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Forecasting Dead Oil Viscosity Using Machine Learning Processes for Niger Delta Region

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ABSTRACT: Prediction of Dead oil viscosity using experimental measurements is highly exorbitant and time consuming, hence the use of forecasting models. Dead oil viscosity is a very important PVT parameter that solve numerous reservoir engineering problems and one of the most required factors for enhanced oil recovery processes. This study utilized two machine learning algorithms of Artificial Neural Network (ANN) and Support Vector Machine (SVM) to predict dead oil viscosity. A total number of 243 data set was obtained from PVT report from Niger-Delta, out of which, 70% were used to train the models, 15% for testing and 15% for validation. Quantitative and qualitative analysis was carried out to compare the performance and reliability of the new developed machine learning models with some selected empirical correlations. The result revealed that the Artificial Neural Network Outperformed Support Vector Machine (SVM) as well as common dead oil viscosity empirical correlations with the best rank of 0.144, highest correlation coefficient of 0.984, Mean Absolute Error (Ea) of 0.205, with a better performance plot, followed by Support Vector Machine model with correlation coefficient of 0.926, Mean Absolute Error (Ea) of 0.199 and the rank of 0.176. The new developed Artificial Neural Network model can potentially replace the empirical models for dead oil viscosity predictions for Niger Delta region.

KEYWORDS: Artificial Neural Network, Dead Oil Viscosity, Empirical Correlation, Machine learning Algorithm, Statical Analysis

1. INTRODUCTION

Reservoir pressure–volume–temperature (PVT) properties are some of the most important parameters used by petroleum engineers for proper reservoir estimation and management [1]. These PVT data are obtained from experimental measurement of the representative fluid samples collected from wellhead or wellbore of the oil reservoir. The accurate measurement of fluid pressure-volume-temperature (PVT) properties such as oil viscosity, oil gravity, solution gas - oil ratio (Rs), dew and bubble point pressure, oil formation volume factor (OFVF) and other PVT fluid properties are essential for estimation of reserves, reservoir performance determination, recovery efficiency, production optimization and design of production systems [2]. It is more profitable to avoid expensive, time-consuming experimental laboratory measurements and to test the validity of the test results hence the application of empirical correlation and machine learning model. The reservoir pressure-volume-temperature property of consign in this research is dead oil viscosity.

Crude oil viscosity is an important physical property that controls and influences the flow of oil through porous media and pipelines. The viscosity, in general, is defined as the internal resistance of a fluid to flow. Oil viscosity is a strong function of many thermodynamic and physical properties such as pressure, temperature, solution gas–oil ratio (GOR), bubble point pressure, chemical composition, gas gravity, and oil gravity ([3], [4], [5], [6], [7]). Viscosity of crude oil is a fundamental factor in simulating reservoirs, forecasting production as well as planning thermal enhanced oil recovery methods that make its accurate determination necessary.

Crude oil viscosity is divided into three categories, namely saturated oil viscosity, undersaturated oil viscosity, and dead oil viscosity, depending on the reservoir pressure [8]. Fig. 1 shows a typical oil viscosity diagram as a function of pressure at constant reservoir temperature.

Dead-oil viscosity: This is the viscosity of the crude oil at atmospheric pressure (no gas is in solution) and system temperature.
Saturated oil viscosity (bubble point) is defined as the viscosity of the oil at the bubble-point pressure and reservoir temperature.
Undersaturated oil viscosity is defined as the viscosity of the crude oil above the bubble point pressure and reservoir temperature.

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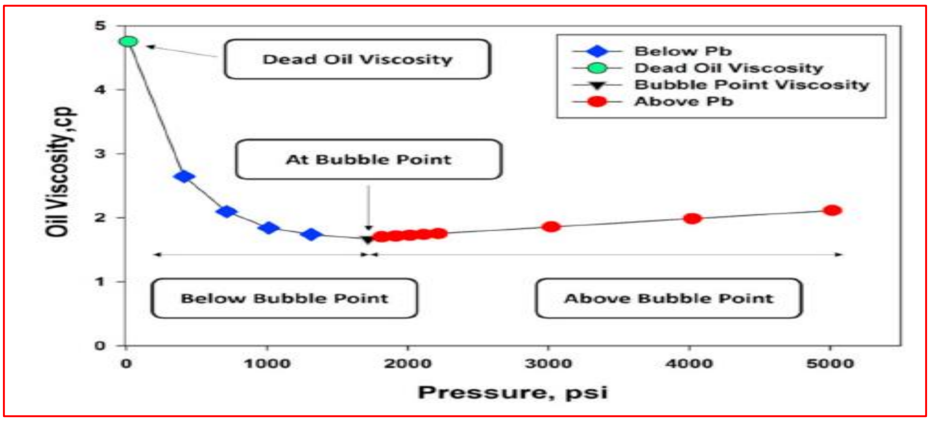

Fig. 1 Typical viscosity trend as a function of pressure [9]

This research work aimed at forecasting dead oil viscosity using machine learning procedures rather than traditional empirical methods which is more powerful, fast, and accurate. Several empirical correlations exist for predicting dead oil viscosity ([10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22],[23], [24], [25]). The first traditional correlation was developed by Andrade, who presented a correlation of great simplicity, which has one input parameter of temperature, and led to exciting results at high temperatures [26]. [10] presented correlation charts by analyzing 953 crude oil samples from 747 oil fields in the USA and California using inputs of oil gravity and temperature. [27] and [28] summarized the ranges and data origins used by some famous authors in developing dead oil viscosity correlation.

