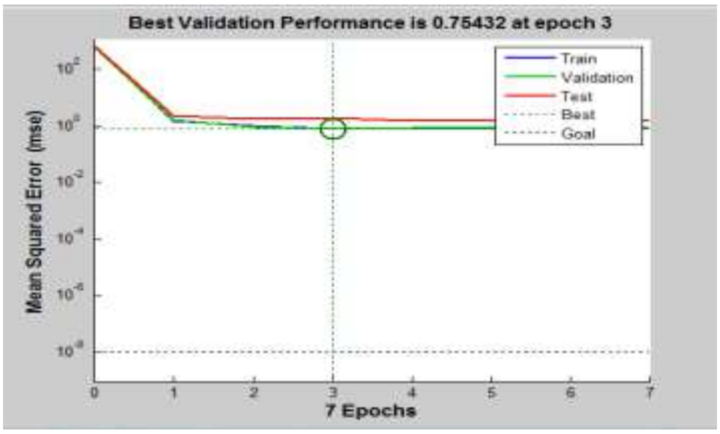

Figure 9. Performance for Testing, Validity and Training Data.

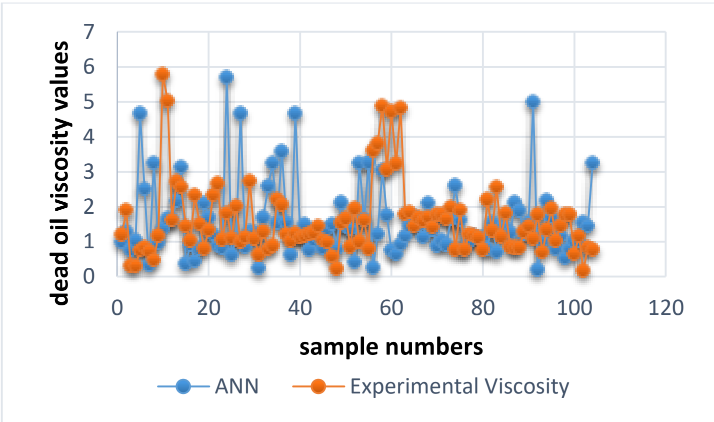

Figure 10. Match Data for Dead Oil Viscosity " Predicted and Experimental "

The ANN model gave the best results when it compared with other correlation and new development correlation. The accuracy comparison of statistical analysis between artificial neural network and other correlations is showed in the Table 4. ANN prediction is the most accurate out of other correlations. A cross plot of error diagram is shown in Figure 11.

Table 4. Accuracy Statistical Analysis of Artificial Neural Network.

Correlation	***AD***%	***AAD***%
Beal's	46.46	0.1191
Beggs & Robinson	41.68	0.0974
Glaso's	46.92	0.1212
Egbogah-Jacks	61.15	0.1421
Labedi	64.89	0.0372
Petrosky & Farshad	44.88	0.109
Mathematical Correlation	38.5	0.1452
ANN Model	14.4	0.959

