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Modeling Gas Viscosity of High Pressure High Temperature conditions Using Artificial Neural Network

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ABSTRACT: *Viscosity is a measure of a fluid's internal resistance to flow. The industry standard is to measure this property in the laboratory using reservoir samples. The procedures of acquiring experimental data is sometimes very expensive, and time consuming, hence methods such as correlations and equation of state are used to predict this property at reservoir pressure and temperature conditions. Recently, some scholars has reported that the intelligent predictive models like Artificial Neural Network (ANN), Fuzzy Interface System (FIS) and Adaptive Neuro-fuzzy System (ANFIS) give better accuracy as to compare with empirical models. The majority of the existing model were developed using low to moderate data, hence give high error for higher conditions prediction.. The aim of this research paper is to develop ANN intelligent model to predict gas viscosity at high pressure high temperature conditions ie pressure above 10,000psia and temperature above 300^{o}F. The intelligent predictive model was built using 154 laboratory measured data from Niger Delta using MATLAB ANN tool. The data used wasrandomly divided into three parts, of which 60% was used for training, 20% for validation, and 20% for testing.The statistical assessments were employed to assess the accuracy of the new model to the existing empirical correlations. Thegas viscosity artificial neural network (ANN) model gave good prediction when compared to other gas viscosity models with a rank of 2.4639 with mean absolute error MAE of 4.3416 and correlation coefficient (R) of 0.995. The statistical analysis and cross plots demonstrated the superiority of the proposed tool to other existing methods.*

Keywords - *Artificial Neural Network, Gas Viscosity, Empirical correlation, High pressure, high temperature*

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I. INTRODUCTION

Viscosity of natural gas is an important parameter of theoretical and practical significance in the domain of natural gas recovery, transmission and processing. Small errors in gas viscosity affect the inflow performance relationship (IPR) curves and eventually changes the reserves estimate negatively for high pressure high temperature (HPHT) gas reservoirs.Majority of the exiting correlations give large errors at high gas reservoir pressure. High Pressure High Temperature (HPHT) gas reservoirs are defined as reservoirs having pressure greater than 10,000 psia and temperature over 300^{o}F [1].Gas viscosity has been studied thoroughly by many authors such as [2]; [3]; [4]; [5]; [6]; [7] at low – intermediate pressures and temperatures, yet there is still lack of detailed knowledge of gas viscosity for high pressures and high temperature (HPHT) in the oil and gas production. [2] graphical correlations has been the most popular charts in the petroleum industry, because their chart set is perhaps the most complete, including the atmospheric pressure chart, the viscosity ratio charts and correcting charts for non-hydrocarbons. Their correlation was developed, as a function of pseudo-reduced pressure, pseudo-reduced temperature and viscosity ratio. It was reported to have an average of 0.38 absolute error. Carr *et al*. correlation is recommended to be used for gases with specific gravity between 0.55 and 1.22 and a temperature range between 100 and 300^{o}F.

[8] measured the viscosity of gas using Cambridge SPL440 viscometer applying metane sample for pressure at 5,000 to 30,000psia and temperatures from 100 to 400^{o}F. From the measurements, [8] modified the [5] model and comparison was made using data from NIST. The results showed a good performance with the NIST data as to compare to the main [5] correlation.

[6] modeled a viscosity relation for gas in surface and reservoir condition. He developed the correlation using experimental values from gas samples from Nigeria. The authors compared equation formulated with experimental PVT viscosity and then tested the general performance by using it to solve two problems form

which solutions by the complex charts [2] were available.

[1] measured gas viscosity at high pressures and high temperatures (HPHT) using falling body viscometer. The experiments showed that [5] correlation predicted the gas viscosity at low-moderate pressure and temperature, but gave a high error at the elevated conditions. The authors then concluded that an equation for gas viscosity should be developed for higher pressure and temperature region. [9] evaluated some existing viscosity correlation and reported that gas viscosity equations are not reliable at HPHT condition. This can negatively impact the inflow performance relationship (IPR) curves and gave a wrong estimation of reserves at extreme conditions and hence drastically influence production forecasting.

[10] presented a new method to model natural gas viscosity. This method can predict gas viscosity within 1.01 = T_r = 3.0 and 0.01= P_r = 21. The literature review indicated that the data range employed in developing and evaluating gas viscosity are mainly based on low - intermediate data but very little are done for extreme conditions. The need to understand and also to model gas viscosity at HPHT is gradually very vital as investigation/exploration moves to deeper formation where extreme conditions (HPHT) can exist.