Recently, researchers have proved that machine learning/artificial intelligent which is an advanced soft computing tools can create relationship between the input and output data gotten from laboratory experiment [29]. Machine learning is a subfield of artificial intelligent which enables machines to learn from past data or experience without being explicitly programmed [30]. Investigators has documented that the artificial intelligent can serve oil and gas industry to create a more reliable and accurate PVT predictive models ([31], [32], [33], [34], [35], [36], [37]). [31] researched on dead oil viscosity using Radial Basial forward artificial neural network method. He used the input parameters of reservoir pressure, reservoir temperature, stock tank oil gravity and separator gas gravity. The new model gave better prediction than some of the existing dead oil viscosity with average absolute percent error is 8.72% using the test data.

[32] applied nonlinear multivariable regression and nonlinear optimization regression to optimize other correlations. They presented a neural network-based model for dead oil viscosity, in addition to optimization of published correlations.
[34] employed ANN backward propagation procedure with the Levenberg-Marquardt algorithm to optimize the Nigerian crude oil viscosity. The authors utilized 1750 data points to optimize the oil viscosity models for dead and bubble point pressure oil viscosity. Furthermore, [35] proposed an ANN model that used a data set of laboratory measurements on oil samples from Yemen's oil fields involved 545 data points. They expressed that ANN models were appropriate for predicting the dead oil, saturated and under-saturated viscosity). In another study, [36] attempted to model the dead oil viscosity with various machine learning methods. They proposed that correlations can be divided into three classes: those that can predict the dead oil viscosity with limited data, those that predict the dead oil viscosity using limited existing viscosity data, and those that check the quality of the existing data. The authors reported that the machining learning algorithm performed better than the existing empirical correlations by the data set they applied. [27] employed 2247 PVT data points both from light and heavy oil data set to predict dead oil viscosity. The researchers implemented six machine learning algorithms of random forest (RF), lightgbm, XGBoost, MLP neural network, Support Vector machine and SuperLearner simultaneously in predicting oil viscosity. Results indicate that the Super-Learner algorithm showed high performance compared to other used algorithms.

[28] developed ensemble machine learning model for the prediction of dead, saturated and undersaturated oil viscosity. The authors investigated the different functional forms that are normally used in predicting various forms oil viscosity (dead, saturated and unsaturated viscosity). Olosi and his team reported that the best functional parameter for dead oil viscosity are

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temperature and API gravity and for the bubble point oil viscosity, API gravity and bubble point pressure while for oil viscosity above bubble point the best functional form are oil viscosity at the bubble point, dead oil viscosity, bubble point pressure, pressure, and API gravity for all the ensemble SVR model developed. They said that among all the empirical oil viscosity accessed their new ensemble SVR model outperformed other existing oil viscosity evaluated by the statistical parameters they used. They also reported that error margin associated with dead oil viscosity is high. [37] did a novel study on multi-hybrid model for estimating oil viscosity of Iranian crude oil using 600 data points. They used the new multi-hybrid to develop oil viscosity at bubble point and below bubble point using GA and GMDH model. They reported that their new multi-hybrid model performed better than other existing empirical correlations with average absolute per cent error of 3.77, 0.268 and 0.01058 for saturated and undersaturated oil viscosity respectively.

[8] presented a research work on crude oil viscosity determination for light and intermediate crude oil systems using global data. Hybrid model of GA and SVM were used to predict dead oil viscosity by applying 1497 data set. The authors reported that the new machining learning hybrid gave better predictions than some of the existing dead oil viscosity correlations with a 17.17 average absolute per cent error. More literature on dead oil viscosity for both empirical and machine learning can be found in [28]. Based on the literature review, petroleum and gas industry has an interest to develop models that can predict oil viscosity for proper reservoir fluid management and monitoring. Considering these points, the main aim of this study is to build a machine learning model that predicts dead oil viscosity using data from Niger Delta.

2. OVERVIEW OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

Artificial Intelligence (AL) is a method of making a computer/computer-controlled robot, or a software think intelligently like the human mind. It is accomplished by studying the patterns of the human brain and by analyzing the cognitive process. The examples of cognitive abilities of artificial intelligent are learning, reasoning, problem-solving and perception The outcome of any Artificial intelligence research is to develop intelligent systems and software. The major two ways of implementation are through machine learning and deep learning ([38], [39]).

Machine learning is a core sub-area of Artificial Intelligence (AI) that gives it ability to learn. The learning process is achieved by using algorithms to discover patterns and generate insights from the original or measured data they are exposed to. The machine learning algorithms adopted in this study are support vector machine (SVM) and Artificial Nural Network. These algorithms were carefully selected having reported by many authors about their excellency in predicting PVT parameters.

Support Vector Machine (SVM) is a statistical machine learning method that generates input– output mapping functions from a set of training data. It uses the principle of structural risk minimization, seeking to minimize the upper bound of the generalization error rather than just minimizing the training error. In a simple pattern recognition problem, SVM uses a linear separating hyperplane to create a classifier with a maximal margin. When the input cannot be linearly transformed (e.g. complex classification problem or regression problem), SVM first nonlinearly transforms the input space into a higher dimensional feature space. The transformation is achieved by using nonlinear mapping functions which are generally referred to as kernel functions. Typical kernel functions include RBF, Gaussian, and polynomial functions.

