Petroleum & Coal
ISSN 1337-7027
Available online at www.vurup.sk/petroleum-coal
Petroleum & Coal 54 (2) 120-131, 2012

PREDICTION OF CRUDE OIL VISCOSITY USING FEED-FORWARD BACK-PROPAGATION NEURAL NETWORK (FFBPNN)

F. A. Makinde*, C. T. Ako, O. D. Orodu and I. U. Asuquo

Petroleum Engineering Department, Covenant University, Ota, Nigeria
*corresponding author: favour.makinde@covenantuniversity.edu.ng

Received December 14, 2011, Accepted June 5, 2012

Abstract

Crude oil viscosity is an important governing parameter of fluid flow both in the porous media and in pipelines. So, estimating the oil viscosity at various operating conditions with accuracy is of utmost importance to petroleum engineers.

Usually, oil viscosity is determined by laboratory measurements at reservoir temperature. However, laboratory experiments are rather expensive and in most cases, the data from such experiments are not reliable. So, petroleum engineers prefer to use published correlations but these correlations are either too simple or too complex and so many of them are region-based not generic.

To tackle the above enumerated drawbacks, in this paper, a Feed-Forward Back-Propagation Neural Network (FFBPNN) model has been developed to estimate the crude oil viscosity (μ_o) of Undersaturated reservoirs in the Niger Delta region of Nigeria.

The newly developed FFBPNN model shows good results compared to the existing empirical correlations. The μ_o FFBPNN model achieved an average absolute relative error of 0.01998 and the correlation coefficient (R^2) of 0.999 compared to the existing empirical correlations. From the performance plots for the FFBPNN model and empirical correlations against their experimental values, the FFBPNN model's performance was excellent.

Keywords: Viscosity; Undersaturated Reservoir; Back-Propagation; Feed-Forward; Neural Network.

1. Introduction

Viscosity, in general, is defined as the internal resistance of the fluid to flow. Crude oil viscosity is an important physical property that controls and influences the flow of oil through porous media and pipes [1]. The oil viscosity is a strong function of the temperature, pressure, oil gravity, gas gravity, and gas solubility. Whenever possible, oil viscosity should be determined by laboratory measurements at reservoir temperature and pressure. The viscosity is usually reported in standard PVT analyses. If such laboratory data are not available, engineers may refer to published correlations, which usually vary in complexity and accuracy depending upon the available data on the crude oil. Such published correlations include Beal's correlation, the Beggs-Robinson correlation, and Glaso's correlation for dead oil viscosities [12-14], the Chew-Connally correlation, and the Beggs-Robinson correlation etc. for saturated oil viscosities [12-14] and the correlations by Vasquez-Beggs, Labedi, Kahn et al, Kartoatmodjo, Isehunwa et al, Abedini et al etc. for undersaturated oil viscosities [1,11-14].

Based on pressure, the viscosity of crude oils can be classified into three categories:

- Dead-Oil Viscosity,
- Saturated-Oil Viscosity,
- Undersaturated-Oil Viscosity.

1.1 Empirical Correlations for Undersaturated Oil Viscosity

The undersaturated-oil viscosity is defined as the viscosity of the crude oil at a pressure above the bubble-point and at reservoir temperature. Oil viscosity at pressures above the bubble point is estimated by first calculating the oil viscosity at its bubble-point pressure and adjusting the bubble-point viscosity to higher pressures. Vasquez and Beggs, for instance proposed a simple mathematical expression for estimating the viscosity of the oil above the bubble-point pressure. Others include Beal, Khan, Isehunwa et al, Abedini et al and Kartoatmodjo and Schmidt.

1.2 Artificial Neural Network and Previous Works

Petroleum engineers have shown a high degree of open-mindedness in utilizing new technologies from different disciplines to solve old and new petroleum engineering problems. As time changes and new technologies are developed, it is the job of petroleum engineers to utilize such innovations and improve on them. The modern and recently used method for parametric modelling is the Artificial Neural Networks (ANNs). Today, ANNs have emerged as a powerful tool in modelling complex systems and also solving pattern recognition problems such as estimating and predicting oil viscosity for undersaturated reservoirs. Several technical papers and researches have been carried out to address many problems in the oil industry; most specifically are researches done using artificial neural network, which has a most adept feature of analyzing and recognizing patterns.

A neural network can be defined as a model of reasoning based on the human brain. The brain consists of a densely interconnected set of nerve cells, or basic information-processing units, called neurons. The human brain incorporates nearly 10 billion neurons and 60 trillion connections, synapses, between them [2]. By using multiple neurons simultaneously, the brain can perform its functions much faster than the fastest computers in existence today.

Although each neuron has a very simple structure, an army of such elements constitutes a tremendous processing power. A neuron consists of a cell body, soma, a number of fibres called dendrites, and a single long fibre called the axon. While dendrites branch into a network around the soma, the axon stretches out to the dendrites and somas of other neurons. Figure 1 is a schematic drawing of a neural network.

Owing to the plasticity, connections between neurons leading to the 'right answer' are strengthened while those leading to the 'wrong answer' weakened. As a result, neural networks have the ability to learn through experience. Learning is a fundamental and essential characteristic of biological neural networks. The ease and naturalness with which they can learn led to attempts to emulate a biological neural network in a computer.

