Prediction of Bubble Point Pressure Using Artificial Neural Networks in the Niger Delta

Uduma U. Idika

Abstract– A model was developed to predict the bubble point pressure of saturated reservoirs. The model was based on artificial neural networks and was developed using 700 generic data sets which are representative of the Niger Delta region of Nigeria. The data set was first cleaned to remove erroneous and repeated data points. After cleaning, 618 data points were remaining. Of the 618 data points, 463 were used to train the ANN model, 93 were used to cross-validate the relationships established during the training process and the remaining 62 were used to test the model to evaluate its accuracy. A backward propagation network utilizing the LM algorithm was used in developing the model. The first layer consisted of four neurons representing the input values of reservoir temperature, API oil gravity, gas specific gravity, and solution GOR. The second (hidden) layer consisted of 26 neurons, and the third layer contained one neuron representing the output value of the bubble point pressure. The results showed that the developed model provides better predictions and higher accuracy than the existing empirical correlations considered when exposed to an additional 13 data points which were unseen by the model during its development. The model provided predictions of the bubble point pressure with an absolute average percent error of 3.98%, RMSE of 177.6479 and correlation coefficient of 0.9851. Trend analysis was performed to check the behavior of the predicted values of P_b for any change in reservoir temperature, oil API gravity, gas gravity and solution GOR. The model was found to be physically correct. Its stability indicated that it did not overfit the data, implying that it was successfully trained.

Keywords– artificial neural networks, bubble point pressure, correlations, Niger Delta, prediction

1 INTRODUCTION

THE bubble point pressure (P_b) of a hydrocarbon system is defined as the highest pressure at which the first bubble of gas is liberated from the oil [1]. P_b is one of the PVT (*"Pressure-Volume-Temperature"*) parameters. PVT parameters are very important because they are required to carry out reservoir performance calculations. Hence, it is expedient to accurately determine these parameters. Some of the uses of PVT data include:

a) Reserves calculation.
b) Material balance calculation (relating reservoir to surface volume).
c) Design of surface operating facilities.

Conventionally, bubble point pressure can be determined from constant composition expansion (CCE) test (a.k.a. flash liberation, flash vaporization or constant volume expansion). However, in the absence of laboratory measured P_b data, two other methods are used [7]. These are:

a) Equation of State (EOS).
b) Empirical correlations.

Equation of State is based on knowing the detailed composition of the reservoir fluids [3]. This method is very expensive and time consuming. On the other hand, empirical correlations are usually developed with linear or nonlinear multiple regression or graphical techniques. Standing [14], Vasquez and Beggs [15], Glaso [9], Al-Marhoun [2], Petrosky and Farshad [13] derived correlations to estimate bubble point pressure. The main objective of this research is to use artificial neural networks to develop a model for accurate prediction of bubble point pressure using generic data samples that are representative of the Niger Delta region.

As the "neural" part of their name suggest, ANN are brain-inspired systems which are intended to replicate the manner humans learn [5]. It is based on a collection of connected units or nodes called "artificial neurons." Artificial neurons are simplified versions of biological neurons in the brains of animals. Just as human beings learn from their daily experiences, neural networks require data to learn [5]. In most cases (not all), the larger the data set used to train the network, the more accurate it will become. According to Dormehl [5], before training a neural network, the data to be fed into it is divided into three sets. Thes are:

a) Training Data Set: This set of data is used to enable the network establish the various weights between its nodes.
b) Validation Data Set: This set is used to fine-tune the network after the various weights between the nodes have been established.
c) Test Data Set: This set is used to check if the network can successfully turn the input(s) into the desired output(s).

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1.1 Empirical Correlations

Researchers have proposed several graphical and mathematical correlations for determining bubble point pressure over the last seven decades. Gharbi et al. [8] stated that the correlations are essentially based on the assumption that the bubble point pressure is a strong function of reservoir temperature *(T),* solution gas-oil ratio (R_s), oil specific gravity (γ_o) and gas specific gravity (γ_g).

Mathematically:

$$P_b = f(T, R_s, \gamma_o, \gamma_g) \quad (1)$$

Standing [14] presented a graphical correlation for determining the bubble point pressure of crude oil systems. He used 105 experimentally measured bubble point pressures on 22 hydrocarbon systems from California fields. He reported an average error of 4.8% in comparison to experimentally derived bubble point pressures. In 1981, Standing represented his graphical correlation in a mathematical form and advised that the correlation be used with caution if non hydrocarbon components are known to be present in the system [1]. Vasquez et al. [15] used 600 data points from various locations all over the world to develop a correlation for bubble point pressure. They developed two different types of correlations: one for crudes with °API > 30 and the other for crudes with °API ≤ 30. Glaso [9] used 45 oil samples, mostly from the North Sea hydrocarbon system to develop a correlation for the prediction of bubble point pressure. Al-Marhoun [2] developed a correlation for estimating bubble point pressure using 160 experimentally derived bubble point pressures from the PVT analysis of 69 Middle Eastern hydrocarbon mixtures. He reported an average absolute relative error of 3.66% when compared with the experimental data used to develop the correlation. Petrosky et al. [13] used a nonlinear multiple regression software to develop a correlation for gas solubility from which the bubble point pressure can be determined. They constructed a PVT database from 81 laboratory analyses from the Gulf of Mexico crude oil systems. According to them, their correlation predicts bubble point pressures with an average absolute error of 3.28%.