Artificial Neural Network (ANN) is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron receives signals then processes them and can signal neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called edges. Neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer) to the last layer (the output layer), possibly after traversing the layers multiple times. A network is typically called a deep neural network if it has at least 2 hidden layers.

Deep learning is a subcategory of machine learning that provides AI with the ability to mimic a human brain's neural network. It can make sense of patters, noise, and sources of confusion in the data. The three main layers of a neural network are input, hidden and output and they are presented with Fig. 3

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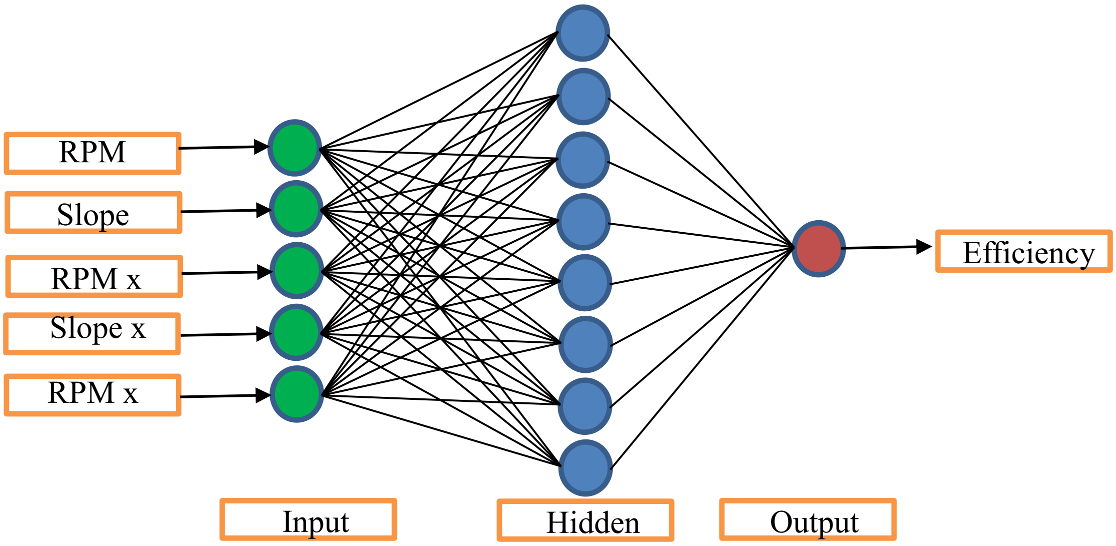

Fig. 3. The three main layers of a artificial neural network

3. METHODOLOGY

3.1 Data Description

The total number of 263 data points was gotten from conventional PVT reports that derive the various fluid properties through liberation process from the Niger-Delta Region of Nigeria. The data parameters applied are gas specific gravity, API gravity of the crude oil, separator temperature, separator pressure and separator gas-oil ratio. The ranges of the data applied are $0.608 < \gamma_g < 2.218, 20.5 < \gamma_{API} < 44.0, 75 < T_S < 104$ °F,$115 < P_S < 2970\ psia, 604.15 < R_s < 2970\ scf/stb$. Tables 1 and 2 show the mean, minimum and maximum values for both training and test data sets used for this study.

Table 1. Summary of Mean, Minimum and Maximum Data values used in training.

Input Parameters	Mean Values	Minimum Values	Maximum Values
Gas Specific Gravity (γ_g)	1.1188	0.608	2.218
Oil API Gravity	41.62	20.50	44.0
Separator Temperature (°F)	98.30	80.0	100
Separator Pressure (Psia)	264.82	115.0	1371
Gas – Oil Ratio (Scf/Stb)	938.27	27.00	2880
Dead oil Viscosity (cp)	2.30	0.13	25.00

Table 2. Summary of Mean, Minimum and Maximum Data values used in testing.

Input Parameters	Mean Values	Minimum Values	Maximum Values
Gas Specific Gravity (γ_g)	1.031	0.573	2.218
Oil API Gravity	40.317	17.45	65.30
Separator Temperature	97.34	75	104
Separator Pressure	207.25	35	1371
Gas – Oil Ratio	604.15	19	2970
Dead oil Viscosity	2.149	0.77	26

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3.2 DATA VALIDATION

Before any experimental PVT data are used for design or study purposes, it is necessary to ensure that there are no error or major inconsistencies that would render any subsequent work useless. Two such means of data validation are the Campbell diagram (Buckley plot) and the Mass Balance Diagram which are otherwise known as cross plot. These techniques were used to validate the data set used in this work.

3.3 MODELLING PROCESSES

Two machine learning algorithms (ANN and SVM) were employed in developing the new dead oil viscosity model for Niger Delta region using MATLAB 9.11 version procedure. The procedures of using machine learning to train experimental data are generally similar which are summarized below:

(i). Importation of the data: The input data which are Gas Specific Gravity (γ_g), Separator Pressure (Psia), Separator Temperature (°F) and gas-oil ratio were imported to the MATLAB platform using the import command.

(ii). Selection of right variables: The input and output vectors are represented in form of matrix I and O respectively. This is to arrange a set "I input" vector and "O output" vectors are organized in columns into first and second matrix in the MATLAB workspace as shown in Equations. 3 and 4.