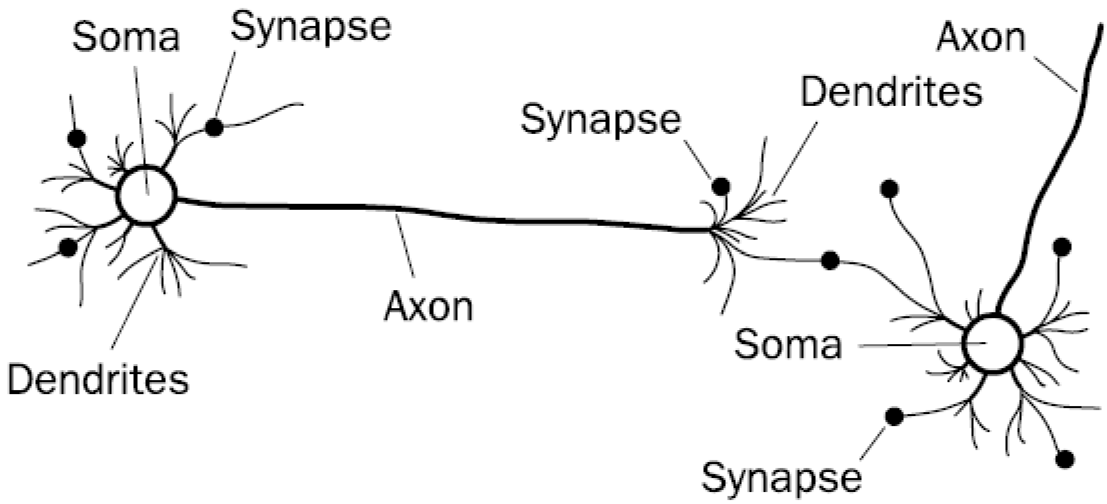

Figure 1 Biological neural network [2]

The complexity of real neurons is highly abstracted when modelling artificial neurons. These basically consist of inputs (like synapses), which are multiplied by weights (strength of the respective signals), and then computed by a mathematical function which determines the activation of the neuron. Another function (which may be the identity) computes the output of the artificial neuron (sometimes independence of a certain threshold). ANNs combine artificial neurons in order to process information.

The first term, "Feed-Forward" describes how this neural network processes and recalls patterns. In a feed forward neural network, neurons are only connected forward. Each layer of the neural network contains connections to the next layer (for example, from the input to the hidden layer), but there are no connections back. This differs from the Hopfield neural network which is also popularly known. The Hopfield neural network is fully connected, and its connections are both forward and backward.

The term "Back-Propagation" describes how this type of neural network is trained. Back-Propagation is a form of supervised training. When using a supervised training method, the network must be provided with both sample inputs and anticipated outputs. The anticipated outputs are compared against the actual outputs for given input. Using the anticipated outputs, the back propagation training algorithm then takes a calculated error and adjusts the weights of the various layers backwards from the output layer to the input layer.

The Back-Propagation and Feed-Forward algorithms are often used together; however, this is by no means a requirement. It would be quite permissible to create a neural network that uses the Feed-Forward algorithm to determine its output and does not use the Back-Propagation training algorithm. Similarly, if you choose to create a neural network that uses Back-Propagation training methods, you are not necessarily limited to a Feed-Forward algorithm to determine the output of the neural network, although such cases are less common than the Feed-Forward Back-Propagation Neural Network. In this study, we will examine only the case in which the Feed-Forward and Back-Propagation algorithms are used together.

Mohaghegh et al [3] 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 [4-7].

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 [6-8].

In this study, the Feed-Forward Back-Propagation Neural Network (FFBPNN) model was used to model the undersaturated crude oil viscosity from the Niger Delta region of Nigeria. The FFBPNN is a multi- layered architecture where 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. The connections have numerical values (weights) associated with them which will be adjusted during the training phase [9].

In his paper, [9] modeled crude oil viscosity with other *PVT* properties for oil and gas systems using Radial Basis Function Neural Network (*RBFNN*). However, previous studies by authors [4-7] on the use of Back Propagation Neural Network (*BPNN*) model to predict *PVT* oil properties did not consider predicting μ_o. 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.

Finally, the work on Prediction of Nigerian Crude Oil Viscosity using Artificial Neural Network by [10] was carried out specifically for estimating crude oil viscosity for saturated reservoirs at bubble point. The 32 data sets used in the work were collected from the Niger delta region of Nigeria. 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.

However, the objectives of this study are to develop a FFBPNN model for predicting μ_o, evaluate and compare the accuracy of the developed model to those of the existing empirical correlations.

2. Methodology

2.1. Using MATLAB Programming Environment to create a FFBPNN

The primary objective of this study is to use the Back-Propagation training functions in the toolbox to train Feed-Forward Neural Networks to predict Undersaturated crude oil viscosity. There are generally four steps in the modelling process: Assembling the training data, creating the network object, training the network, and simulating the network response to new inputs.

2.1.1 Assembling the Training Data

A total of 105 data sets were used in this work and they were collected from the Niger Delta region of Nigeria. The ranges of the data are: reservoir temperature (126 to 289^{o}F), bubble point pressure (375 to 6225psia), reservoir pressure (1830.7 to 9407psia), crude oil viscosity at bubble point (0.03 to 34.32centipoise) and crude oil viscosity above bubble point (0.08 to 43centipoise). Of the 105 data sets, 63 were used to train the *FFBPNN* model, 21 data sets were used to cross-validate the relationships established during training process and the remaining 21 data sets were used to test the *FFBPNN* model to evaluate their accuracy through statistical analysis.

