RESEARCH ARTICLE OPEN ACCESS

Gas- Oil Ratio Prediction Using Machine Learning Procedures for Niger Delta Region

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Abstract:
The laboratory measurement of Gas-Oil Ratio (GOR) is highly expensive and time consuming, hence the use of predictive models like empirical correlations, equation of state and artificial intelligent tools. The solution gas–oil ratio (GOR) is the quantity of gas dissolved at reservoir pressures in reservoir fluids. This study adopted two machine learning procedures of Artificial Neural Network (ANN) and Support Vector Machine (SVM) to predict GOR. A total number of 852 data set was obtained from PVT report from Niger-Delta, out of which, 70% (596) were used to train the models, 15% (127) for testing and 15% (127) for validation. Quantitative and qualitativeanalysis were carried out to compare the performance and reliability of the new developed machining learning models with some selected empirical correlations. The result revealed that the Artificial Neural Network performed better than the Support Vector Machine (SVM) as well as some common selected GOR correlations.ANN performed better than other evaluated tool with the best rank of 0.139, highest correlation coefficient of 0.98, Mean Absolute Error (E_a) of 0.41, with a better performance plot, followed by Support Vector Machine model with correlation coefficient of 0.95, Mean Absolute Error (E_a) of 0.163 and the rank of 0.1616. Obomanu and Okpobiri (1947) performed better than other evaluated empirical correlations with the Rank of 0.1751 and correlation coefficient 0.95.This study recommends Obomanu and Okpobiri (1947) correlation to be used to predict GOR for Niger Delta region in absence of this new intelligent tool developed in this research.The new developed Artificial Neural Network model can potentially replace the empirical models for gas-oil ratio predictions for Niger Delta region for quick predictions and higher accuracy.

Keywords — **Artificial Neural Network, Gas-Oil Ratio, Support Vector Machine, Machine learning Algorithm, Statistical Analysis**

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I. INTRODUCTION

The PVT (pressure-volume-temperature) fluid properties play a crucial role in the analysis and understanding of petroleum reservoirs. PVT correlations are commonly used to estimate fluid properties such as saturation pressure, solution gas-oil ratio, formation volume factors (for oil, gas, and water), fluid viscosities, and fluid compressibility when laboratory measurements are unavailable [1]. The phase and volumetric behaviour of petroleum reservoir fluids is referred to as PVT, and it involves the analysis of gas, oil, and reservoir brine properties. Equations of state (EOS) and correlations are used to predict PVT properties in absence of experimental measurement. Equations of state methods are based on the fundamental principles of thermodynamics, while correlations are developed by fitting available regional data [2]. These properties can be obtained from a laboratory experiment using representative reservoir fluid samples. However, they are not always available because the cost of conducting PVT laboratory experiment repeatedly on an oil system is huge and the interpolation severity associated with reading tables and charts is unavoidable [3].

Among those PVT properties, Gas-oil-Ratio (GOR) is our primary interest in this study. The solution gas–oil ratio (GOR) is the quantity of gas dissolved at reservoir pressures in reservoir fluids [4]. It can also be described as the ratio of the gas volume that comes from the produced oil at atmospheric pressure measured in standard cubic feet (SCF) to the volume of oil produced after the dissolved gas has evolved from it at the surface, measured in STB (Fig. 1). The gas-oil ratio (GOR) serves as a dynamic indicator, providing insights on the quantity of gas that is dissolved within the oil at varying depths and pressures. Solution gas-oil ratio is one of the most notable components of PVT correlations that has a very major impact on the oil viscosity, the compressibility of oil, oil formation volume factor and used also for calculating the in-situ total reservoir fluid rate. These correlations utilize basic PVT properties which are temperature, pressure, gas specific gravity, oil API and solubility that are easy to be measured experimentally in the laboratory.

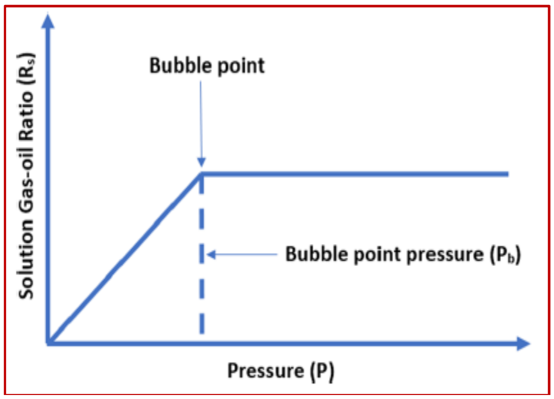

Fig. 1. Typical Solution GOR relationship with Pressure

Many researchers such as [5], [6], [7], [8], [9],[10],[11], [12], [13], [14],[15],[16] have developed empirical models that predicts Gas- Oil Ratio. [13] and [14] are indigenous gas- oil ratio correlations for Niger Delta regio. Standing was the first author that presented GOR empirical equation in 1947. He used 105 experimentally measured data from California crude oil and natural gases. The developed correlation depends on reservoir bubble point pressure, specific Gas gravity, API gravity, and temperature.