1.2 Artificial Neural Networks

An artificial neural network is simply a collection of *"neurons"* with *"synapses"* connecting them [12]. It is a computational method that has the ability to realize an input-output mapping even when the exact relationship between the input and output is unknown [10]. The connection is usually organized into three main layers, interconnected by modifiable weights which are represented by links [12]. The layers include:

a) Input layer.
b) Hidden layer(s).
c) Output layer.

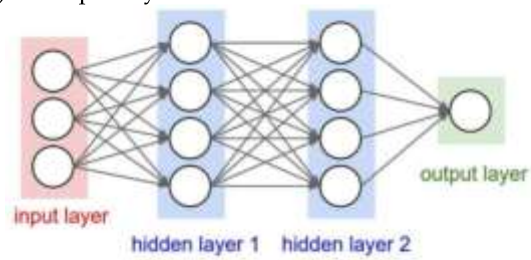

Fig. 1: Schematic of an Artificial Neural Network. Source: Dormehl [5]

The circles in fig. 1 above represent the neurons while the arrows are the modifiable weights. ANNs consist of a collection of simple processing units that communicate by sending signals to each other over a large number of weighted connections. Essentially, they are combinations of neurons, biases, activation functions, and links on which weights are applied [3]. The links connect neurons in one layer to those in the next layer.

Not quite long, artificial neural networks have been used in a number of areas in petroleum engineering. One of such areas is the accurate prediction of bubble point pressure in the absence of laboratory measurements. Gharbi et al. [8] developed a neural network for accurate prediction of bubble point pressure as a function of solution gas-oil ratio (R_s), oil specific gravity(γ_o), gas specific gravity (γ_g) and reservoir temperature *(T).* The authors used 498 experimentally obtained data sets of different crude oil and gas mixtures from the Middle East region to train their neural network. After investigating several neural network architectures, they arrived at a conclusion that a neural network structure of 4-8-4-1 best predicted the bubble point pressure. The authors, after training their neural network used 22 additional measured PVT data points which were not seen by the network during the training phase to validate their neural network. When they compared their model output (P_b) with the laboratory measured data points, they reported an average relative error of -1.89%, a standard deviation of 8.91% and a correlation coefficient of 0.962. Their model proved to be more accurate in predicting bubble point pressure when they compared it with the empirically derived correlations of Standing, Glaso and Al-Marhoun. Fath et al. [6] proposed a recent numerical model based on ANN for the prediction of bubble point pressure as a function of solution gas-oil ratio (R_s), oil gravity$(°API)$, gas specific gravity (γ_g) and reservoir temperature *(T).* In developing and evaluating their model, the authors used 760 experimental data sets gathered from oil fields around the world. Their data set which was gotten from literature covered a wide range of crude oil samples with different compositions and thermodynamic conditions from various geographical locations around the world. They performed an optimization process on networks with different structures and reported that a network structure of 4-6-1 was observed to be the most efficient for predicting the bubble point pressure of crude oils. Cuptasanti et al. [4] developed a network for predicting P_b using the MATLAB software. The network had a single hidden layer with a structure of 4-10-1. Inputs to the network were $R_s, T, API, and\ \gamma_g$, while the output was P_b. The authors in developing the FFBP network trained it with gradient descent with momentum and the LM was the learning algorithm. The network used the hyperbolic tangent sigmoid (TANS) transfer function between inputs and hidden layers and linear activation function for output computations. Kazemi [11] used MATLAB to construct FFBP networks with LM optimization routine. The entire data set used by the author was extracted from 55 PVT reports of the Southern Iranian oil fields, Asmari and Bangestan reservoirs. In order to accurately predict P_b, the author trained and tested the black oil and the correlation based models using 157 datasets. The black oil model and the correlation based model had similar network structure of 4-6-3-1. However, for the black oil model, the author used a log-sigmoid transfer function in the first hidden layer and a TANS function in the second hidden layer while, the TANS function was utilized for both hidden layers in the correlation based model.

2 MODEL DEVELOPMENT

700 generic data points which are representative of the Niger Delta region were used to develop the model. Each data point contained:

a) Solution gas oil ratio (R_s).
b) Reservoir temperature (T).
c) Gas gravity (γ_g).
d) API oil gravity ($°API$).
e) Bubble point pressure (P_b).

After cleaning the data to eliminate erroneous and repeated data points, 618 data points were remaining. Out of the 618 data points, 75% (463 data points) were used to train the neural network, 15% (93 data points) were used to cross-validate the relationship established during the training process while 10% (62 data points) were used to evaluate the model's accuracy. In order to prevent problems such as reduced accuracy and network instabilities in the course of developing the model, the output data was normalized to between {0,1} using the equation below:

$$P_{b\_norm} = \frac{P_b - P_{b\_min}}{P_{b\_max} - P_{b\_min}} \quad (2)$$

where:

P_{b_norm} is the normalized value of the P_b variable

P_b = value of the P_b variable to be normalized

P_{b_min} = minimum value of the P_b variable in the data set

P_{b_max} = maximum value of the P_b variable in the data set

Statistical descriptions of the data set used in developing the model are given in the table below:

Table 1: Statistical description of data set used in developing the model

Description / Properties	MIN	MAX	MEAN	STANDARD DEVIATION
Reservoir temp. (°F)	157	281	209	25.1920
Oil Gravity (°API)	20.70	52.80	36.91	3.6896
Gas Gravity (air = 1.0)	0.579	1.444	0.777	0.1082
Solution GOR (scf/STB)	139.93	2300.00	714.17	393.6164
Bubble Point Pressure (psia)	399	6100	2551	1016.0280

MATLAB software was utilized in developing the model. The inputs to the developed neural network are reservoir temperature(°F), gas gravity (air = 1.0), oil gravity($°API$) and solution gas oil ratio (scf/STB) while the output is bubble point pressure (P_b). Levenberg-Marquardt (LM), Bayesian Regularization (BR) and Scaled Conjugate Gradient (SCG) training algorithms were considered in training the model. The LM training algorithm was found to be the best training algorithm for the model. The model was developed using a Backward Propagation Network (BPN). In a BPN, the input is propagated forward while the error is propagated backwards. The transfer function of the neurons is sigmoid or s-shaped. The sigmoid function has a minimum value of zero, a maximum value of one and is differentiable everywhere with a positive slope. The form of the sigmoid transfer function is:

$$F_{(x)} = \frac{1}{1+e^{-x}} \quad (3)$$

The output from a neuron is expressed using the mathematical equation:

$$y_t = f\left(\sum_{i=1}^{N} w_{ti} x_i + b_t\right) \quad (4)$$

where:

$x_1, x_2, \dots, x_N$ denote input data.

$w_{t1}, w_{t2}, \dots, w_{tN}$ are attached weights of the lines connecting the neurons.

b is the bias.
f refers to the activation function.
y is the neuron output.

During training, the network's errors were computed using the backward propagation algorithm. The weights of all the interconnections between the neurons were then adjusted based on the magnitude of the error and a parameter called the learning rate until the ANNs learnt the correct input-output behaviors. The training phase took several days of computing time to obtain the adequate input-output performance. The fitting procedure from which the weights of the models were determined was performed using a least-squares minimization routine. Going by this routine, the sum squared of the relative error between the calculated (predicted) and the experimental data is to be minimized. The flow chart which illustrates the process of developing the model is shown in fig. 2 below.

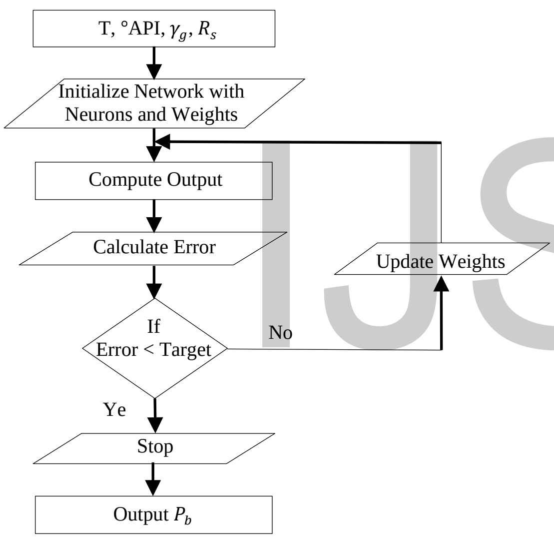

Fig. 2: Flow chart for Developing the Model Using ANN

2.1 Statistical Error Analysis

The performance and accuracy of the newly developed ANN model was evaluated by comparing its' predictive capabilities with those of widely accepted correlations. The empirical correlations considered were those of Standing, Glaso, Al-Marhoun and Petrosky-Farshad.

First, the ability of the various correlations to predict P_b given the 618 data points used to develop the models was compared with that of the new ANN model. Thereafter, the newly developed model was used to predict P_b given additional 13 data points which were unseen by the model during its development (training, validating and testing phases). The empirical correlations were also used to predict P_b of these 13 data points and comparisons were made between the predictive capabilities of the ANN model and that of the various correlations considered using 4 common statistical error analysis techniques, namely: percentage error, average absolute percentage error, root mean square error and correlation coefficient.

2.2 Graphical Error Analysis

Cross plots were used to achieve this. It entails plotting the predicted values against the experimental values in order to obtain a cross plot. Thereafter, a straight line referred to as a "perfect model line" is drawn from the origin at an angle of 45°. This line represents the points on which the predicted values are equal to the experimental values.

By means of analysis, the closer the cross plot is to the perfect model line, the better the accuracy and performance provided by the corresponding model.

3 RESULTS AND DISCUSSIONS

After comparing several network architectures, a network having one hidden layer which contains 26 neurons was found to best predict the bubble point pressure. Thus, the network architecture of the proposed model is **4-26-1** as can be seen in fig. 3 below:

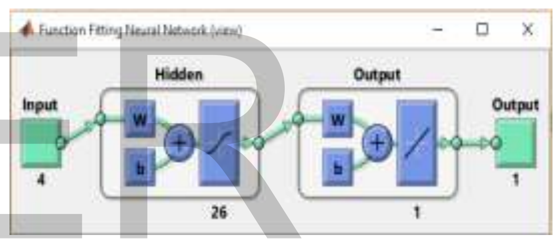

Fig. 3: Network Structure for the Bubble Point Pressure Model

During training, it was observed that the best validation performance was at epoch 35 with a very small mean squared error of 0.0023111. The training was stopped at this point to avoid the model from memorizing the data sets instead of generalizing. Fig. 4 below shows the training performance. A close look shows that the training was complete as soon as the validation line stopped decreasing. Fig. 4 also shows that the MSEs of the ability of the model to predict P_b using the 463 data points for training, 93 data points for cross validation and 62 data points for testing is very low.