(I) Input data = $f\left(\gamma_g, T_{sp}, P_{sp}, R_{sp}, \gamma_{API}\right)$ (1)

(O) Target data = $[\mu_{od}]$ (2)

(iii). Data Point Division: The total size of the data point applied in this study is 243. The data set was divided into three parts which are training, validation, and testing. The model was trained with 70% (170) of the data points, 15% (36) was used for validating the model and 15% (36) was used for testing the trained models.

(iv). Function Selection: Imbedded in any machine learning program is a function that is design to estimate the model parameters. For support vector machine is the kernel function and for ANN is activation function. Different types of kernel function for SVM are Linear, Polynomial, Radial Basis, and Sigmoid Functions. In this study Radial Basis Function (RBF) (Equation 3) is used because is the most popular choice because of its high level of accuracy. The type of activation functions for ANN are linear, binary, probabilistic and sigmoid functions. Sigmoid activation function (Equation 4) with Levenberg-Marquradt algorithm is used in this study because of it's popularity in high level of accuracy and the capacity to differentiate everywhere with a positive slope.

$$K\left(x_i, x_j\right) = e^{-\gamma|x_i - x_j|^2} \quad (3)$$

$$\mathrm{f(x)} = \frac{1}{1+e^{-x+T}} \quad (4)$$

where T is a threshold or transfer value

(iv) Method of simulation: The two methods applicable are supervised and unsupervised learning. This work used supervised learning approach for the SVM modelling. Supervised, also known as supervised machine learning is defined using labelled datasets to train algorithms that classify data or predict outcomes accurately. As input data is fed into the model, it adjusts its weight until the model has been fitted appropriately, which occurs as part of the cross-validation process.

Unlike supervised learning, which uses unlabeled data. From the data, it discovers pattern that help solve for cluttering or association problem. Supervised model keeps iterating the provided value (the measured output) to obtain a near criterion. The detailed description on artificial neural network and support vector machine modelling procedures can be in [40], [41].

3.4 Evaluation Methods (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, which are 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 Rank) into a single comparable parameter called Rank was used. 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;

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$$Min\ Rank = \sum_{j=1}^{m} S_{i,j} q_{1,j} \tag{5}$$

Subject to $$\sum_{i=1}^{n} S_{i,j} \tag{6}$$

With $$0 \le S_{ij} \le 1 \tag{7}$$

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-R) and the rank (Z), (or weight) of the desired correlation. The optimization model outlined in Equations 5 to 7 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. 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 [25].

Performance plots were used for qualitative screening. It is a graph of the predicted versus measured gas compressibility data 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.

4. RESULTS AND DISCUSSION

After the training of the measured data using the two machine learning algorithms of ANN and SVM, the trained models were tested with 36 (15%) data points that were not previously used during training and validation processes. These data points were randomly selected by the MATLAB tool to test the accuracy and stability of the new developed model. The predictions and performance of the two new intelligent models were compared with data from the field and the estimations from other dead oil viscosity empirical correlations like [16], [15, [25] and [17]. These empirical correlations were carefully selected having reported by some researchers of their excellent performance in predicting dead oil viscosity. Two out of four selected correlations were developed precisely for Niger-Delta Region ([16], [25]).

The results of the statistical assessment adopted in this research are presented in Table 3 and Fig. 3 for all the dead oil viscosity empirical correlations and the two intelligent models examined. The results show that the two intelligent models gave a better prediction than all the empirical correlations investigated. Between the two-machining learning algorithm investigated, ANN emerged the best with the rank value of 0.144, mean absolute error of 0.205 and best correlation coefficient of 0.984. The support vector machines regression algorithm predicted the dead oil viscosity with the rank value of 0.176, mean absolute error of 0.199 and correlation coefficient of 0.926 for the data set studied. It is evident that the machine learning models proposed in this study are more reliable, accurate and robust than other published correlations in terms of statistical parameters employed.

It can be observed from Table 3 and Fig. 4 that all the intelligent models performed better than the empirical correlations examined. The empirical correlations of [25] and [16] which are indigenous correlations performed better than the foreign ones which are [15] and [17]. The trend of the locally developed correlations is expected because correlations performed better in their region. [25] performed better than other evaluated correlations with the rank value of 0.177, mean absolute error 0.226 and correlation coefficient o.949 followed by [16] with the rank value of 0.18, mean absolute error of 0.221 and correlation coefficient of 0.931. This study recommends [25] correlation to be used in predicting dead oil viscosity in absence of machining learning model.

This study has once again proven the reliability and efficient performance of machining learning algorithm in predicting the reservoir PVT properties. The ANN model developed in this research is a very big powerful tool to forecast dead oil viscosity for Niger Delta region in terms of root mean squared error, absolute average percent error, standard deviation, correlation coefficient and Rank.