[11] presented a report on natural gas viscosity measurement at high pressure and high temperature for a sour natural gas mixture. The measurement was done using capillary tube viscometer at pressures ranging from 10.3 to 138MPa and temperatures up to 444 K. The authors also developed a comprehensive model to predict natural gas viscosity in a wide range of pressures, temperatures and compositions. They concluded that their new developed correlation performed better than other existing equations with the absolute error of 2.4%.

[12] presented a paper on laboratory measurement of gas viscosity at High Pressure and High Temperature (HPHT) using natural gas samples from Niger-Delta region. The capillary electromagnetic viscometer was used to measure gas viscosity for pressures of 6,000 psia to 14,000 psia; at temperatures of 270 ^oF and 370 ^oF. The authors also did a comparative study of some commonly used gas viscosity models in oil and gas industry, Among all the equations studied [6] performed better than other evaluated correlations with the mean relative error of -5.22 and absolute error of 8.752 for the temperature of 270^oF while [4] came out the best for the temperature of 370^oF with mean relative error of -16.88 and 16.88 for absolute mean error. [3] and [8] were also among the correlation studied by the authors but their error margin is very high for the data set used. Cross plots showed the poor performance of the evaluated correlations using the measured data at HPHT conditions. The authors concluded that gas viscosity correlations in literature are not very reliable at HPHT conditions.

[13] presented a model for predicting gas viscosity for carbon iv oxide bearing gas samples. The new equation is developed with 1539 experimental data measured at 250 to 450K and 0.10 t0 140MPa. The authors reported that their model performed better than other eight equations valuated with the maximum relative deviation of 0.98%.

Recently, [14] did a study on development of model to predict natural gas viscosity at high pressure high temperature conditions. They usedMicrosoft Excel Solver in building the model using 154 data set from Niger Delta region of Nigeria. Both quantitative and qualitative assessments were employed to evaluate the accuracy of the model to the existing empirical correlations. The authors state that new developed gas viscosity correlation gave good prediction when compared to other gas viscosity models with Mean Average Error of 3.4443, coefficient of correlation of 0.9556 and Rank of 2.004 which is acceptable for accurate engineering calculations.

1.1 Artificial Neural Network

` To address the complexity and inaccuracy of the correlations, a new predictive tool is used in this study to estimate gas viscosity which is 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 tasks [15].

The theory that inspires neural network systems is drawn from many disciplines: primarily from neuroscience; engineering, and computer science; secondarily from psychology, mathematics, and physics. These sciences are working toward the common goal of building intelligent system [15]. Artificial neural network initially grew from the full understanding of some ideas and aspects about how biological systems work, especially the human brain. Neural systems are typically organized in layers. Layers are made up of a number of interconnected nodes (artificial neurons), which contain activation functions. Patterns are presented to the network via the input layer, which communicates to one, or more hidden layers where the actual processing is done through a system of fully or partially weighted connections **(**Fig. 1**).** The hidden layers then linked to the output layer. Neural network contains some sort of learning rule that modifies the weights of the connections according to the input patterns. They are also called parallel-distributed processing system, which depicts the parallel operations of the nodes or neurons in a network processing system. Sometimes they are referred to as adaptive system because; the values of these connections can change so that the network can perform more effectively and efficiently.

