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PREDICTION OF NIGERIAN CRUDE OIL VISCOSITY USING ARTIFICIAL NEURAL NETWORK

O. Omole, O.A. Falode* and Deng A. Deng

Department of Petroleum Engineering, University of Ibadan, Ibadan, Nigeria
**corresponding author: falodelias@yahoo.com*

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Abstract

The viscosity parameter is a very important fluid property in reservoir engineering computations. It should be determined in the laboratory but most of the time; the data is not either reliable or unavailable. Hence, empirical correlations were derived to estimate them. However, the success of the correlations in prediction depends on the range of data at which they were originally developed in the region.
In this study, artificial neural network (*ANN*) was used to address the inaccuracy of empirical correlations used for predicting crude oil viscosity. The new artificial neural network model was developed to predict the crude oil viscosity using 32 data sets collected from the Niger Delta Region of Nigeria. About 17 data sets were used to train the model, 10 sets were used to test the accuracy of the model, and remaining 5sets to validate the relationships established during the training process. The test results revealed that the back propagation neural network model (*BPNN*) were better than the empirical correlations in terms of average absolute relative error and correlation coefficient.

Keywords: Viscosity; Oil, Empirical; Neural Network; Back propagation.

1. Introduction

The crude oil viscosity is a very important physical property that controls and influences the flow of oil through porous media and pipes and is a strong function of reservoir temperature, reservoir pressure, gas gravity, oil gravity, and gas solubility. It is defined as the internal resistance of fluid to flow. Oil viscosity could be determined in the laboratory studies on available bottom hole samples at reservoir temperature and pressure and reported in standard PVT analyses. In case where laboratory data are not available or unreliable, Chew-Connally, Beggs-Robinson et al derived the correlations to estimate the crude oil viscosity at bubble point pressure [2,3,4,9,13]. 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[11]. To address the complexity and inaccuracy of the correlations, a new predictive tool was developed in this study to estimate the Nigerian crude oil viscosity using artificial neural networks (*ANNs*). The *ANNs* are biologically inspired, non – algorithmic, non – digital, massively parallel distributive, adaptive information processing systems. They resemble the human brain in acquiring knowledge through learning process and in storing knowledge in interneuron connection strengths [1,10,11]. A new model was developed using 32 data sets: 17 sets were used to train the model, 5 sets to validate the relationship established during the training process, and 10 sets were used to test the accuracy of the model.

2. Empirical correlations for crude oil viscosity

Most crude oil viscosity correlations use oil API gravity and reservoir temperature to estimate dead oil viscosity (μ_{od}) while solution gas oil ratio (R_s**)** and dead oil viscosity (μ_{od})

are used to estimate saturated oil viscosity (μ_{ob}). The saturated oil viscosity (μ_{ob}) and differential pressure above bubble point pressure are then used to predict undersaturated oil viscosity. Some of the studies which were carried out to develop empirical correlations for the estimation of the crude oil viscosity at bubble point are below:

In 1959, Chew- Connally used 457 crude oil samples to develop a graphical correlation which was later expressed mathematically by Standing, in 1981, to estimate oil saturated viscosity(μ_{ob}). In 1975, Beggs and Robinson collected 2,073 crude oil viscosity sets to propose an empirical correlation that estimated the saturated oil viscosity (μ_{ob}). The studies concluded that the performance of the correlations suffer outside the range of application [4,12,13].

3. Artificial neural networks

Boomer et al.[14] and Corpoven et al.[15] defined artificial neural network (*ANN*) as a computing system made up of a number of simple, highly interconnected elements which process information by its dynamic response to external inputs. Mohagheh et al.[16] described that *ANN* is a biologically inspired computing scheme which is an analog, adaptive, distributive and highly parallel system that has been used in many disciplines and has proven to have potential in solving problems that require pattern recognition. They resemble the human brain in acquiring knowledge through learning process and in storing knowledge in interneuron connection strength [1,5,6,7,8,10].

The advantages of *ANN* over the conventional correlations are: neural networks have large degrees of freedom for fitting parameters, and thus, capture the systems' non-linearity better than regression methods and they are 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 while it is impossible to make any further change in a linear or non linear regression model as soon as a model development is over [1,7,8,17] In this study, the back propagation neural network (*BPNN*) was used to model the Nigerian crude oil viscosity. The *BPNN* is multi- layered information flows from the input to the output through at least one hidden/middle layer. Each layer contain neurons that are connected to all neurons in the neighboring layers. The connections have numerical values (weights) associated with them which will be adjusted during the training phase [1,10,12].