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Table 3. Statistical Accuracy of Dead Oil Viscosity for Different Machining Learning Algorithm and Empirical Correlations Using Niger-Delta Data

AUTHORS	%MRE	%MAE	%SRE	%SAE	R	Rank
ANN	**0.106**	0.205	0.172	0.147	0.984	**0.144**
SVM	0.138	0.199	0.193	0.261	0.926	**0.176**
Ikiensikimama (2009)	0.182	0.226	0.186	0.205	0.949	**0.177**
Egbogah and Jack (1990)	0.192	0.221	0.187	0.201	0.931	**0.179**
Petrosky and Farshad (1995)	0.203	0.219	0.195	0.263	0.941	**0.189**
Labedi (1982)	0.217	0.241	0.197	0.211	0.934	**0.192**

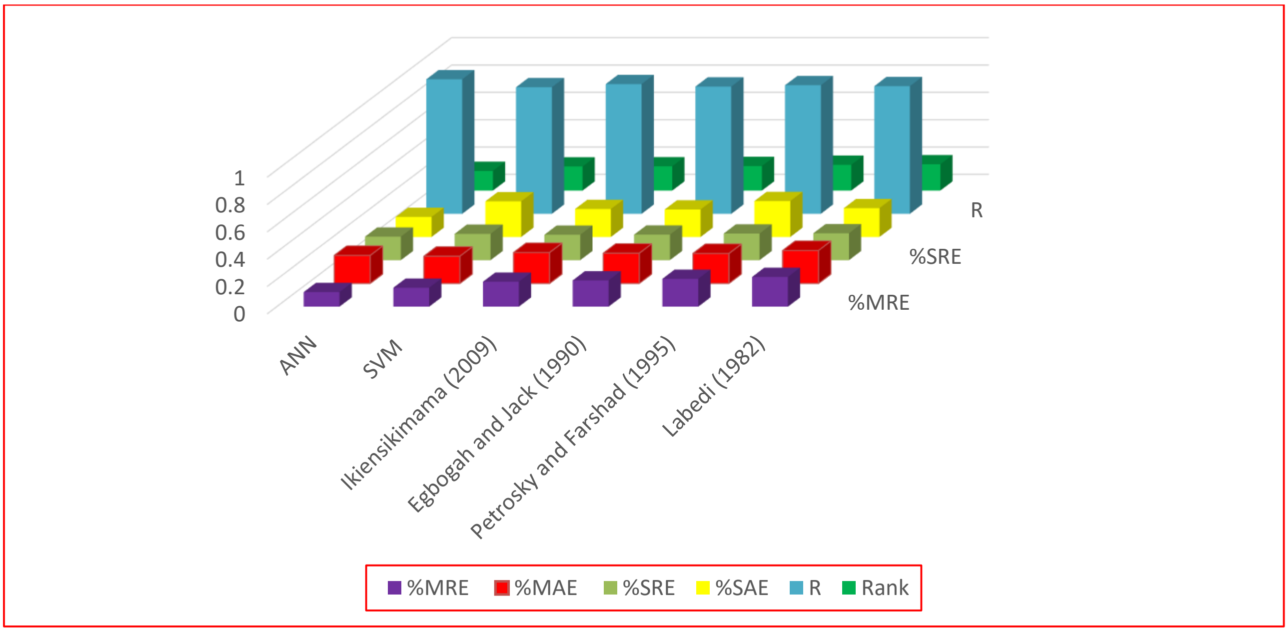

Fig. 3. Comparison of the Statistical Accuracy for Different Machine learning and correlations using Niger -Delta Data

Figs. 4 to 7 illustrate cross plots of the predicted versus experimental dead oil viscosity values for training, validation and test data for the intelligent models examined. A cross plot is a graph of predicted versus measured properties with a 45° reference line to readily ascertain the correlation's fitness and accuracy.

Figs. 5 and 7 show the cross plots of ANN and SVM models using test data. It can be observed from Figs. 5 and 7 that they follow the trend of Figs. 4 and 6 which are plotted using training data of ANN and SVM. Figs. 5 and 6 also showed tightest cloud of points around the 45° line with very good clusters at low band like the training data indicating the excellent agreement between the experimental and the predicted data. In addition, this indicates the superior performance of Artificial Neural Network and Support Vector Machine models. The accuracy of the new developed model indicates that the ANN intelligent model does not over fit the data, which implies that it was successfully trained and can be used in predicting dead oil viscosity for Niger-Delta region of Nigeria.

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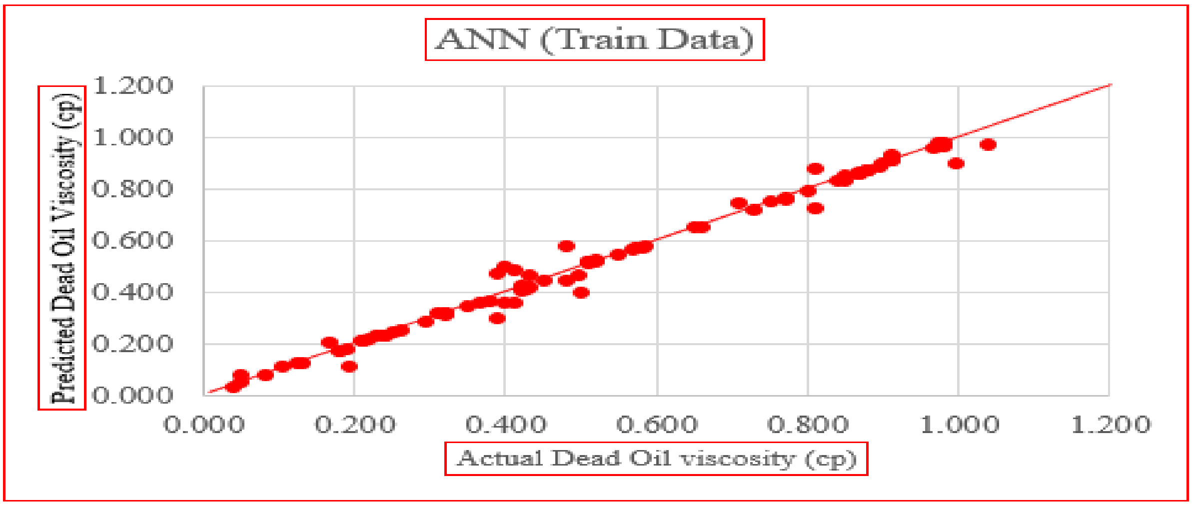