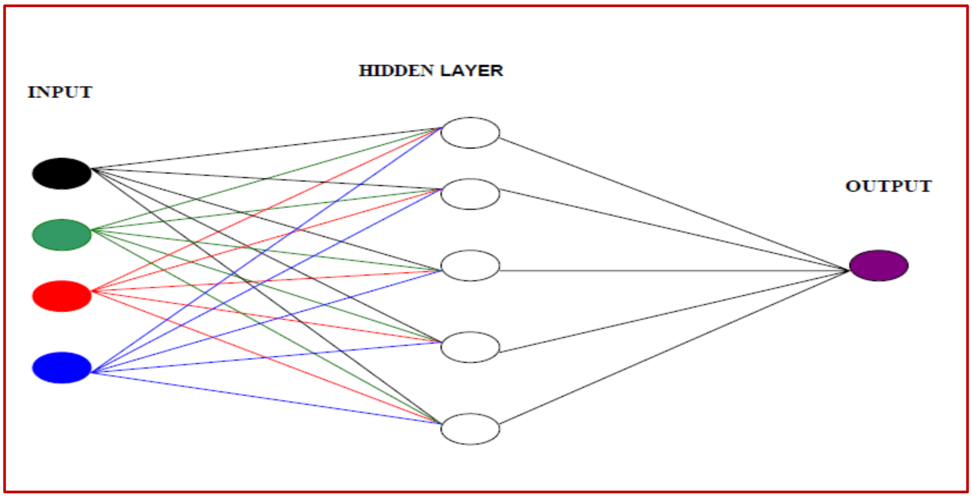

Fig. 1: Schematic of an artificial neural network with one-hidden layer

The advantage of ANN over the conventional correlations is that, neural networks have large degrees of freedom for fitting parameters, and thus, capture the systems' non-linearity better than regression methods. They are also superior to the regression models in that they could be further trained and refined when additional data become available and hence improve their prediction accuracy. On the other hand, it is impossible to make any further change in a linear or nonlinear regression model as soon as a model development is over [16].

Many investigators recognized that the neural network can serve the petroleum industry to create more accurate reservoir fluid properties models [17], [18], [19], [20], [12]. [17] presented three new models to predict the dew-point pressure for gas condensate reservoir: traditional correlations, non-parametric and artificial neural networks. He reported that artificial neural network perform better than the other two methods employed. [18] proposed an ANN structure for prediction of hydrocarbon viscosity using 800 experimental data and with accuracy of 3.65%.

[19] modelled a gas viscosity using Artificial neural network (ANN) based on back-propagation method. They built the model using 3841 experimental data both for testing and training. The designed neural network can predict the natural gas viscosity using pseudo-reduced temperature and pseudo-reduced pressure with AARD% of 0.221. The authors concluded that the comparison indicated that the proposed method can provide accurate results

[20] developed intelligent models which includes Artificial Neural Network (ANN), Fuzzy Interface System (FIS) and Adaptive Neuro-fuzzy System (ANFIS) for the prediction of gas compressibility factor. The authors observed and reported that the accuracy of intelligent predicting models for Z factor is significantly better than conventional empirical models. They reported that the three intelligent model developed, ANN model outperforms other models considering all data and 263 field data points of an Iranian offshore gas condensate with R^2 of 0.9999, while the R^2 for best empirical correlation was about 0.8334.

[12] did a work on developing ANN model to accurately predict the gas compressibility factor; as well to compare its performance with existing empirical gas compressibility factor correlations. The new model was developed using 513 PVT data points obtained from Niger-Delta region of Nigeria. The data used was randomly divided into three parts, of which 60% was used for training, 20% for validation, and 20% for testing. The authors did both quantitative and qualitative assessments to evaluate the accuracy of the new model to the existing empirical correlations. They concluded that the ANN model performed better than the existing empirical correlations by the statistical parameters used having the lowest rank of 1.37 and better performance plot.

It can be seen from the literature that only [19] has attempted to model gas viscosity correlation using ANN intelligent predictive model but they used low to moderate temperature and pressure data. Therefore there is a need to model gas viscosity for higher region, hence, the aim of this work is to develop ANN model to accurately predict the gas viscosity for high pressure high temperature gas reservoir; as well as to compare its performance with the existing empirical gas viscosity correlations.

II. METHODOLOGY

2.1 Data Acquisition and Analysis

The most important decisions in approaching the development of an artificial neural network model is choosing the content and sources of the data for the model. A set of 154 data points was used in developing the artificial neural network model in in this research. The data was gotten from laboratory measurement of gas viscosity using natural gas samples from Niger Delta region of Nigeria. The gas viscosity samples was measured using Electromagnetic Viscometer for the pressure range of 6000 to 1400psia at the temperatures of 270°F and 370°F.Table 1 shows the minimum, maximum and mean values of the reservoir temperature, reservoir pressure, gas gravity, reduced temperature, reduced pressure and experimental gas viscosity values for the measured gas viscosity at 270°F and 370°F for the pressure of 6000 – 14000 Psia.