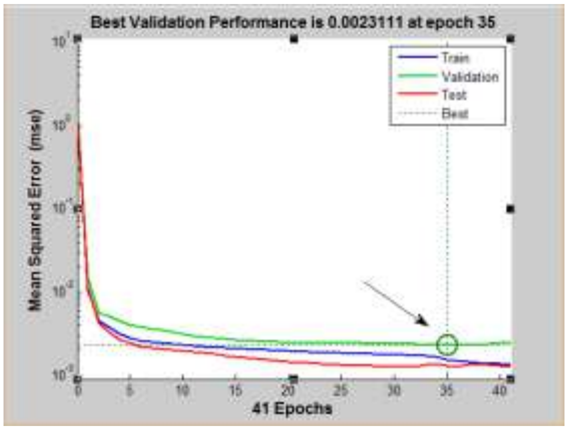

Fig. 4: Best Validation Performance of the Model

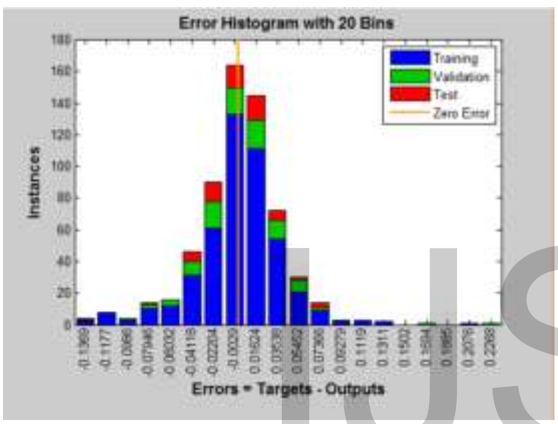

Fig. 5: Error Distribution of the ANN Model

Fig. 5 above shows that the errors obtained by using the developed model in predicting the bubble point pressures of the 618 data points is more concentrated around the zero error line. The "targets" are the experimentally determined bubble point pressures while the "outputs" are the bubble point pressures predicted by the ANN model.

The correlations of Standing, Glaso, Al-Marhoun and Petrosky-Farshad were used to predict P_b using the 618 data points used to develop the ANN model in order to determine the performance of the newly developed model. The figs below show the result of the various correlations considered as well as that of the newly developed model.