4. Review of literature on artificial neural networks model for crude oil viscosity

Several papers on neural networks have been presented to address many problems in the oil industry. Notable among the papers is the work of El-Sharkawy [12] who modeled crude oil viscosity with other *PVT* properties for oil and gas systems using radial basis function neural network (*RBFNN*). However, previous studies [5,6,7,8] on the use of back propagation neural network (*BPNN*) model to predict *PVT* oil properties do not attempt predicting μ_{ob}. It was also believed in the same studies that the application of neural networks required the use of large number of data sets to get the desired results. The present study which aimed at predicting μ_{ob} by developing back propagation neural network model (*BPNN*) has demonstrated that a reliable *ANN* model could in fact be developed using fewer data sets. The objectives of this study are to develop *ANN* models for predicting μ_{ob}, evaluate and compare the accuracy of the *ANN* models to those of the empirical correlations.

5. Mathematics of back propagation neural network

The benefit of the following mathematical derivative is to show us how the back propagation neural network (*BPNN*) works in reality.

From Fig 1, the derivative is conducted between layer (*I*) and layer (*K*). Let I_p represents the net input signals to a node (*j*) in a layer (*J*) and W_{ji} stands for the weights of the connection from a node (*i*) in layer (*I*) to a node (*j*) in layer (*J*).

Due to input pattern,X_{pi}, I_p is defined as the sum of the inputs to a node (*j*) or neuron (*j*) in the middle (hidden) layer (*J*) as in the shown expression:

$$I_{pj} = \sum_{J} W_{ji} * X_{pi} = \text{net} \qquad (1)$$

Where W_{ji} is the weight of the neuron (j) in the middle layer (J) associated with the neuron (i) in the layer (I), and I_{pj} is the net input of the neuron (j) in the layer (J) or input pattern for the hidden layer, X_{pi} *is* an input pattern in the input layer (I). Then, the output, $O_{pj,}$ from a node (j) or neuron (j) in the middle (hidden) layer (J) because of input pattern X_{pi} is defined as:

$$O_{pj} = \frac{1}{[1+\exp(-Ipj)]} = f(x) \quad (2)$$

Similarly, the net input to a node (n) or neuron (n) in the layer (K) due to the input pattern, X_{pi}, of the input layer (I), can be defined as follows:

$$I_{pk} = \sum_{k} W_{ni} * X_{pi} = \text{net} \quad (3)$$

Where W_{ni} is the weight factor. Hence, the output from a node (n) in the output layer (K) or layer (K) caused by the input pattern, X_{pi}, is defined as:

$$O_{pk} = \frac{1}{[1+\exp(-Ipk)]} = f(x) \quad (4)$$

As soon as the neural network undergoes the learning processes, the mean square error criterion (E) is defined as a half of the sum of the squared difference between the actual outputs of output nodes of the network (O_{pk}) and our desired output (d_{pk}) given as:

$$E = ½ \sum_{k} \sum_{p} (d_{pk} - O_{pk})^2 \quad (5)$$

Equation (5) is the objective function, which will be minimized during learning iterations or the minimization of the above error depending on weights as reported by Al-Kaabi et al.[18] and by the Widrow – Hoff theory as reported by Magali et al.[19].

Learning is achieved by changing the weights by an incremental value, ΔW_{ni}. This value is defined as proportional to, E, by:

$$\Delta W_{ni} = -\eta * (\frac{\partial E}{\partial W_{ni}}) \quad (6)$$

Applying the chain rule to the right- hand of equation (6), we have:

$$\frac{\partial E}{\partial W_{ni}} = \frac{\partial E}{\partial O_{pk}} * \frac{\partial O_{pk}}{\partial net} * \frac{\partial net}{\partial W_{ni}} \quad (7)$$

Taking the derivative of I_{pk} with respect to W_{ni} in equation (3), we obtain

$$\frac{\partial I_{pk}}{\partial W_{ni}} = \frac{\partial \sum_{k} W_{ni} * X_{pi}}{\partial W_{ni}} = X_{pi} = \frac{\partial net}{\partial W_{ni}} \quad (8)$$

Taking a derivative of (E) with respect to (O_{pk}) in equation (5), we have

$$\frac{\partial E}{\partial O_{pk}} = - (d_{pk} - O_{pk}) \quad (9)$$

By definition, let δ_{pk} represents a local error defined as:

$$\delta_{pk} = (\frac{\partial E}{\partial I_{pk}}) \quad (10)$$

Using the chain rule to expand equation (10), we have:

$$\delta_{pk} = \frac{\partial E}{\partial O_{pk}} * \frac{\partial O_{pk}}{\partial I_{pk}} \quad (11)$$