Table1. Data Range used for training and testing gas ViscosityANN model

Parameter	Minimum	Maximum	Mean
Reservoir Temperature (°R)	730.0	830.0	780.0
Reservoir Pressure (Psia)	6014.7	14014.7	10323.51
Specific gravity	0.6056	1.1457	0.7356
Reduced Temperature	1.8732	2.12	2.00
Reduced Pressure	9.7	20.9122	15.4540
Experimental gas viscosity	0.0214	0.0388	0.0289
C_1	90.05	90.44	90.245
C_2	4.06	4.07	4.065
C_3	1.29	1.29	1.29
i-C_4	0.29	0.29	0.29
n-C_4	0.31	0.41	0.36
i-C_5	0.09	0.51	0.3
n-C_6	0.08	0.10	0.09
C_7^+	0.14	0.25	0.195
N_2	0.13	0.14	0.135
CO_2	3.00	3.21	3.105

2.2 Neural network architecture for developing gas viscosity ANN Model

Matlab neural network module was used to build the network using back-propagation algorithm with the Levenberg-Marquardt procedure for the optimization procedure [21]. Back propagation Neural Network (BPNN) is a multi-layered network, and information flows from the input to the output through at least one hidden/middle layer. Each layer contains neurons that are connected to all neurons in the neighboring layers. The connections have numerical values (weights) associated with them. During the training phase, the weights are adjusted according to the generalized delta rule. Training is completed when the network is able to predict the given output.

A three layers network was used in this work. A Levenberg- Marquardt algorithm was used to train the three-layer network. The first layer consists of three neurons representing the input values of pseudo-reduced temperature, pseudo-reduced pressure and Average Molecular Weight. The second (hidden) layer consists of 30 neurons, and the third layer contains one neuron representing the output values of natural gas viscosity. The data was randomly divided into three parts, of which 60% was used for training, 20% for validation, and 20% for testing. The training group which is 60% consist of 92 data set and was used to train the network; the second set (31 data sets) was used to test the error during the training, this is called cross validation and31data set to test the accuracy and trend stability. Cross validation gives the ability to monitor the general performance of the network and prevent the network from over fitting the training data. In a BPNN, the input activity is transmitted forward while the error is propagated backwards. The neurons in the BPN use a transfer function that is sigmoid or S shaped. A key feature of the sigmoid function is that it has a minimum value of 0 and a maximum value of 1 and is differentiable everywhere with a positive slope. The derivative of the transfer function is required to calculate the error that is back-propagated and it is also easy to calculate.

2.3 Correlation Comparison

To compare the performance and accuracy of the new model to other empirical correlations, two forms of analyses were performed which are quantitative and qualitative screening. For quantitative screening method, statistical error analysis was used. The statistical parameters used for the assessment were percent mean relative

error (MRE), percent mean absolute error (MAE), percent standard deviation relative (SDR), percent standard deviation absolute (SDA) and correlation coefficient (R).
For correlation comparison, a new approach of combining all the statistical parameters mentioned above (MRE, MAE, SDR, SDA and R) into a single comparable parameter called Rank was used [22]. The use of multiple combinations of statistical parameters in selecting the best correlation can be modeled as a constraint optimization problem with the function formulated as;

$$\mathbf{Min}\ Z_i = \sum_{j=1}^{m} S_{i,j} q_{i,j} \tag{1}$$

Subject to

$$\sum_{i=1}^{n} S_{i,j} \tag{2}$$

with

$$0 \leq S_{ij} \leq 1 \tag{3}$$

Where $S_{i,j}$ is the strength of the statistical parameter j of correlation i and q_{ij}, the statistical parameter j corresponding to correlation i. j = MRE, MAE, …. R^1, where $R^1 = (1\text{-}R)$ and Z_i is the rank, (or weight) of the desired correlation. The optimization model outlined in equations 1 to 3 was adopted in a sensitivity analysis to obtain acceptable parameter strengths. The final acceptable parameter strengths so obtained for the quantitative screening are 0.4 for MAE, 0.2 for R, 0.15 for SDA, 0.15 for SDR, and 0.1 for MRE. Finally, equation 3 was used for the ranking. The correlation with the lowest rank was selected as the best correlation for that fluid property. It is necessary to mention that minimum values were expected to be best for all other statistical parameters adopted in this study except R, where a maximum value of 1 was expected. Since the optimization model (Equations 1 to 3) is of the minimizing sense a minimum value corresponding to R must be used. This minimum value was obtained in the form (1-R). This means the correlation that has the highest correlation coefficient (R) would have the minimum value in the form (1-R). In this form the parameter strength was also implemented to 1-R as a multiplier. Ranking of correlations was therefore made after the correlations had been evaluated against the available database.