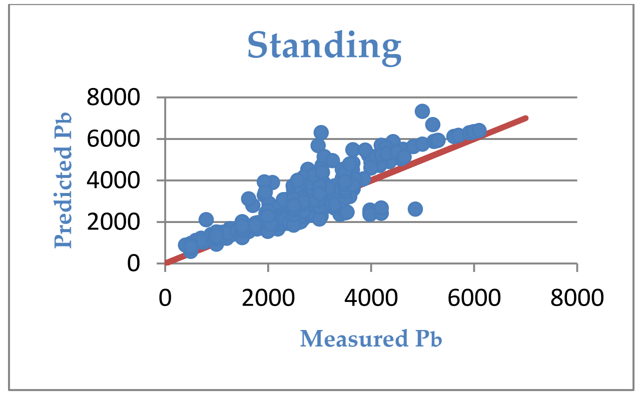

Fig. 6: Standing's Prediction using the 618 data points

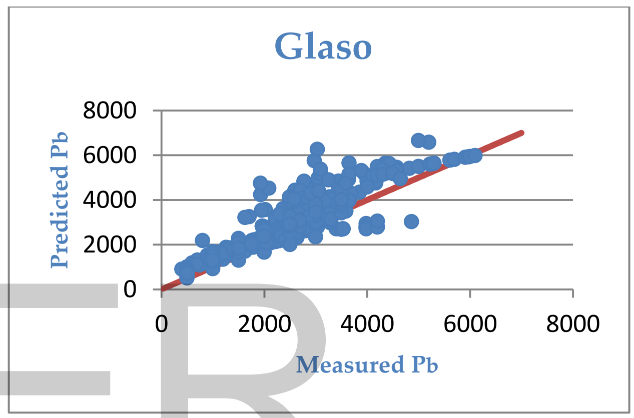

Fig. 7: Glaso's Prediction using the 618 data points

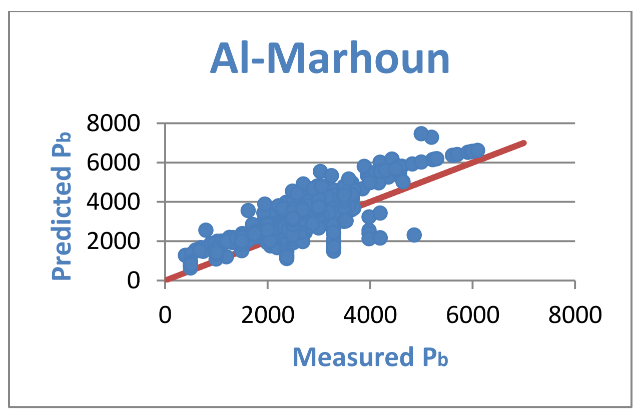

Fig. 8: Al-Marhoun's Prediction using the 618 data points

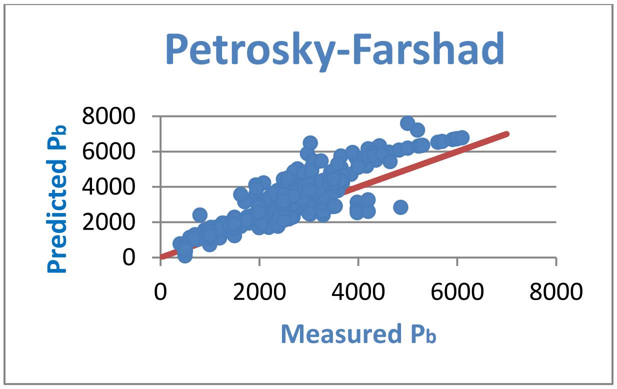

Fig. 9: Petrosky-Farshad's Prediction using the 618 data points

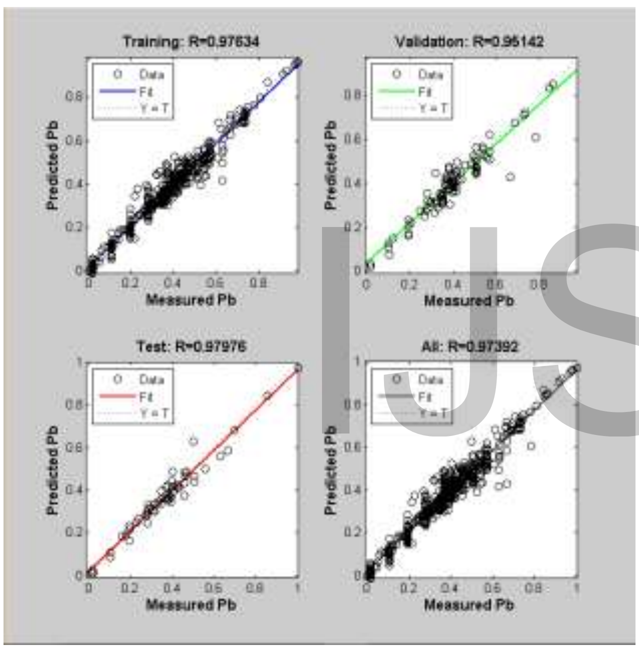

Fig. 10: ANN Model's Prediction of the 618 Data Points

From figs. 6-10 above, it is clear that amongst the correlations considered, that of Standing best predicts the bubble point pressure given the 618 data points used to develop the ANN model in this study. However, it is not as accurate as the newly developed ANN model as the plot of the new model are more clustered to the unity gradient line.

Again, the ANN was used to predict the bubble point pressures of additional 13 data points which were unseen to the network during its developmental (training, validation and testing) phases. The table below shows the comparison between the ANN model and the various correlations considered.

Table 2: Statistical Analysis of the Model and Various Correlations

Model	AAPE	RMSE	R
Standing (1947)	12.75	430.4427	0.9680
Glaso (1980)	16.67	470.3761	0.9798
Al-Marhoun (1988)	23.17	654.3869	0.9550
Petrosky-Farshad (1993)	17.77	660.3918	0.9732
ANN (this study)	3.98	177.6479	0.9851

From table 2 above, it is clear that the new model outperforms all the empirical correlations studied in terms of the absolute average percent error, root mean square error and correlation coefficient.

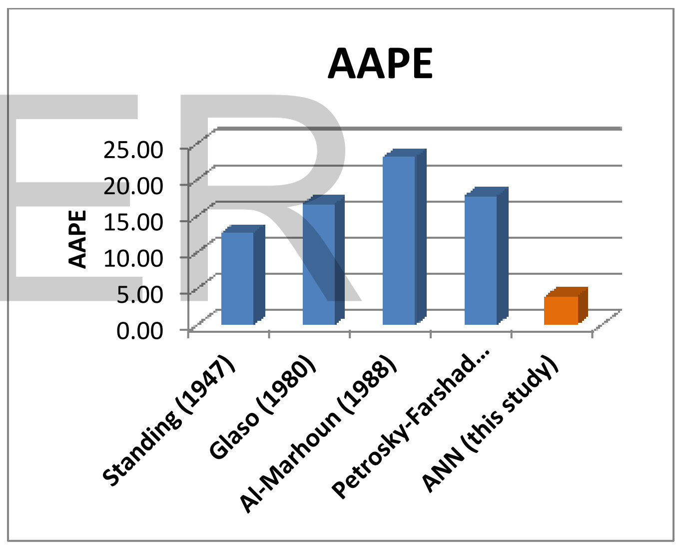

Fig. 11: Comparison between AAPE of Empirical Correlations and the Developed Model

Clearly, fig. 11 above shows that the average absolute percent error of the developed ANN model is much smaller than those of the various correlations considered.