From equation (4), taking a derivative of O_{pk} with respect to I_{pk}, we have:

$$\frac{\partial O_{pk}}{\partial I_{pk}} = f(I_{pk}), \quad (12)$$

Where the right- hand of the above equation is the transfer function of our neural network.
Substituting Equations (8), (9), and (12) into equation (7), we obtain:

$$\Delta W_{ni} = \eta * (d_{pk} - O_{pk}) * f(I_{pk}) * X_{pi} \quad (13)$$

Equation (8) gives the required weight change within a link between a node (i) in layer J and a node (n) in the output layer k.
η is usually denoted the learning rate that takes any value between 0 and 1.
A popular modification to increase the learning rate of the back propagation algorithm is the use of a momentum term as reported by Al - Kaabi et al.[18]. Hence, the change in the link or weight with the momentum term can be defined and added as follows:

$$\Delta W_{ni}(n+1) = \eta * \delta_{pk} * f(I_{pk}) * X_{pi} + \alpha * \Delta W_{ni}(n) \quad (14)$$

Where α takes values between 0 and 1.
Also, the weight change (ΔW_{ij}) between the input layer (I) and hidden layer (J) can be derived as follows:
The learning of the neural network is accomplished by changing the weight between the links by the following incremental value ΔW_{ij}, which is defined as follows:

$$\Delta W_{ij} = -\eta * \frac{\partial E}{\partial W_{ij}} \quad (15)$$

Applying the chain rule in the right- hand side of the equation (15), we have

$$\frac{\partial E}{\partial W_{ij}} = \frac{\partial E}{\partial O_{pj}} * \frac{\partial O_{pj}}{\partial net} * \frac{\partial net}{\partial W_{ij}} \quad (16)$$

Taking the derivative of E with respect to O_{pj} in Equation (5), after replacing the subscript k for j, we have

$$\frac{\partial E}{\partial O_{pj}} = (d_{pj} - O_{pj}) \quad (17)$$

Taking the derivative of O_{pj} with respect to net or I_{pj} in Equation (2), we have:

$$\frac{\partial Opj}{\partial net} = f(net) \quad (18)$$

Taking a derivative of net or I_{pj} with respect to W_{ij} in Equation (1), we get:

$$\frac{\partial net}{\partial Wij} = \frac{\partial \sum Wij * xpi}{\partial Wij} = Xpi \quad (19)$$

At the hidden layer (J), the local error is equal to the following:

$$\delta_{pj} = \frac{\partial E}{\partial O_{pj}} * f(net) \quad (20)$$

From Equations (16), (17), (18), (19), and (20) , we obtain the final results

$$\Delta W_{ij} = \eta * \delta_{pj} * X_{pi} \quad (21)$$

For the weight update using the gradient rule, we find;

$$W_{ij}(n+1) = W_{ij}(n) + \eta * \delta_{pj} * X_{pi} \quad (22)$$

6. Data acquisition and analysis

The 32 data sets used in this work were collected from the Niger delta region of Nigeria. The ranges of the data are the following: reservoir temperature (154 to 234°F), oil gravity (19–45.4°API), solution gas oil ratio(210–3100 SCF/BBL), gas gravity(0.690-1.118, air = 1.0),

bubble point pressure (1420– 4845 psia), and crude oil viscosity at the bubble point (0.22 - 3.91 centipoise).

Of the 32 data sets, 17 were used to train the *ANN* models, 5 data sets were used to cross – validate the relationships established during training process and the remaining 10 data sets were used to test the *ANN* models to evaluate their accuracy through statistical analysis.

7. Analysis of the results of μ_{ob} *ANN* model

A computer simulation program for Nigerian crude oil viscosity model was written in the C^{++} programming language to predict μ_{ob}. Then, the 17 data sets were normalized and used in the μ_{ob} *ANN* model as a training file. The model inputs were reservoir temperature, reservoir pressure, oil gravity, gas gravity, and solution gas - oil ratio. The output is crude oil viscosity at the bubble point. The learning rates, the momentum factor and the number of iterations were used as training parameters. The computed outputs were compared with the desired output to compute the error (Equation 5), which was back propagated through the system causing it to adjust the weights (Equations 13&14), which control the network. Several topologies including the proposed one were examined, but in the long run, the final result of the training phase on the μ_{ob} *ANN* model converged at (0.01) learning rate and (7) neurons in the hidden layer. The stability of the training phase means the μ_{ob} *ANN* model output was very close to their field values. Therefore, the new μ_{ob} *ANN* model topology becomes three layers (i.e. one input layer, one hidden layer, and one output layer) as shown in Figure 2.