Fig. 4. Artificial Neural Network Cross-Plot for the Train Data

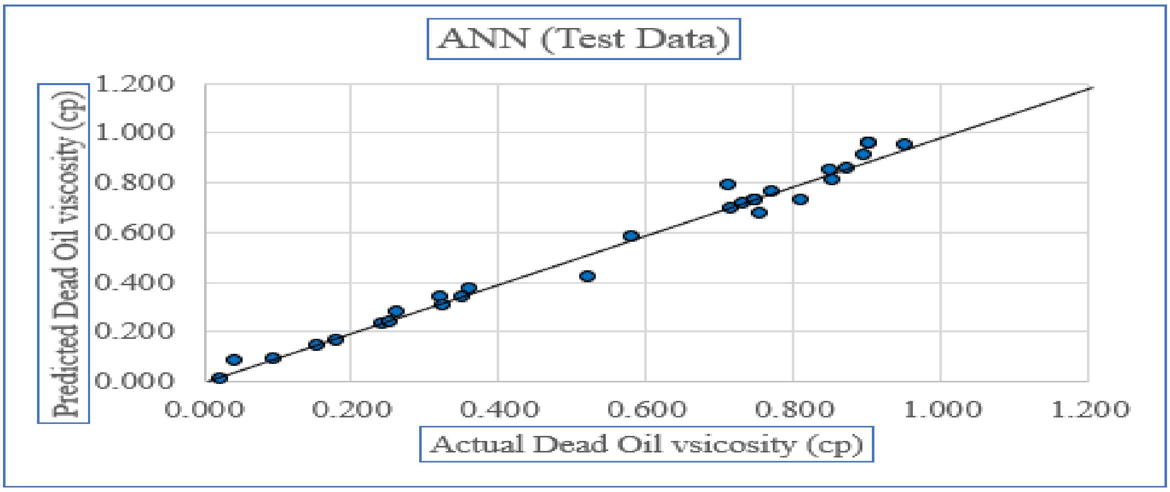

Fig. 5. Artificial Neural Network Cross-Plot for the Test Data

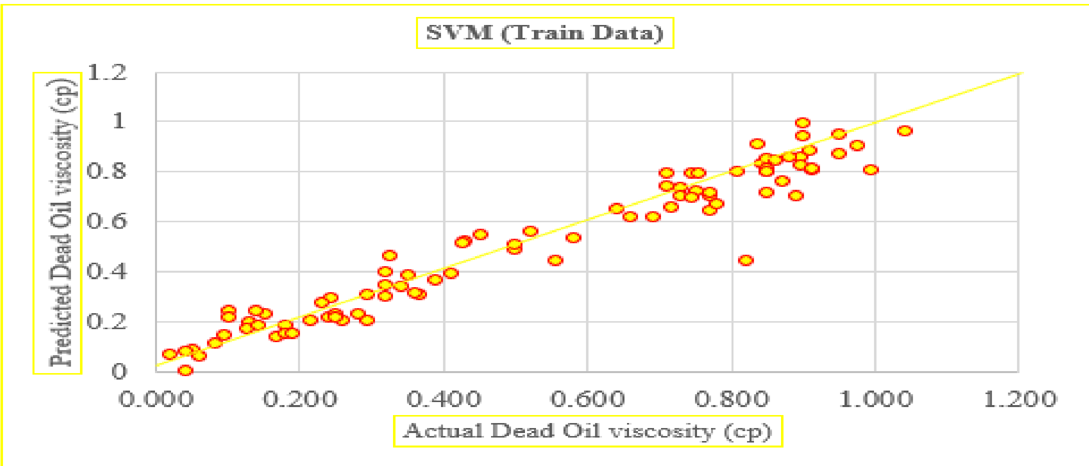

Fig. 6. Support Vector Machine Cross-Plot for the Train Data

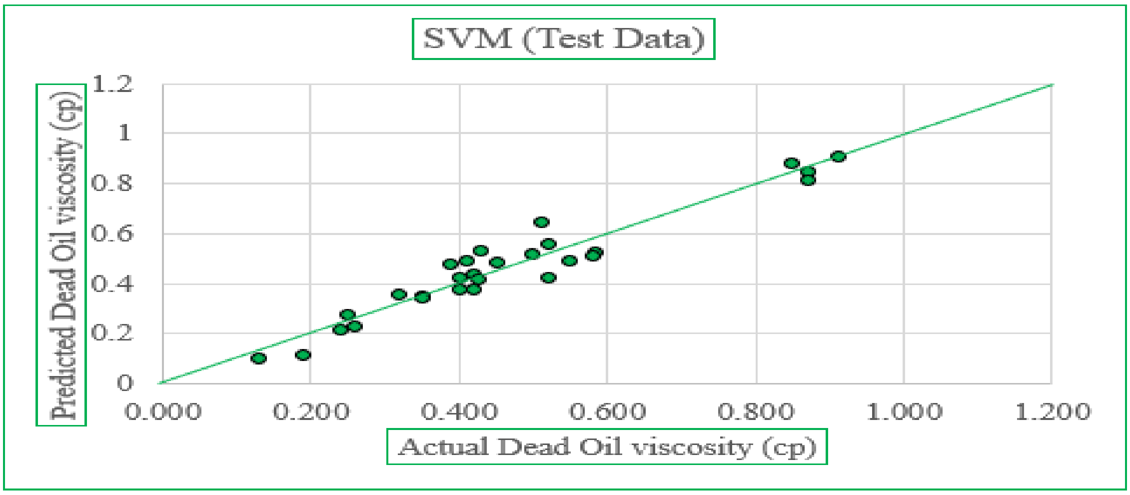

Fig. 7. Support Vector Machine Cross-Plot for the Test Data

5. CONCLUSION

The use of two machine learning algorithms like Artificial neural network and support vector machine has been adopted in the research for dead oil viscosity predictions using data from Niger Delta of Nigeria. The research revealed that Artificial neural that predicts the dead oil viscosity better than support vector machine and empirical correlations examined with the best rank of 0.144 and better performance plot. This leads to a bright light of machine learning modeling and will assist petroleum exploration engineers to estimate various reservoir properties with better accuracy, leading to reduced exploration cost and time with increase in productions. Ikiensikimama empirical correlation performed better than all the four dead oil viscosity equations evaluated with the rank value of 0.177 followed by Egbogah and Jack with the rank value of 0.179. Ikiensikimama correlation can be used to predict dead oil viscosity for Niger Delta Region in absence of these new developed intelligent tools for Niger Delta region for proper reservoir simulation and management.

REFERENCES

1. Ahmed, T. (2013). Equations of State and PVT Analysis; Gulf Publishing Company: Houston, TX, USA.
2. McCain, W. D. (1991). “Reservoir fluid property correlations- State of the Art,” SPE Reservoir Engineering, pp 266-272.