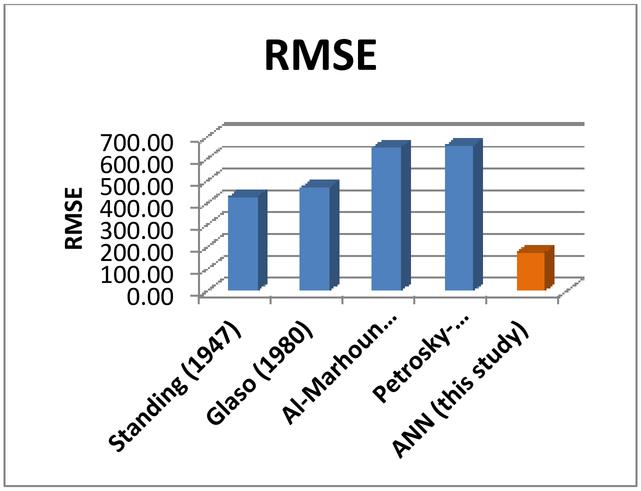

Fig. 12: Comparison between RMSE of Empirical Correlations and the Developed Model

Fig. 12 clearly shows that the root mean square error of the developed model is smaller than those of the empirical correlations considered. Fig. 13 below shows that the correlation coefficient of the developed ANN model is higher than that of the other correlations compared.

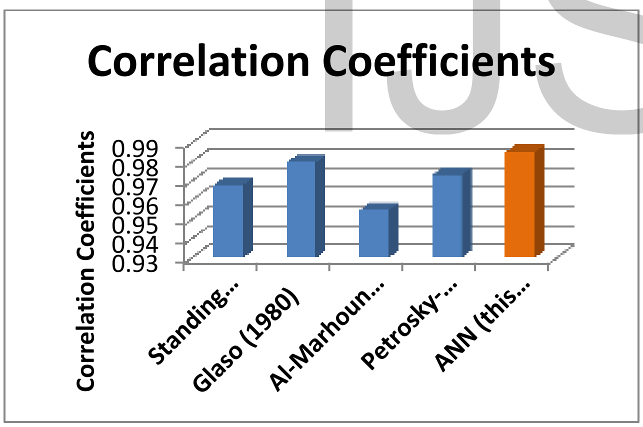

Fig. 13: Comparison between Correlation Coefficients of Empirical Correlations and the Developed Model

The figs. below show the cross plot of the predictions of the various correlations and the ANN model against the experimentally obtained values.