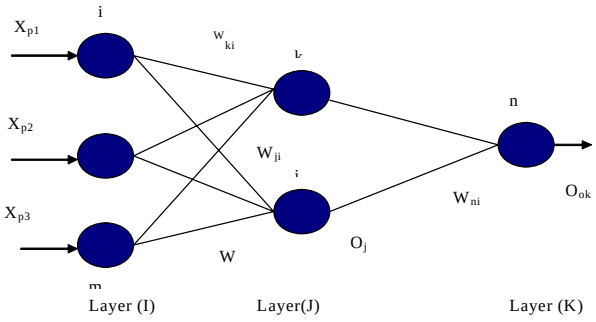

Fig. 1 One output layer back propagation neural network

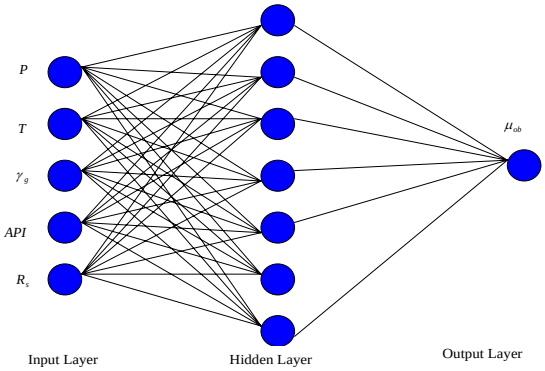

Fig. 2 A schematic of the achieved artificial neural network topology used for μ_{ob}

As soon as the training process was over, the error of our training process was examined using the 5 data sets which were not included in those used for the training phase to cross – validate the relationship established during training process. It was found out that the errors of the validation phase decreased in the same manner as the training phase progresses, which indicates that a good relationship was developed. To finally decide whether the training phase result was good or bad, the remaining 10 data sets that were not seen by the μ_{ob} *ANN* model were used to test the model. The result in Table 1 showed that the μ_{ob} *ANN* model was able to closely predict the test data.

8. Discussion of the results of μ_{ob} *ANN* model

After training the neural network, the *ANN* crude oil viscosity model was tested using the testing data. The results were compared with field data and the predictions of other empirical correlations (namely Chew-Connally, and Beggs- Robinson) are shown in Tables 1. The statistical analysis presented in Table 2 indicates that the average absolute relative error was 0.06781 for μ_{ob} *ANN* model, 0.45852 for Chew-Connally correlation, 0.1741 for Beggs- Robinson correlation. The correlation coefficient was 0.9989 for the μ_{ob} *ANN* model, 0.9473 for Chew-Connally correlation, 0.9367 for Beggs- Robinson correlation. The fact that the *ANN* μ_{ob} model gave the lowest average absolute relative error of 0.06781 and the

highest correlation coefficient of 0.9989 as compared to those obtained using other correlations, clearly demonstrated that the *ANN* μ_{ob} model were better predictors of viscosity than all the empirical correlations as graphically illustrated in Figures 1, 2, 3 and 4.

Table 1: The results for the data used for the testing phase of μ_{ob} mModel

R_s	R_s	*Gasgra*	*API*	*P*	μ_{ob}	μ_{obnn}	$\mu_{obchew-connally}$	$\mu_{obbeg-robinson}$
1042	219	1.118	19	2951		0.28	1.2	1.03
1119	183	0.920	40.6	2736		0.3	0.28	0.28
977	188	0.870	39.4	2858		0.3	0.32	0.3
1237	180	0.940	43.4	2655		0.3	0.24	0.24
210	154	0.73	23.3	1680		3.84	4.71	3.5
3100	215	1.048	45.4	4340		0.15	0.54	0.14
1232	216	0.78	43.8	3963		0.22	0.21	0.21
1137	212	0.78	44.1	3710		0.23	0.22	0.22
1053	216	0.91	38.2	2965		0.29	0.29	0.28
950	214	0.77	39.8	3614		0.25	0.28	0.27

Table 2: The Statistical Analysis for μ_{ob} Model

Correlation	Chew-Connally	Begg-Robinson	Neutral Network
Ave. absolute relative error (E_{ave})	0,45852	0,1741	0,06781
Minimum absolute relative error (E_{min})	3,8	3,12	0,12532
Maximum absolute relative error (E_{max}) correlation coefficient (R^2)	0,225806	0,391304	0,347826