For qualitative screening, performance plots were used. The performance plot is a graph of the predicted versus measured properties with a 45^o reference line to readily ascertain the correlation's fitness and accuracy. A perfect correlation would plot as a straight line with a slope of 45^o.

III. RESULTS AND DISCUSSION

3.1 Correlations Evaluation

The trained ANN predictive model was tested with 31 data points that were not previously used during training and validation. Those data were randomly selected by the MATLAB tool to test the accuracy and stability of the model. The performance of the ANN model was compared with test data and the prediction from other empirical correlations such as [14], [5], [6] and [4], [3] and [8]. These predictive correlations were carefully selected, having been developed specifically for the prediction of gas viscosity. [14] and [8] were only the correlation developed for high pressure and high temperature conditions.

Figs. 2 and 3 show the statistical accuracies for all the gas viscosity models examined using both test and training data respectively. It can be found from Figure 2 chart that, the ANN ranked best with numerical value of 2.4639 with MAE of 4.3416 and correlation coefficient (R) of 0.995, followed by [14] with the rank of 3.4293 while [5] has the rank of 14.1145 and correlation coefficient of 0.8918for the entire data set studied. The good performance of [14] is expected because the model was developed specially for the higher region and bad performance of [8] may be from the data set.

Majority of the existing correlation evaluated using HPHT measured data showed a very large discrepancy, but the deviation associated with [4] correlation gave a better result as to compare with other evaluated equations with correlation coefficient of 0.952808 and MAE of 6.7748 with a rank of 3.850149. [3] and [8] correlations gave a very high error margin which cannot be quantify and were not picked in the plot.