2.1.1.1 Normalization of Input Data

The training data were normalized using equation (1) below, before being presented to the network for training. This step was taken to ensure that input data with different ranges were transformed into one similar range and allows for easier and faster model training.

$$X_{new} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

2.1.2 Creating the Network Object

Just as described previously, the FFBPNN in this study begins with an input layer. The input layer is connected to a hidden layer; the hidden layer is then connected to output layer. In this study, the architecture used for the neural network consist of one input layer, one hidden layer and lastly, the output layer which is the undersaturated crude oil viscosity, μ_o.

- ✓ **The Input Layer**

The input layer is the conduit through which the external environment presents a pattern to the neural network. Once a pattern is presented to the input layer, the output layer will produce another pattern. In essence, this is all the neural network does. The input layer should represent the condition for which we are training the neural network. Every input neuron should represent some independent variable that has an influence over the output of the neural network. Putting all of the above into consideration and previous works/correlations carried out on predicting Undersaturated crude oil viscosity (not with ANN though), the input layer is made with four(4) neurons which are Reservoir Temperature, Bubble Point Pressure, Reservoir Pressure and the saturated viscosity.

- ✓ **The Hidden Layer**

There are really two decisions that must be made regarding the hidden layers: how many hidden layers to actually have in the neural network and how many neurons will be in each of these layers. Firstly, examine how to determine the number of hidden layers to use with the neural network:

Option 1: **No Hidden Layer** – gives a network that is only capable of representing linear separable functions or decisions.

Option 2: **One Hidden Layer** – gives a network that is capable of approximating any function that contains a continuous mapping from one finite space to another.

Option 3: **Two Hidden Layers** – give a network that is capable representing an arbitrary decision boundary to arbitrary accuracy with rational activation functions and can approximate any smooth mapping to any desired accuracy.

Putting the above into consideration, using one hidden layer will be ideal and appropriate for the prediction of the undersaturated crude oil viscosity.

The second problem in this phase is to determine the number of neurons to be used in the hidden layer. While considering the number of neurons to be used in the hidden layer, two likely problems could occur: underfitting and overfitting.

Using too few neurons in the hidden layers will result in something called underfitting. Underfitting occurs when there are too few neurons in the hidden layers to adequately detect the signals in a complicated data set. Using too many neurons in the hidden layers can result in several problems. First, too many neurons in the hidden layers may result in overfitting. Over-fitting occurs when the neural network has so much information processing capacity that the limited amount of information contained in the training set is not enough to train all of the neurons in the hidden layers. A second problem can occur even when the training data is sufficient. An inordinately large number of neurons in the hidden layers can increase the time it takes to train the network. The amount of training time can increase to the point that it is impossible to adequately train the neural network. Obviously, some compromise must be reached between too many and too few neurons in the hidden layers. Amidst all of the above problems, a set of guidelines or simply known as the Rule-of-Thumb was used in order to determine the correct number of neurons to use in the hidden layers, such as the following:

- The number of hidden neurons should be between the size of the input layer and the size of the output layer.
- The number of hidden neurons should be 2/3 the size of the input layer, plus the size of the output layer.
- The number of hidden neurons should be less than twice the size of the input layer.

These three rules, coupled with the suggestion by Hossein Kaydani (unpublished) who stated that the number of neurons in the hidden layer should range between L/2 (lower bound) and 3L(upper bound) – L is the number of input variables - were used to provide a starting point for selecting the correct number of neurons to be used. Ultimately, the selection of the architecture for the neural network came down to trial and error. After various considerations, a hidden layer with ten (10) neurons was attained.

✓ **The Output Layer**

The output layer of the neural network is what actually presents a pattern to the external environment. The pattern presented by the output layer can be directly traced back to the input layer. The number of output neurons should be directly related to the type of work that the neural network is to perform.

To determine the number of neurons to use in your output layer, you must first consider the intended use of the neural network. If the neural network is to be used to classify items into groups, then it is often preferable to have one output neuron for each group that input items are to be assigned into. Therefore, for this study; one neuron is used which is the Undersaturated crude oil viscosity.

✓ **Neural Network Architecture**

After careful selection of input layer, number of layers and neurons in the hidden layer, and the output layer; the neural network architecture was achieved.

The FFBPNN has one hidden layer of sigmoid neurons followed by an output layer of linear neurons. See Figure 2 under data analysis and discussion of results for the achieved network architecture.

After careful consideration of the input, hidden, output layer and the neural network architecture, the network was created using the newff command in MATLAB workspace.

The output layer size is determined from the targets. With this, the neural network was created as follows:

```
>> net = newff (Input_Data,Output_Data,10);
```

There are ten neurons in the hidden layer. The default transfer function for hidden layers is tan-sigmoid, and for the output layer is linear. Where the command, ***net*** is the Feed-Forward Back-Propagation Neural Network, Input_Data refers to the input data consisting of Reservoir Temperature (126 to 289^{o}F), Bubble Point Pressure (375 – 6225 psia), Reservoir Pressure (1830.7 - 9407psia) and the saturated viscosity at bubble point (0.03-34.32 cP). Thirdly, the Output_Data refers to the output data used in this study which is the undersaturated crude oil viscosity (0.08 – 43cP). Lastly, the ten (10) in the command line refers to the number of neurons in the hidden layer. This command creates the network object and also initializes the weights and biases of the network; therefore the network is ready for training.

2.1.3 Training the network

There are many variations of the Back-Propagation training algorithm, several of which were considered but the Levenberg-Marquardt (trainlm) was chosen.

```
>>net.trainFcn = 'trainlm';
```

The training parameters for trainlm are epochs, show, goal, time, min_grad, max_fail, mu, mu_dec, mu_inc, mu_max, and mem_reduc.