3. Rowane, A.J., Babu, V.M., Rokni, H.B., Moore, J.D., Gavaises, M., Wensing, M., Gupta, A., Mchugh, M.A. (2019). “Effect of composition, temperature, and pressure on the viscosities and densities of three diesel fuels”. J. Chem. Eng. Data 64 (12), 5529–5547. https://doi.org/10.1021/acs.jced.9b00652.
4. Safdari, M. and Shadloo, M.S., (2020). “Application of support vector machines for accurate prediction of convection heat transfer coefficient of nanofluids through circular pipes”. Int. J. Numer. Methods Heat Fluid Flow 2017002. https://doi.org/ 10.1108/HFF-09-2020-0555. S
5. Derevich, I.V. and Gromadskaya, R.S. (2002). “Effect of dissolved gases on the viscosity of petroleum”. Theor. Found. Chem. Eng. 36 (6), 583–588.
6. Talebkeikhah, M., Amar, M.N., Naseri, A., Humand, M., Hemmati-Sarapardeh, A., Dabir, B. and Seghier, M.E.A.B. (2020). “Experimental measurement and compositional modeling of crude oil viscosity at reservoir conditions”. J. Taiwan Inst. Chem. Eng. 109, 35–50. https://doi.org/10.1016/j.jtice.2020.03.001.
7. Giwa, S.O., Sharifpur, M., Goodarzi, M., Alsulami, H. and Meyer, J.P. (2021). “Influence of base fluid, temperature, and concentration on the thermophysical properties of hybrid nanofluids of alumina–ferrofluid: experimental data, modeling through enhanced ANN, ANFIS, and curve fitting”. J. Therm. Anal. Calorim. 143 (6), 4149–4167. https://doi.osrg/10.1007/s10973-020-09372-w.
8. Hemmati-Sarapardeh A, Aminshahidy B, Pajouhandeh A. (2016). “A soft computing approach for the determination of crude oil viscosity: light and intermediate crude oil systems”. J Taiwan Inst Chem Eng 59:1–10