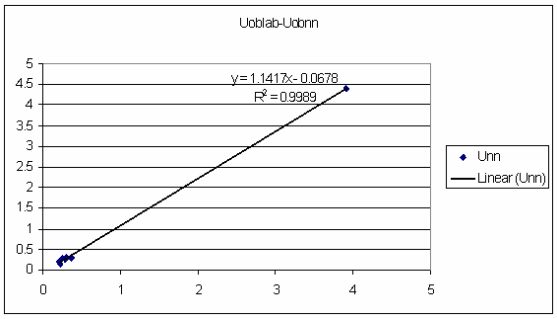

Fig. 3 Comparison of the estimated crude oil viscosity versus experimental crude oil viscosity (μ_{ob} *ANN* model).

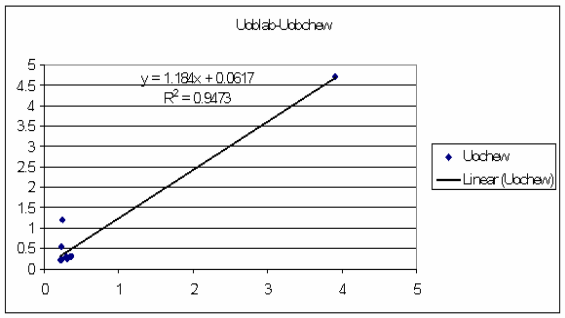

Fig. 4 Comparison of the estimated crude oil viscosity versus experimental crude oil viscosity (Chew-Connally correlation).

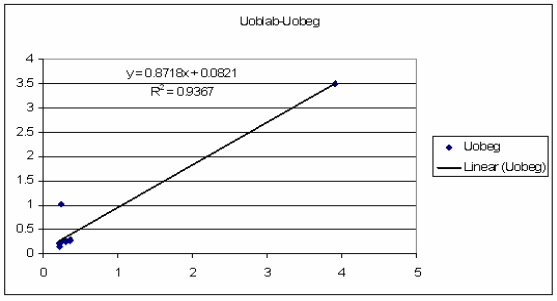

Fig. 5 Comparison of the estimated crude oil viscosity versus experimental crude oil viscosity (Beggs-Robinson correlation).

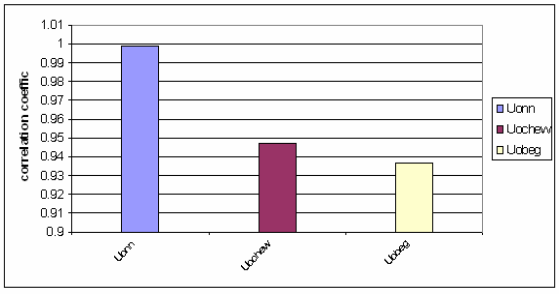

Fig.6 Comparison of different correlation coefficients for different correlations of μ_{ob}

9. Conclusion

The newly developed back propagation neural network (*BPNN*) model for predicting crude oil viscosity was better than the empirical correlations.

The μ_{ob} *ANN* model, achieved the lowest average absolute relative error of 0.06781 and the highest correlation coefficient of 0.9989 as compared to existing empirical correlations.

From the scatter diagrams for the *ANN* models and empirical correlations against their experimental values, the *ANN* models data points performed better than the existing empirical correlations.

Nomenclature

PVT	Pressure, Volume, Temperature
μ_{ob}	Crude oil viscosity at the bubble point
P_b	Bubble point pressure, psia.
R_s	Gas solubility, scf/stb
T_f	Reservoir temperature, F
API	Oil gravity
γ_g (G.G)	Gas gravity
γ_o	Specific oil gravity
E_{ave}	Average absolute relative error
E_{min}	Minimum absolute relative error
E_{max}	Maximum absolute relative error
ANN	Artificial neural network
W_{ji}	Weight between neuron (i) in the layer (I) and neuron (j) in the layer(J)
W_{ni}	Weight between neuron (i) in the layer (J) and neuron (n) in the layer (k)
α	Momentum factor
E	Error
δ	Derivative of E with respect to Ipk = Local Error
η	Learning rate constant
BPNN	Back propagation neural network
RBFNN	Radial basis function neural network
PE	Processing element
X_{pi}	Input pattern in the input layer

Subscript

P, I , J , and K	layers
Ji	between layers i and j
Ni	between layers j and k
$f_k(I_{pk})$	Sigmoid Transfer Function Derivative

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