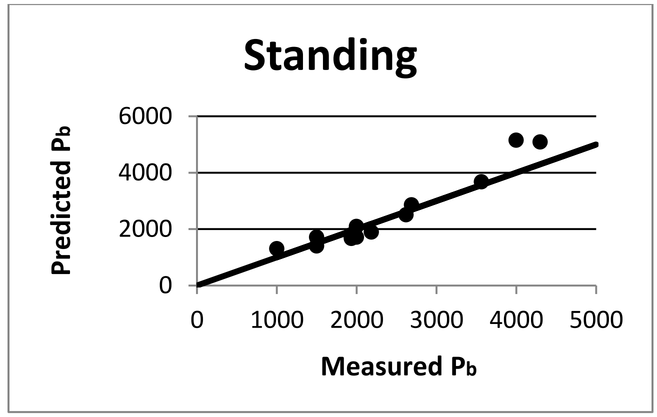

Fig. 14: Standing's Prediction

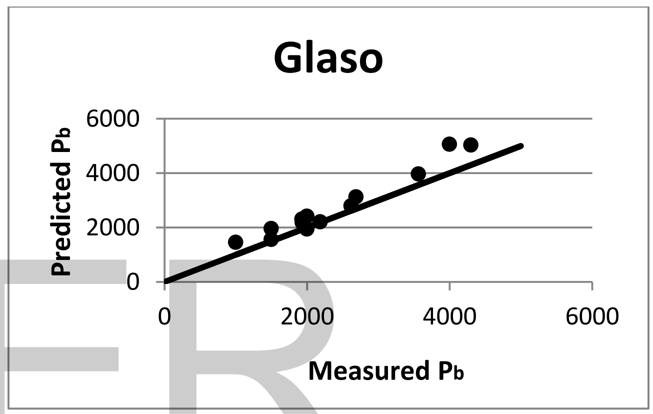

Fig. 15: Glaso's Prediction

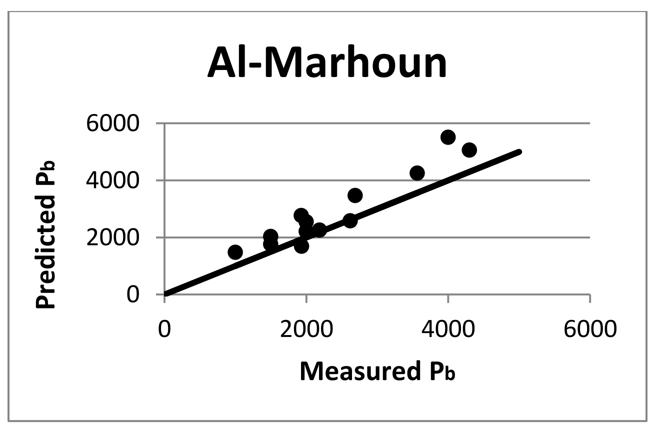

Fig. 16: Al-Marhoun's Prediction

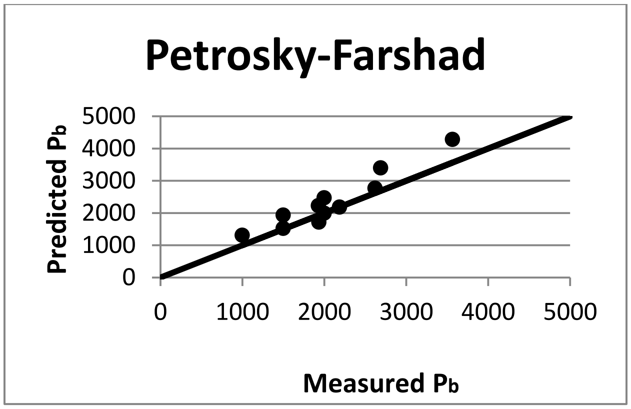

Fig. 17: Petrosky-Farshad's Prediction

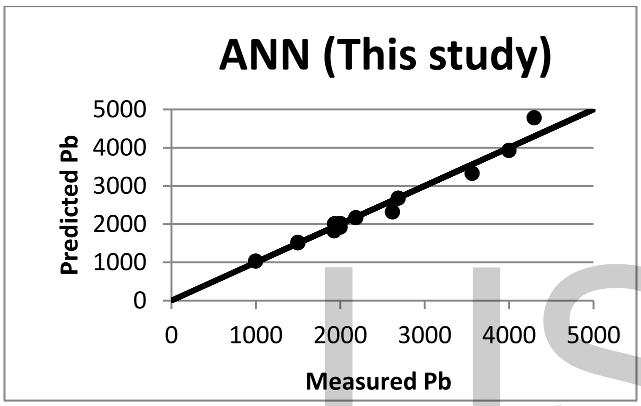

Fig. 18: ANN Model's Prediction

A close look at the various cross plots (fig. 14 –fig. 18) show that the predictions of the ANN model are closer to the unity gradient line (perfect model line) than those of the empirical correlations considered.

4 TREND ANALYSIS

In order to confirm that the newly developed model obeys physical law, the model was used to predict P_b while temperature, oil gravity, gas gravity and solution GOR were varied independently. The model was tested using hypothetical intermediate data points and the dependence of P_b on reservoir temperature (T), oil gravity (°API), gas gravity and solution GOR was studied.

4.1 Effect of Temperature on Bubble Point Pressure

Temperature was varied between 240°F and 275°F while other properties considered were kept constant (oil gravity = 35°API, gas gravity = 0.80 and solution GOR = 600scf/stb).

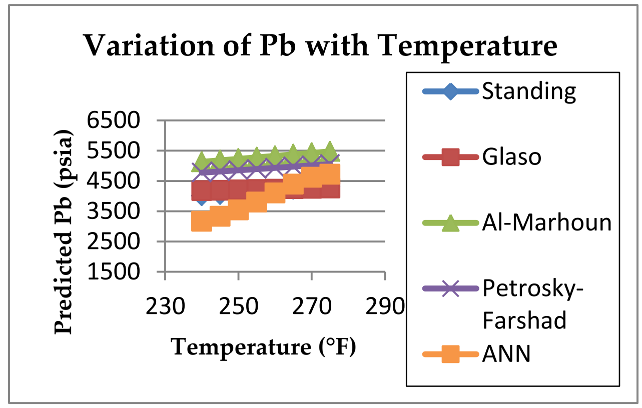

Fig. 19: Effect of Temperature on Bubble Point Pressure

As expected from physical laws, the bubble point pressure increased with increasing temperature as can be seen in fig. 19 above.

4.2 Effect of Oil Gravity on Bubble Point Pressure

Oil gravity was varied between 25°API and 35°API while other properties considered were kept constant (reservoir temperature = 150°F, gas gravity = 0.65 and solution GOR = 600scf/stb).

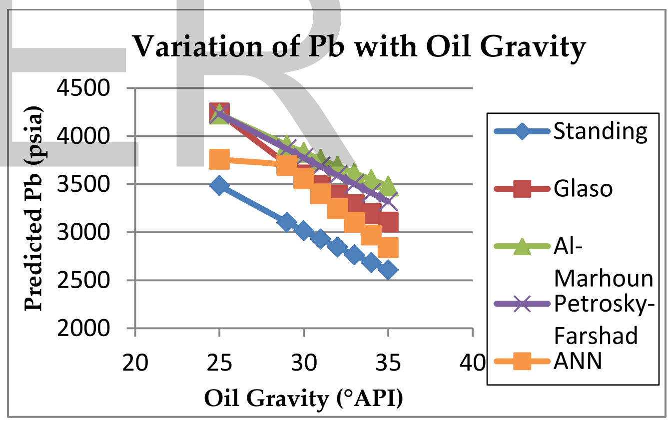

Fig. 20: Effect of Oil Gravity on Bubble Point Pressure

As expected from physical laws, the bubble point pressure decreased with increasing oil gravity (°API) as can be seen in fig. 20 above.