After the neural network was created and the training function set, other parameter of the trainlm Back-Propagation method were adjusted using the command codes below:

>> net.trainFcn = 'trainlm';
>> net.trainParam.show = 5;
>> net.trainParam.epochs = 300;
>> net.trainParam.goal = 1e-5;
>> net = train(net,Input_Data,Output_Data);

Training stops when any of these conditions occurs:

- The maximum number of epochs (repetitions) is reached.
- The maximum amount of time is exceeded.
- Performance is minimized to the goal.
- The performance gradient falls below min_grad.
- mu exceeds mu_max.
- Validation performance has increased more than max_fail times since the last time it decreased (when using validation).

The following code was used to set the Mean squared error performance function (MSE) in the Levenberg-Marquardt training algorithm (trainlm):

>> net.performFcn = 'mse';

Before the network was trained, the data used for training, testing and validating the network was divided using the dividerand and divideind commands.

The command codes cycle samples between the training set, validation set, and test set according to percentages. The data set is distributed as 60% of the samples to the training set, 20% to the validation set and 20% to the test set as follows:

>> [trainInput_Data,valInput_Data,testInput_Data,trainInd,valInd,testInd] = dividerand(Input_Data);
Divide the target data accordingly using divideind:
>> [trainOutput_Data,valOutput_Data,testOutput_Data] = divideind(Output_Data,trainInd,valInd,testInd);

2.1.4 Simulating the network response to new inputs

The function sim simulates the network. Sim takes the network input (Input_Data) and the network object (net) and returns the network outputs. The code below was used to simulate the network.

y= sim(net,Input_Data)

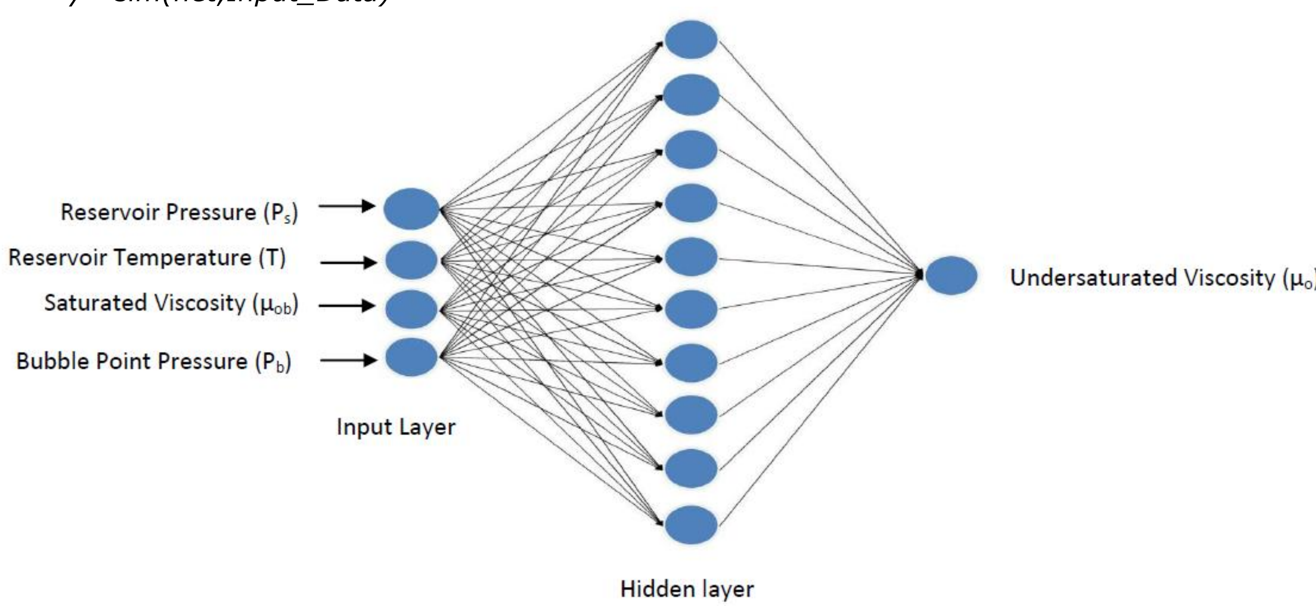

Figure 2: A schematic of the achieved FFBPNN topology

3. Data Analysis and Discussion of Results

A total of 105 data sets were used in this work. The ranges of the data are the following: reservoir temperature (126 - 289°F), bubble point pressure (375 – 6225psia), reservoir pressure (1830.7 - 9407psia), crude oil viscosity at bubble point (0.03 – 34.32centipoise) and crude oil viscosity above bubble point (0.08 - 43centipoise). Of the 105 data sets, 63 were used to train the *ANN* models, 21 data sets were used to cross-validate the relationships established during training process and the remaining 21 data sets were used to test the *ANN* models to evaluate their accuracy through statistical analysis. The neural network converged after 117 iterations with 10 neurons in the hidden layer. Figure 2 shows the achieved schematic representation of the network.

3.1 STATISTICAL ERROR ANALYSIS

Statistical and graphical error analyses have been used to assess the performance of the FFBPNN model developed in this work. Two of such error analyses methods were used, which are: coefficient of determination (R^2) and Percent Average Relative Error (AARE).

3.1.1 COEFFICIENT OF DETERMINATION, R^2

The coefficient of determination is a simple statistical parameter that tells how the model fits the data, and thereby represents a measure of the utility of the model. In general, the closer the value of R^2 is to 1, the better the model fits the data.
The achieved output i.e. the undersaturated crude oil viscosity gotten from the FFBPNN model was then plotted against the experimental viscosity to get the relative deviation illustrated in Figure A1, Appendix A.