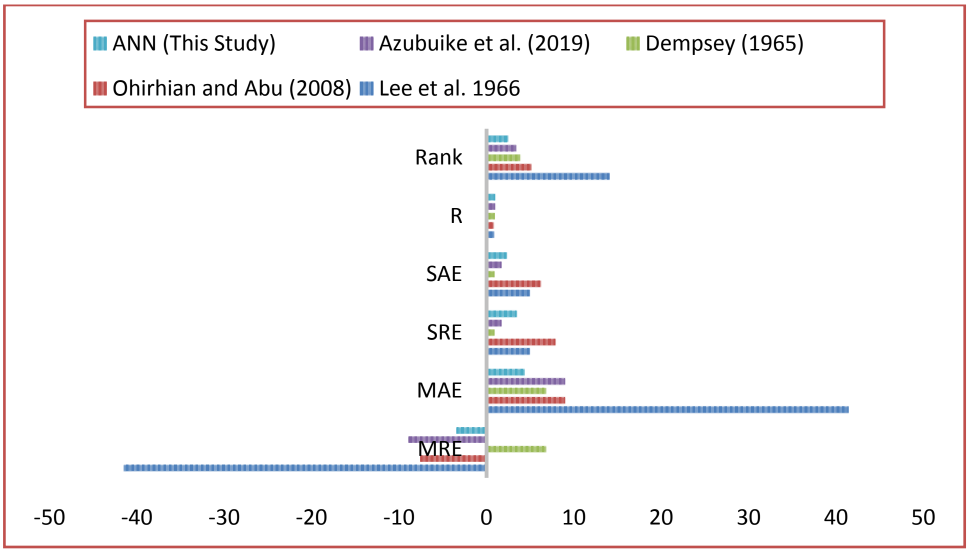

Fig. 2: Statistical Accuracy for Different Correlations using test data

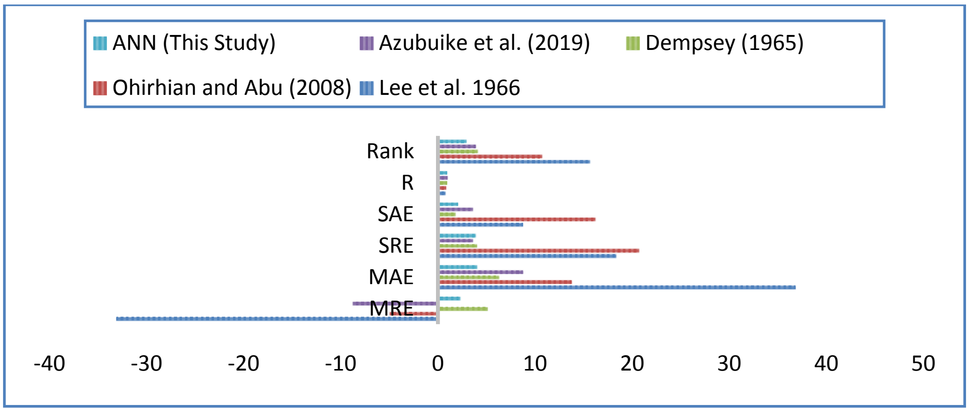

Fig. 3: Statistical Accuracy for Different Correlations using training data

Figs. 4 - 8 show cross plots that compared experimental gas viscosity data with some of the existing and artificial neural network model output. Compared to other cross plots, Fig. 4 shows the tightest cloud of points around the 45° line indicating the excellent agreement between the experimental and the calculated data values followed by Fig. 7. Again, this shows the superior performance of the ANN model as compared to other empirical correlations.

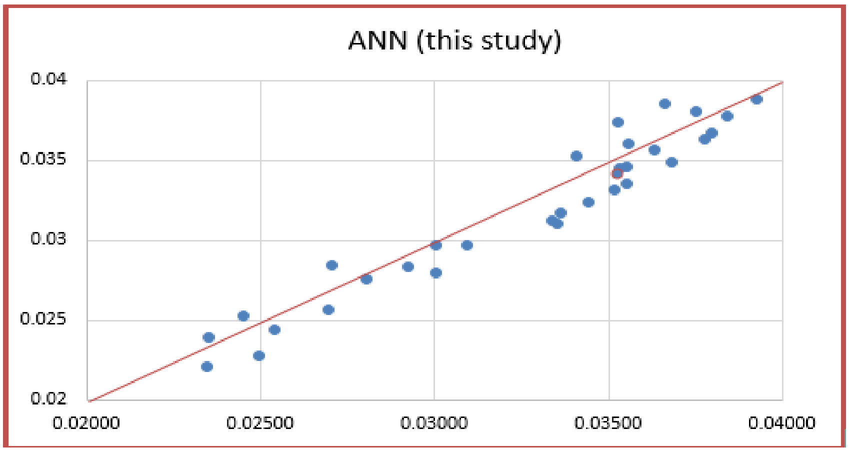

Fig. 4: Plot of predicted against measured gas viscosity for ANN (this Study)