9. Bahonar, E. Chahardowli M, Ghalenoei, Y and Simjoo, M (2021). "New correlations to predict oil viscosity using data mining techniques", Journal of Petroleum Science and Engineering https://doi.org/10.1016/j.petrol.2021.109736
10. Beal, C. (1946). "The viscosity of air, water, natural gas, crude oil and its associated gases at oil field temperatures and pressures". Trans AIME 165:94–115
11. Beggs, H. D. and Robinson, J. R. (1975). "Estimating the viscosity of crude oil systems". J Pet Technol 27:1140–1141
12. Glaso, O. (1980). "Generalized Pressure-Volume-Temperature Correlations." J. Petrol. Technol. (32), 785–795. https://doi.org/10.2118/8016-pa
13. Kaye, S.E. (1985). "Offshore California Viscosity Correlations", Technical Report, No. TS85000940; Chevron Oil Field Research Co. (COFRC): La Habra, CA, USA.
14. Al-Khafaji, A.H., Abdul-Majeed, G.H. and Hassoon, S.F., (1987). "Viscosity correlation for dead, live and undersaturated crude oils". J. Petrol. Res 6 (2), 1–16.
15. Petrosky, G. E. and Farshad, F.F. (1995). "Viscosity Correlations for Gulf of Mexico Crude Oils". SPE 29468, Production Operations Symposium, Oklahoma City, Oklahoma,2-4, ISBN 978-1-55563- 448-3.
16. Egbogah, E.O. and Jack N. T. (1990). "An improved temperature-viscosity correlation for crude oil systems". J. Pet. Sci. Eng., 4, 197–200.
17. Labedi, R. (1982). "Improved correlations for predicting the viscosity of light crudes". J. Pet. Sci. Engineering. (Journal of Petroleum Science and Engineering), 8, 221– 234.
18. Kartoatmodjo T, and Schmidt, Z. (1994) "Large data bank improves crude physical property correlations". Oil Gas J 92(27):27
19. De Ghetto G, and Villa, M. (1994). "Reliability analysis on PVT correlations". In: European petroleum conference, SPE, London, 25–27
20. Bennison, T., (1998). "Prediction of heavy oil viscosity. In: IBC Heavy Oil Field Development", Conference, vol. 2, p. 4. December.
21. Elsharkawy, A.M., and Alikhan, A.A. (1997). "Correlation for Predicting Solution Gas/Oil Ratio, Oil Formation Volume Factor, and Undersaturated Oil Compressibility", J. Petrol. Sci. Eng. (17), 291–302. https://doi.org/10.1016/S0920-4105(96)00075-7.
22. Hossain,M.S., Sarica, C., Zhang, H.-Q., Rhyne, L. and Greenhill, K. (2005). "Assessment and development of heavy oil viscosity correlations". In Proceedings of the SPE International Thermal Operations and Heavy Oil Symposium, Calgary, AB, Canada, 1–3.
23. Naseri, A., Nikazar, M. and Dehghani, S.M. (2005). "A correlation approach for prediction of crude oil viscosities". J. Pet. Sci. Eng., 47, 163–174
24. Al-amoudi, L.A., Salem, B., Fahd, K., Patil, S. and Baarimah, S.O., (2019). "Development of Artificial Intelligence Models for Prediction of Crude Oil Viscosity".
25. Ikiensikimama, S. S. (2009). *Reservoir Fluid Property Correlations*, Chi Ikoku Petroleum Engineering Series, IPS Publications, Port Harcourt.
26. Andrade, E.N. da C. And Group, N. P., 1930. The viscosity of liquids. Nature 125 (3148), 309–310
27. Hadavimoghaddam, F., Ostadhassan, M., Heidaryan, E., Sadri, M. A., Chapanova, I., Popov, E., Cheremisin, A. and Rafieepour, Rafieepour S. (2021). "Prediction of Dead Oil Viscosity: Machine Learning vs. Classical Correlations", https://doi.org/10.3390/en1404930.
28. Oloso MA, Khoukhi A, Abdulraheem A, and Elshafei M. (2009). "Prediction of crude oil viscosity and gas/oil ratio curves using recent advances to neural networks". In: SPE/EAGE Reservoir Characterization and Simulation Conference, SPE, Abu Dhabi,UAE, 19–21.
29. Makinde, F.; Ako, C.; Orodu, O. and Asuquo, I. (2012). "Prediction of crude oil viscosity using feed-forward back-propagation neural network
(FFBPNN)". Pet. Coal, 54, 120–131.

30. Anadu, F. and Mbachu, I. I. (2023). "Gas Compressibility Factor Prediction Using Machining Learning Algorithmic Protocol for Niger – Delta Gas Reservoir", International Journal of Current Science Research and Review, DOI: 10.47191/ijesrr/V-i10/-16
31. Elsharkawy, A M (1998). "Modeling the properties of crude oil and gas systems using RBF network". In: SPE Asia pacific oil and gas
32. Naseri, A., Yousefi, S.H., Sanaei, A. and Gharesheikhlou, A.A., (2012). "A neural network model and an updated correlation for estimation of dead crude oil viscosity'. Brazilian J. Petrol. Gas 6 (1), 31–41. https://doi.org/10.5419/bjpg2012-0003..jk,l,
33. Omole O, Falode O. A. and Deng A D. (2009). "Prediction of Nigerian crude oil viscosity using artificial neural network". Pet Coal 151:181–188
34. Adeeyo, Y.A., and Saaid, I. M., (2017). "Artificial neural network modelling of viscosity at bubblepoint pressure and dead oil viscosity of Nigerian crude oi"l. In: SPE Nigeria Annual International Conference and Exhibition, pp. 95–106. https://doi.org/ 10.2118/189142-ms.
35. Al-amoudi, L.A., Salem, B., Fahd, K., Patil, S., Baarimah, S.O., 2019. Development of Artificial Intelligence Models for Prediction of Crude Oil Viscosity.
36. Sinha, U., Dindoruk, B., Soliman, M., 2020. Machine learning augmented dead oil viscosity model for all oil types. J. Petrol. Sci. Eng. 195, 107603. https://doi.org/ 10.1016/j.petrol.2020.107603.
37. Ghorbani, B., Ziabasharhagh, M. and Amidpour, M. (2014). "A hybrid artificial neural network and genetic algorithm for predicting viscosity of Iranian crude oils". J. Nat. Gas Sci. Eng., 18, 312–323
38. Duggle, N. (2023). Introduction of Artificial Intelligence A Beginner's Guide Art Materials , Simple Learn.
39. Terra, J. (2023). Exploring Intelligent Agents in Artificial Intelligent
40. White H. (1989): "Learning in Artificial Neural: A Statistical Perspective". Neural Computer., 1:425–464.
41. Zhoa, C. Y. Zhang, H.X Liu, M.C, Hua Z.D., and B.T Fan, "Application of Support Vector Machine (SVN) for Prediction Toxic Activity of Different Data Sets", Toxicology 217, pp. 105-119, 2006.

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