3.1.2 PERCENT AVERAGE ABSOLUTE RELATIVE ERROR, E_r

This is a measure of the deviation of estimated values from the experimental data. It indicates the relative absolute deviation in percentage from the observed values; the lower the value, the better the correlation. It is expressed as:

$$E_r = \frac{1}{N}\left(\sum_{i=1}^{N}\left|\frac{X_{obs} - X_{est}}{X_{obs}}\right|\right)\times 100 \qquad (2)$$

Using the data analysis formula for Percent Absolute Relative Error, the relative error was found to be 0.01998.

3.2 COMPARISON WITH PUBLISHED CORRELATIONS

Undersaturated oil viscosity correlations, usually use saturated crude oil viscosity and pressure above the bubble point to predict viscosity of undersaturated oil reservoirs. These correlations include Beal, Vasquez and Beggs, Khan, Isehunwa et al., Abedini et al. and Kartoatmodjo and Schmidt.

However, statistical error analysis was carried out on these six different models to check the accuracy of the FFBPNN model using the same set of data. Figures A2, A3, A4, A5, A6 and A7 respectively show the cross plot for undersaturated oil viscosity for Beal, Vasquez and Beggs, Khan, Isehunwa et al., Kartoatmodjo and Schmidt and Abedini et al. in Appendix A while Table 1 below presents the summarised results of the statistical analysis carried out on all the correlations considered and the FFBPNN model

Table 1: Statistical Analysis for Crude Oil Viscosity above Bubble Point

	Beal's	Kahn et al.	Isehunwa et. al	Vasquez et. al	Schmidt et. al	Abedini et al	This study
Average Abs. Relative Error,E_r	1.92920	0.22037	0.29559	1.65824	5.18188	12.8207	0.01998
Coefficient of Determination,R^2	0.996	0.998	0.998	0.993	0.996	0.993	0.999

4. Conclusion and Recommendations

Generally, the most common method for calculating viscosity of crude oils is viscosity correlations. However these correlations fail to predict oil viscosities at wide range of operating conditions such as pressure and temperature but work well in the region where the data used to develop them came from except if generic.

Here, based on reservoir data obtained from the Niger Delta region of Nigeria; a new model has been developed for prediction of undersaturated oil viscosity. Validity and accuracy of this model has been established by comparing the obtained results of this model and the existing correlations with experimental data for Niger Delta crude oil samples. Checking the results of this model shows that the obtained results for Niger Delta undersaturated oil viscosities in this work are in agreement with experimental data compared with the empirical correlations considered in this work.

The newly developed FFBPNN model for predicting undersaturated crude oil viscosity shows good results compared to the empirical correlations. The μ_o FFBPNN model achieved an average absolute relative error of 0.01998 and the relative deviation correlation coefficient of 0.999 as compared to existing empirical correlations. From the cross plots for the FFBPNN model and empirical correlations against their experimental values, the FFBPNN model data points' performance was excellent. The FFBPNN model employed simple relationships and do not require the knowledge of dead oil viscosity to obtain bubble point viscosity. However, the correlations should prove to be applicable for predicting undersaturated oil viscosity for any region having properties within the range of data used in this study.

Acknowledgments

The authors appreciate and acknowledge the faculty and staff of the Department of Petroleum Engineering, Covenant University for the conducive atmosphere provided for this study.

Nomenclature

P	=	Reservoir Pressure, psia
P_b	=	Bubble Point Pressure, psia
T	=	Reservoir Temperature, ^{o}R
μ_{oann}	=	Oil Viscosity Derived Using FFBPNN (This Study)
μ_{ob}	=	Saturated Oil Viscosity (cp)
μ_o	=	Undersaturated Oil Viscosity (cp)
R^2	=	Correlation Coefficient
E_r	=	Percent Average Absolute Relative Error
BPNN	=	Back Propagation Neural Network
α	=	Momentum Factor
FFBPNN	=	Feed Forward Back Propagation Neural Network
mu	=	mew
X_{obs}	=	observed/experimental value
X_{est}	=	estimated value

References

[1] Abedini, R., Abedini A. and Yakhfrouzan, N. E., 2010:"A New Correlation for Prediction of Undersaturated Crude Oil Viscosity", Petroleum and Coal, 52(1) pp.50 – 55.
[2] Shepherd, G.M. and Koch, C.,1990: "Introduction to synaptic circuits, The Synaptic Organisation of the Brain", G.M. Shepherd, ed., Oxford University Press, New York, pp. 3 – 31.
[3] Mohaghegh. S. and Ameri, 1995: "Artificial Neural Network As A Valuable Tool for Petroleum Engineer", SPE 29220.
[4] Goda,H.M , Shokir,E.M , Fattah, K.A and Sayyouh,M.H.,2003: "Prediction of the PVT Data Using Neural Network Computing Theory" , SPE 85650.
[5] Osman,E.A., Abdel-Wahab,O. A and Al-Marhoun,M.A.,2001 :"Prediction of Oil PVT Properties Using Neural Networks" , SPE 68233, pp.187.

[6] Gharbi,R.B. and Elsharkawy,A.M.,1997:"Universal Neural Network Based Model for Estimating The PVT Properties of Crude Oil Systems", SPE 38099, pp.14 – 6.

[7] Gharbi,R.B and Elsharkawy,A.M.,1997 : "Neural Network Model for Estimating the PVT Properties of Middle East Crude Oils" ,SPE 37695.