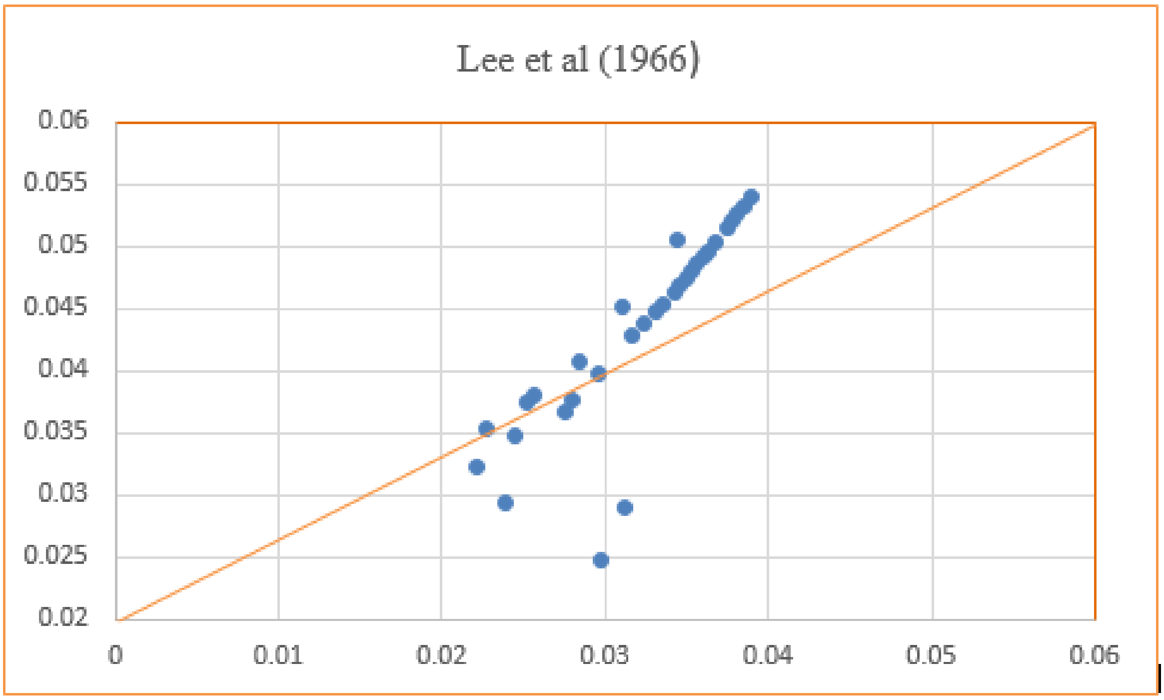

Fig. 5. Plot of predicted against measured gas viscosity for Lee et al (1966)

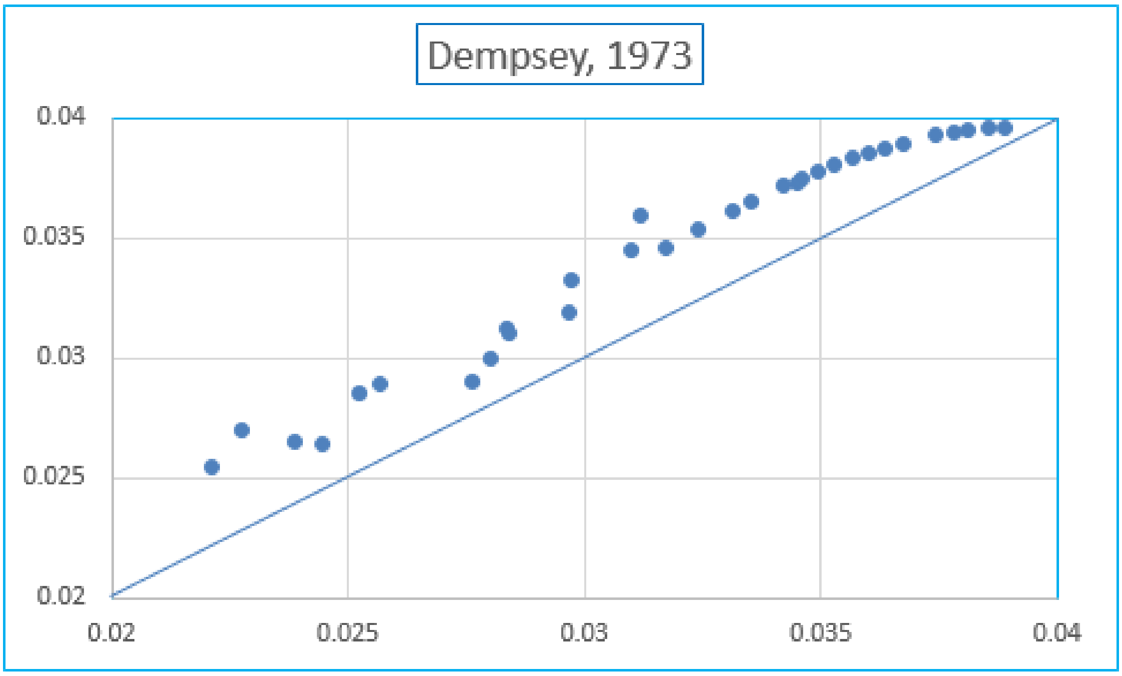

Fig. 6. Plot of predicted against measured gas viscosity for Dempsey (1973)