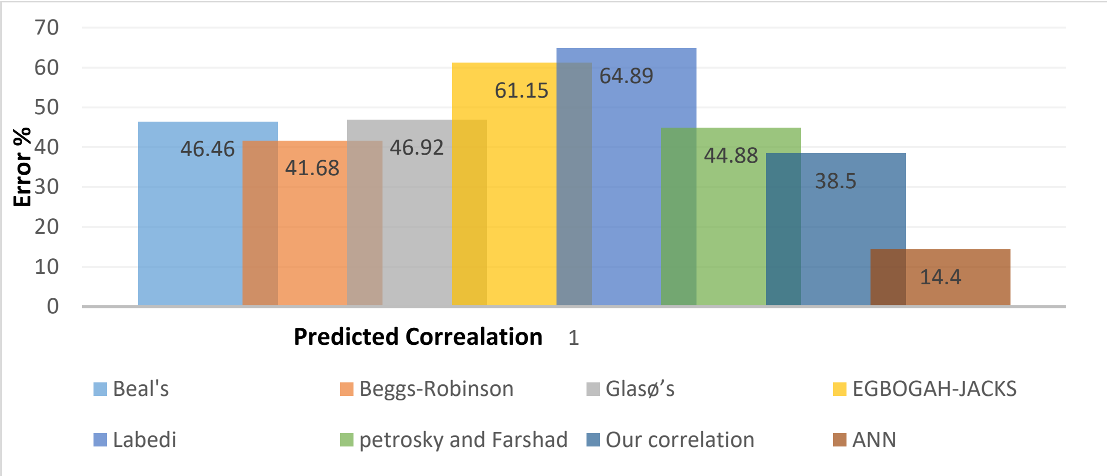

Figure 11. Error Diagram with ANN

CONCLUSION

A new mathematical and ANN model has been developed to predict the dead-oil viscosity for Libyan crude oil. The study shows the ANN model gives the best prediction with the average absolute error of 14.4 % and a correlation coefficient of 95.91%. Meanwhile result from the new mathematical model has a coefficient of 14.52% and an average absolute error of 38.5 %. Both models have given better estimation for dead-oil viscosity than the commonly applied oil viscosity correlations such Beal's, Begg & Robinson, Glaso's, Egbogah-Jack, Labedi, and Petrosky & Farshad. Also, it is found that the trial and error is the best method to obtain the number and members of the hidden layer. For future work, other PVT properties for Libyan dead oil viscosity such as compressibility, total oil formation volume factor and Solution gas oil ratio, bubble point pressure should be conducted to check whether are symethatically with the international correlations or should be improved as the dead oil viscosity.

ACKNOWLEDGMENT

The authors would like to thank Eng. Aisha Rifai for her unconditional support and encouragement. The authors also would like to express their appreciation to China university of petroleum CUP, Sebha University and Universitas Islam Riau (UIR) for the administration supports for making this study possible.

REFERENCES

Al-Marhoun, M A, and E A Osman. 2002. "Using Artificial Neural Networks to Develop New PVT Correlations for Saudi Crude Oils." In Abu Dhabi International Petroleum Exhibition and Conference, Society of Petroleum Engineers.

Beal, Carlton. 1946. "The Viscosity of Air, Water, Natural Gas, Crude Oil and Its Associated Gases at Oil Field Temperatures and Pressures." Transactions of the AIME 165(01): 94–115.

Beggs, H Dale, and JRs Robinson. 1975. "Estimating the Viscosity of Crude Oil Systems." Journal of Petroleum technology 27(09): 1–140.

Boukadi, F, S Al-Alawi, A Al-Bemani, and S Al-Qassabi. 1999. "Establishing PVT Correlations for Omani Oils." Petroleum science and technology 17(5–6): 637–62.

Egbogah, Emmanuel O, and Jack T Ng. 1990. "An Improved Temperature-Viscosity Correlation for Crude Oil Systems." Journal of Petroleum Science and Engineering 4(3): 197–200.

Gharbi, R B, and Adel M Elsharkawy. 1997. "Neural Network Model for Estimating the PVT Properties of Middle East Crude Oils." In Middle East Oil Show and Conference, Society of Petroleum Engineers.

Glaso, Oistein. 1980. “Generalized Pressure-Volume-Temperature Correlations.” Journal of Petroleum Technology 32(05): 785–95.

Labedi, R. 1992. “Improved Correlations for Predicting the Viscosity of Light Crudes.” Journal of Petroleum Science and Engineering, 8, (1992).

Naseri, A., Nikazar, M., & Dehghani, S. M. 2005. “A Correlation Approach for Prediction of Crude Oil Viscosities.” Journal of petroleum science and engineering, 47(3-4), 163-174.

Petrosky Jr, G E, and F F Farshad. 1995. “Viscosity Correlations for Gulf of Mexico Crude Oils.” In SPE Production Operations Symposium, Society of Petroleum Engineers.

Samba, Mohammed A, and ZUHER SYIHAB. “Development Of A Predective Model For Eor Water Alternating Gas Injection Using Proxy Model Derivided From Artificial Neural Network Model.”