[8] Farshad, F.F., Garber, J.D, Lorde ,J.N., 2000: "Predicting temperature profiles in producing oil wells using artificial neural networks", Engineering Computations, Vol. 17 Iss: 6, pp.735 – 754.

[9] El-Sharkawy, A.M., 1998: "Modeling the Properties of Crude Oil and Gas Systems Using RBF Neural Network", SPE 49961.

[10] Omole, O., Falode, O.A. and Deng A. D., 2009: "Prediction of Nigerian Crude Oil Viscosity Using Artificial Neural Network", Petroleum and Coal, 51(3), pp. 181 – 188.

[11] Isehunwa, O. S., Olamigoke, O., and Makinde, A. A.,2006: 'A Correlation to Predict the Viscosity of Light Crude Oil', SPE 105983.

[12] Trevor Bennison, 1998: "Prediction of Heavy Oil Viscosity", Paper Presented at the IBC Heavy Oil Field Development Conference, London.

[13] Tarek, A. H., 2001: "Reservoir Engineering", 2nd ed., Gulf Publishing Company, Houston, Texas.

[14] Tarek, A. H.,: "Reservoir Engineering Handbook", Gulf Publishing Company, Houston, Texas, 77252.

APPENDIX A

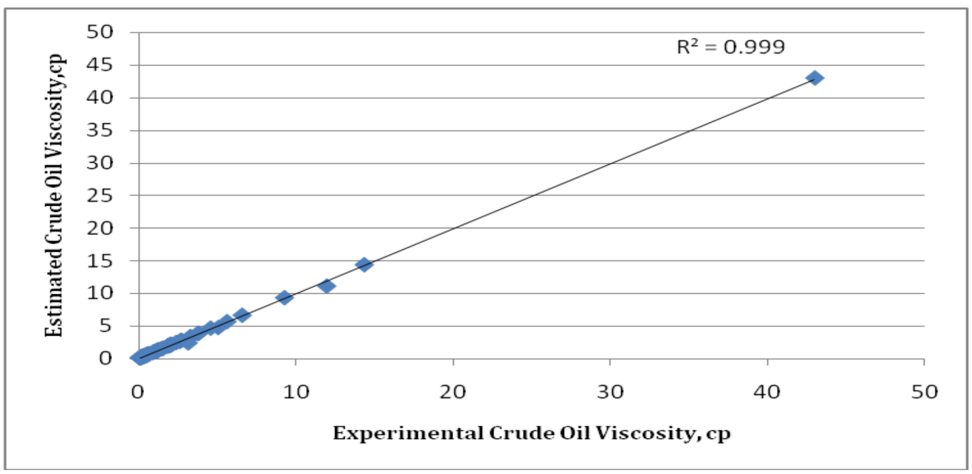

Figure A1: Cross plot for oil viscosity above bubble point (**μ_{oann}, FFBPNN**).

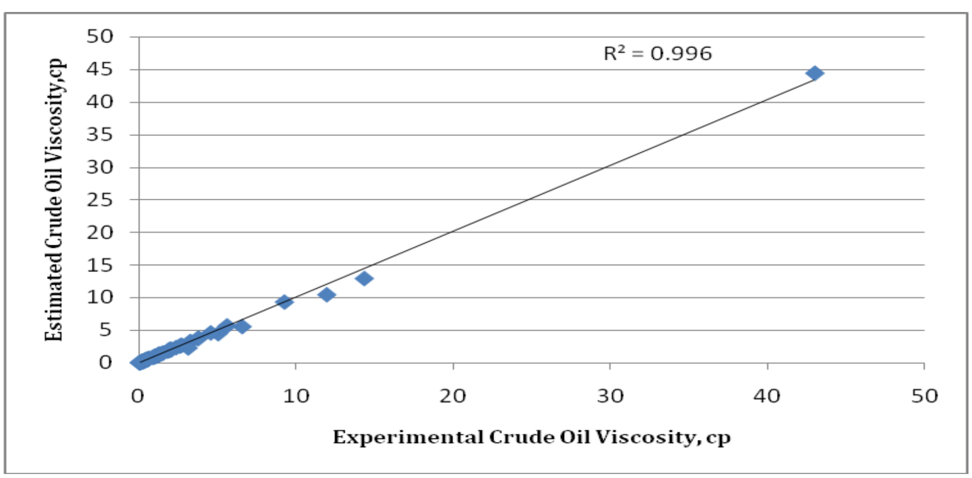

Figure A2: Cross plot for oil viscosity above bubble point (**μ_o, BEALS**).

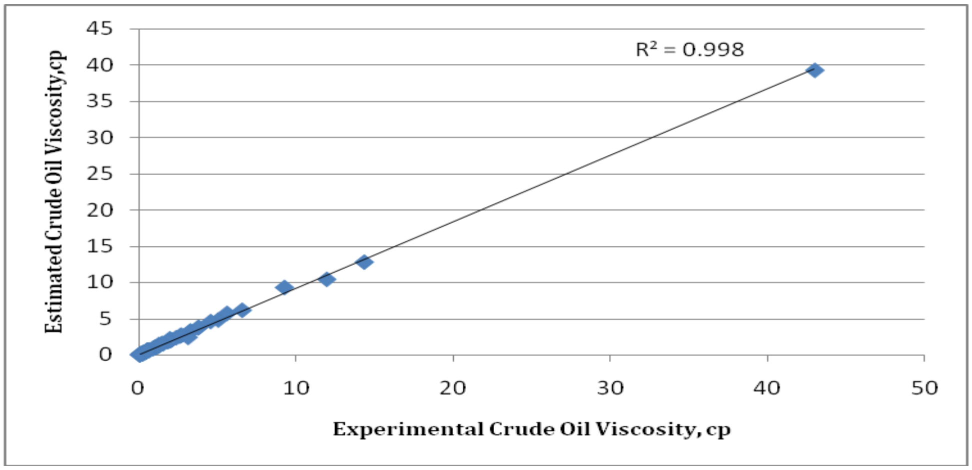

Figure A3: Cross plot for oil viscosity above bubble point (**μ_o, KAHN**).