4.3 Effect of Gas Gravity on Bubble Point Pressure

Gas gravity was varied between 0.40 and 0.65 while other properties considered were kept constant (reservoir temperature = 150°F, oil gravity = 40°API and solution GOR = 1200scf/stb).

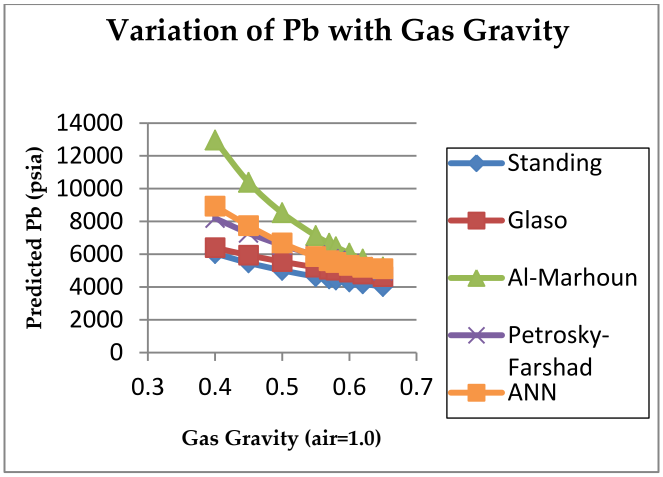

Fig. 21: Effect of Gas Gravity on Bubble Point Pressure

In line with physical laws, the bubble point pressure decreased with increasing gas gravity (air = 1.0) as can be seen in fig. 21 above.

4.4 Effect of Solution GOR on Bubble Point Pressure

Solution GOR was varied between 200scf/stb and 700scf/stb while other properties considered were kept constant (reservoir temperature = 150°F, oil gravity = 35°API and gas gravity = 0.65).

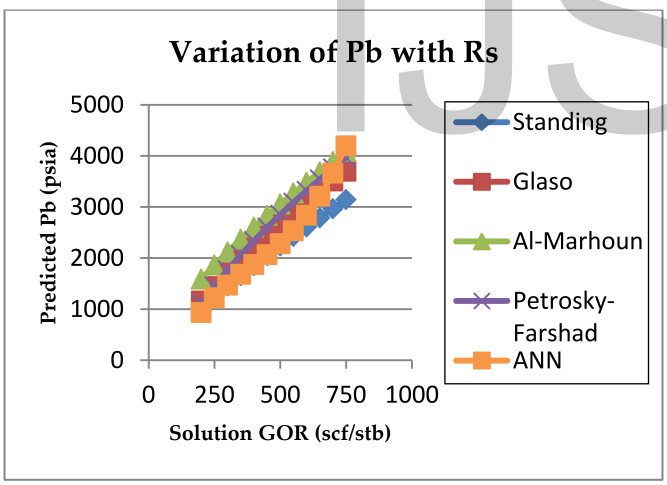

Fig. 22: Effect of Solution GOR on Bubble Point Pressure

In line with physical laws, the bubble point pressure increased with increasing solution GOR as can be seen in fig. 22 above.

5 CONCLUSION

This study presents a model for the accurate prediction of bubble point pressures of Niger Delta crude oils. Various statistical error analysis performed revealed that the model is more accurate than existing widely accepted correlations in the prediction of bubble point pressure of the Niger Delta crude oils. In developing the model, 700 generic data points which are representative of the Niger Delta region were used. Each data point contained solution gas oil ratio (R_s), reservoir temperature (T), gas gravity (γ_g), API oil gravity ($°API$) and bubble point pressure (P_b). After cleaning the collected data to eliminate erroneous and repeated data points, 618 data points were remaining. Out of the 618 data points, 75% (463 data points) were used to train the neural network, 15% (93 data points) were used to cross-validate the relationship established during the training process, while 10% (62 data points) were used to evaluate the model's accuracy. Additional 13 data points (which were unseen by the model while it was being developed) were used to compare the predictive capability of the model and those of certain widely accepted correlations. The model proved to better predict the bubble point pressure than all the correlations tested. Trend analysis was also performed on the developed model to verify that it obeys physical laws.

6 NOMENCLATURE

AAPE: Average Absolute Percent Error

ANN: Artificial Neural Network

BPN: Backward Propagation Network

BR: Bayesian Regularization

CCE: Constant Composition Expansion

EOS: Equation of State

LM: Levenberg-Marquardt

P_b: Bubble Point Pressure

PVT: Pressure-Volume-Temperature

RMSE: Root Mean Square Error

SCG: Scaled Conjugate Gradient

TANS: Hyperbolic Tangent Sigmoid Transfer Function

7 APPENDIX

Instructions for using the model

The developed model and its parameters can be made available upon request to the author. Thereafter, in MATLAB software, change the working directory to the requested directory (i.e. folder containing the ANN model).

Example:

Calculate the bubble point pressure of reservoir oil with the following properties:

a) Reservoir temperature = 223ºF

b) API oil gravity = 34.10 ºAPI

c) Gas specific gravity = 0.706

d) Solution gas-oil ratio = 586scf/STB.

Solution:

The following command shown in fig. A below should be entered in the MATLAB command window after clearing the workspace and loading the ANN model. Pb_calc gives the bubble point pressure of the given reservoir oil.

Fig. A: Instructions on using the model

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