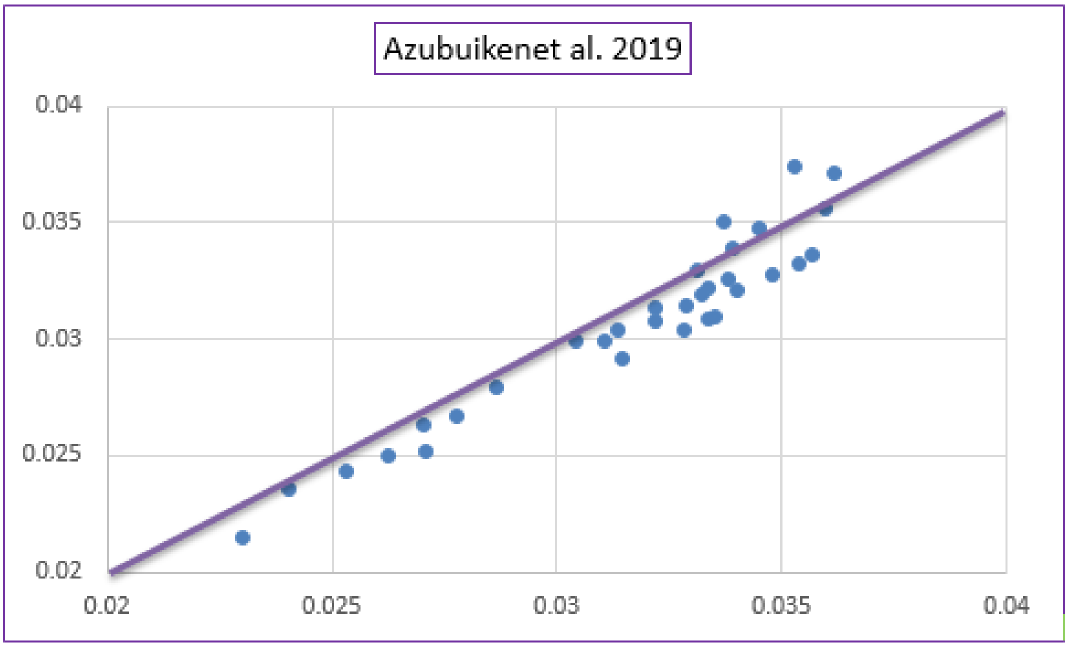

Fig. 7. Plot of predicted against measured gas viscosity Azubuike et al. (2019)

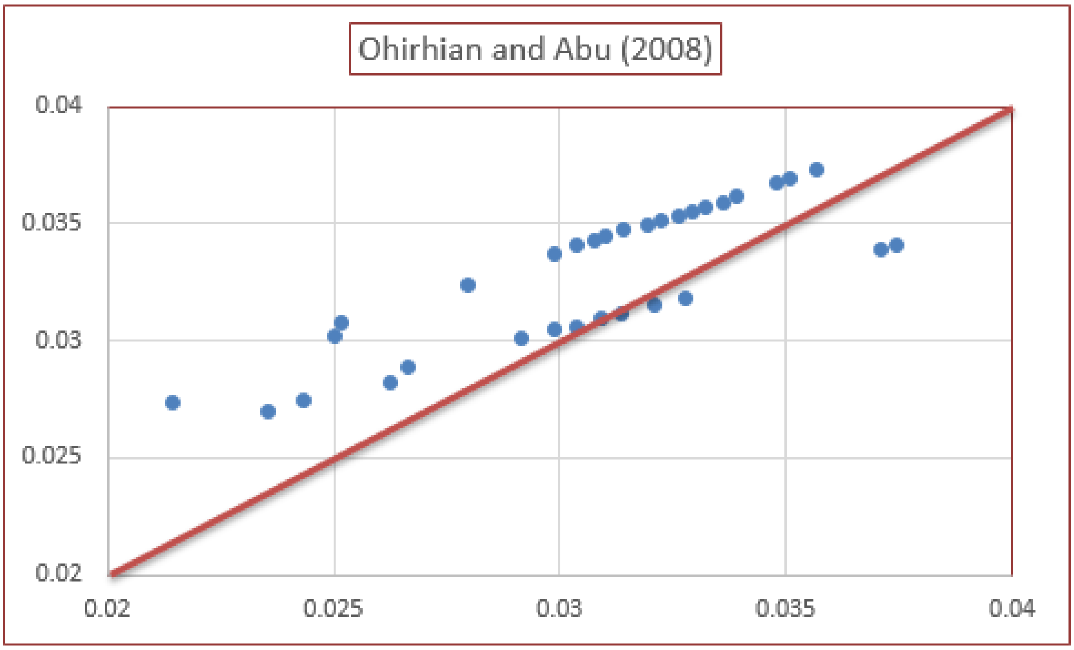

Fig. 8. Plot of predicted against measured gas viscosity for Ohirhian and Abu (2008)

IV. CONCLUSION

A model based on artificial neural network approach has been developed to estimate gas viscosity. Pseudo-reduced temperature, pseudo-reduced pressure and average molecular weight were the input variables and gas viscosity is the output variable. The efficiency of the model was tested against several commonly used models for gas viscosity estimation. Based on the findings of this work, the artificial neural network model shows a good performance in term of accuracy having the lowest rank of 2 .4639 and better performance plots.

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