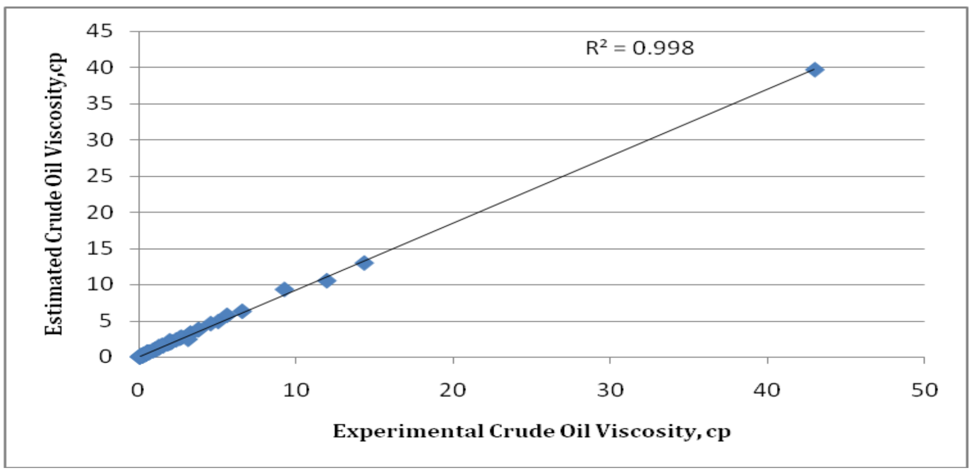

Figure A4: Cross plot for oil viscosity above bubble point (**μ_o, ISEHUNWA**).

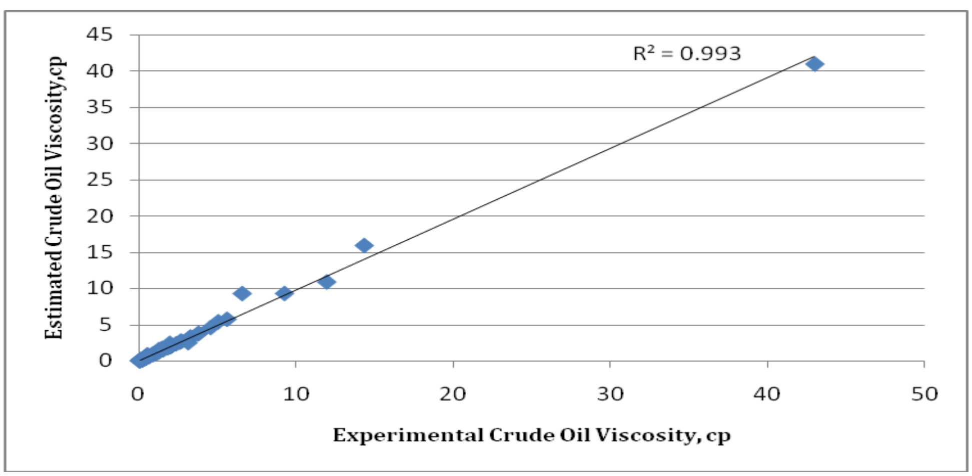

Figure A5: Cross plot for oil viscosity above bubble point (**μ_o, VASQUEZ-BEGGS**).

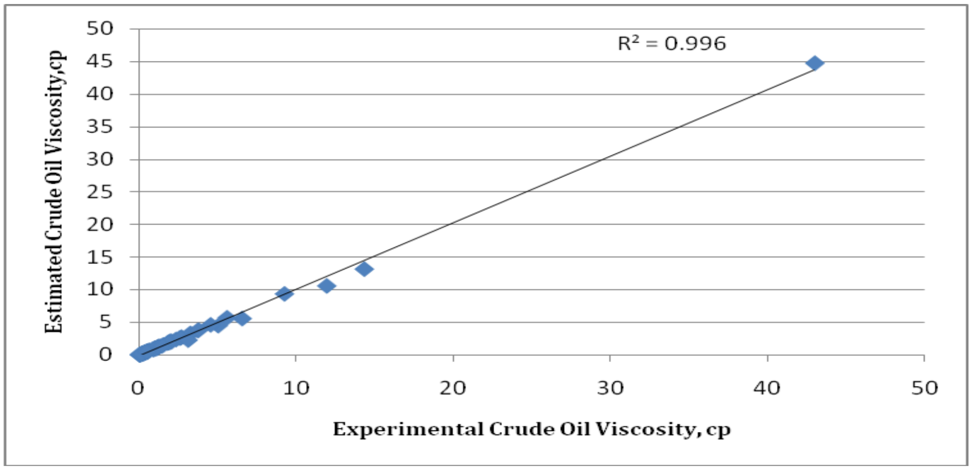

Figure A6: Cross plot for oil viscosity above bubble point (**μ_o, KARTOATMODJO-SCHMIDT**)

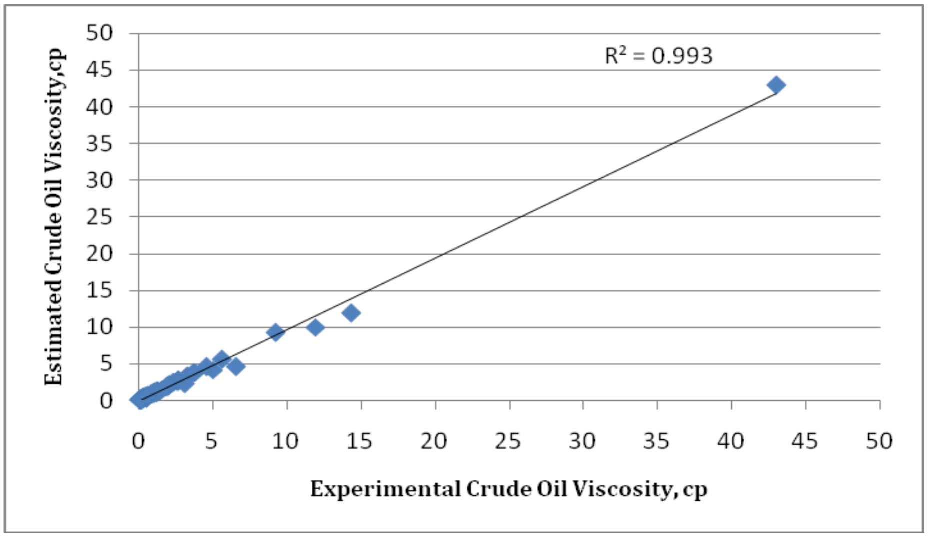

Figure A7: Cross plot for oil viscosity above bubble point (**μ_o, R. ABEDINI**)

APPENDIX B

BEAL'S CORRELATION

Beal (1946) presented a graphical correlation for estimating the viscosity of Undersaturated crude oil. This correlation proposes that for any specified oil, when only pressure is the variable, viscosity varies linearly with the pressure. Standings (1981) expressed Beal's chart in the following mathematical form:

$$\mu_o = \mu_{ob} + 0.001\ p - p_b\ \left(0.024\mu_{ob}^{1.6} + 0.038\mu_{ob}^{0.56}\right) \qquad (B1)$$

Using equation B1 above and the same data samples used in this study, the absolute relative error was determined (Table1).

KAHN'S CORRELATION

From a total of 1503 experimental data points on Saudi Arabian crude oils, Kahn et al. (1987) developed the following equation for determining the viscosity of the undersaturated crude oil. This correlation ignores the effect of μ_{ob} on the coefficient which is multiplied by μ_{ob} to predict μ_o.

$$\mu_o = \mu_{ob} \exp\left(9.6 \times 10^{-5}\left(p - p_b\right)\right) \qquad (B2)$$

As previously done, using equation (B3) above and the same data samples used in this study, the absolute relative error was determined (Table1).

ISEHUNWA et al. CORRELATION

From data samples from over 400 oil reservoirs from the Niger Delta region of Nigeria, a correlation for predicting undersaturated crude oil viscosity was attained. The correlations employ simple relationships and do not require the knowledge of dead oil viscosity to obtain bubble point viscosity:

$$\mu_o = \mu_{ob} e^{1.02\times10^{-4}\left(p-p_b\right)} \tag{B3}$$

The data samples used in the formulation of this correlation were taken through a process of smoothening, in which data samples are particularly chosen based on their defined closeness to the experimental output. This is done in order to neglect insignificance output produced by the correlation that is far off the experimental output and to produce better R^2 values. Using the same data samples used in this study (see appendix A), the absolute relative error was determined (Table1).

VASQUEZ-BEGGS'S CORRELATION

From a total of 3,593 data points, Vasquez and Beggs (1976) proposed the following expression for estimating the viscosity of the undersaturated crude oil:

$$\mu_o = \mu_{ob}\left(\frac{p}{p_b}\right)^m \tag{B4}$$

Where:

$$a = \left[-3.9\left(10^{-5}\right)p\right] - 5$$

$$m = 2.6\left(p^{1.187}\right)\left(10^a\right)\frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

As previously done, using equation (B4) above and the same data samples used in this study, the absolute relative error was determined (Table1).

KARTOATMODJO AND SCHMIDT CORRELATION

Like Beal's work, this correlation proposes that for any specified oil, when only pressure is the variable, viscosity varies linearly with the pressure.

$$\mu_o = 1.0008\mu_{ob} + 0.001127\ p - p_b\ \left(-0.006517\mu_{ob}^{1.8148} + 0.038\mu_{ob}^{1.59}\right) \tag{B5}$$

As previously done, using equation (B5) above and the same data samples used in this study, the absolute relative error was determined (Table1).

3.2.5 R. ABEDINI et al. CORRELATION

R. Abedini and his co-authors presented the correlation in equation (B6) for the prediction of Iranian undersaturated crude oil viscosity. Their correlation does not require compositional information and can be used for Iranian black oil type fluids:

$$\mu_o = \mu_{ob} + 0.001\ p - p_b\ \ a_1\mu_{ob}^{b1} + a_2\mu_{ob}^{b2} + a_3\mu_{ob}^{b3} + a_4p_b^{b4} + a_5p_b^{b5} + a_6p_b^{b6} - a_7p_b^{b7} \tag{B6}$$

Using equation (B6) above and the same data samples used in this study, the absolute relative error was determined (Table1).