After the development of [5] GOR correlations, several authors had tended to improve or proposed new empirical correlations for GOR.[7]correlation was developed through the study of 45 reservoir fluid samples that were obtained from the North Sea crude. Thecalculated solution gas-oil ratio depends on API gravity, reservoirpressure and temperature, and specific gas.[13]developed two correlations for estimating gas-oil ratio and oil formation volume factor for Nigerian crude oils samples. The authors used 503 data points sets from 100 Nigerian reservoirs in the Niger Delta region. They used [8] bubblepoint pressure correlation form in the development of their predictive models. This correlation will also be used in assessing the performance and behaviour of the new machine learning models for this study.[14] in their research work developed two correlationsfor predicting bubble point oil formation volume factor and bubble pointsolution gas–oil ratio using MATLAB and Excel Solver platform. They used 250 data set from Niger-Delta in developing the new models. They reported that their new models performed better than the PVT industry correlation with a Rank of 3.4 for bubble point Oil formation volume factor and 9.6 Rank for Bubble point solution gas oil ratio. [14] is one of selected correlation to be used in evaluating the performance of the new intelligent models since it was developed using Niger -Delta data. [15] did evaluation study on GOR and OFVF correlations on a regional basis. The region investigated include the Middle East, Central and South America, North America, Africa, and Asia. The results showed that[5] and [7] gave better performance than other GOR correlations evaluated based on AARE for the full data range utilized. The authors also developed universal new empirical correlation for the GOR. [15] presented the list of gas- oil ratio correlations and their main features as they appeared in open literature.

Recently, artificial intelligent based models have become a hot topic inengineering applications and are efficiently applied in manyPetroleum and Gas engineering calculations. Examples of some of these artificial intelligent tool are random forest (RF), lightgbm, Extreme Gradient boost, artificial neural network, Support Vector machine,Super Learner andneuro-fuzzy inferencesystem. Lately, researchers like [16], [17],[18], [19],[20],[21],[22] and[23]have adopted the use of artificial intelligent/machine learning in predicting the PVT reservoir properties.

[16] 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. [21] used adaptive neuro-fuzzy inferencesystem (ANFIS) machine learning approach to develop a model that predicts gas-oil ratio below the bubble point. The authors use a total number of 376 data point from Sudanese oil fields. Mohammed and his team reportedtheir proposed ANFIS model performed better than other gas-oil ratio evaluated correlations with an average absolute percent relative error of 10.60%and a correlation coefficient of 99.04.

[20] utilized three machine learning Artificial NeuralNetwork (ANN) models, Functional Networks (FNs) and Support Vector Machines (SVMs)to predict the oil–gas ratio for volatile oil and gas condensate reservoirs. The modelswere developed based on17,941 data points at the ratio of 70% for training, 15% for validation, and 15% for testing.Results obtained using these techniques showed that the ANN model predicted the oil–gas ratio for volatile oil withan average square correlation coefficient of 0.9999 and an average relative error of 0.15% while FNs predicted volatile gas-oil ratio with anaverage correlation coefficient of 0.9635 and an average relative error of 27.6%. The authors concluded that SVMs gave the best resultswith an average correlation coefficient of 0.9990 and an average relative error of 0.12%. The results concluded that ANNand SVM artificial intelligent performed better Functional Networks (FNs) for the data set investigated. From the open literature, not much work has been done on solution gas- oil ratio using artificial intelligent tools for Niger – Data region hence, the study focuses on developing a machine learning algorithm for prediction of gas-oil ratio for Niger Delta region.

II. 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 analysing 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 ([24]; [25]).

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.

A. *Support Vector Machine*

Support Vector Machine is a type of machine learning algorithm that can be used for classification, regression, and outlier detection. Support vector machine model work by finding a hyperplane that separates the data into two classes with the maximum margin. The margin is the distance between the hyperplane and the closest data points All models for the support vector machine were tested to determine the model that best predict the solution gas/oil ratio. These models include Linear support vector machine model, quadratic support vector machine model, cubic support vector machine model, Fine Gaussian support vector machine model, Medium Gaussian, and Coarse Gaussian support vector machine model.

B. *Artificial Neural Network (ANN)*

Artificial neural networks (ANNs) are a type of machine learning algorithm that is inspired by the structure and function of the human brain. Artificial neural network models are made up of interconnected nodes, called neurons arranged in layers. Each neurons receives and processes information from its inputs, applying a mathematical function (activation function) to generate an output. These outputs are then sent to other neurons in the next layer, forming a complex web of information processing. Artificial neural network models can be trained to perform a variety of tasks, including classification, regression, and forecasting.

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

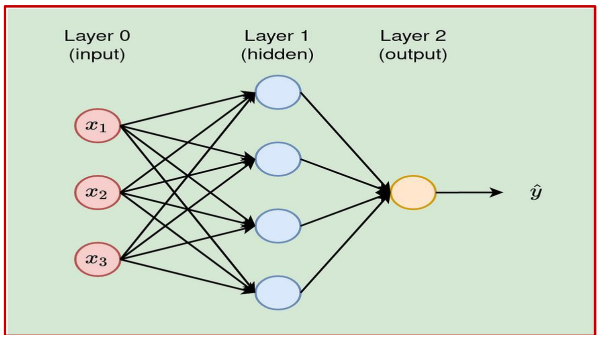

Fig. 3. The three main layers of artificial neural network

III. METHODOLOGY

A. *Data Description*

The functionality of gas-oil ratio with other parameters using machine learning method requires data points that are large. These data points include natural gas gravity of the gas phase, API gravity of the crude oil, temperature of the reservoir; pressure of the reservoir; formation volume factor of the oil and bubble point pressure of the reservoir fluid. These data points are gathered from wells around the Niger Delta region. A total of 852 data points were used for the machine learning models.The range of the data for each parameter are $0.531 < \gamma_g < 1.659$ for specific gas gravity, $17.92 < \gamma_{API} < 84.53$ for API gravity of the crude oil, $36.5 < T_R < 260$ °F for the reservoir temperature; $25 < P_R < 5000\, psia$ for the reservoir pressure, $0.175 < B_o < 1.55\, rb/stb$ for the formation volume factor, $20 < P_b < 4000\, psia$ for the bubble point pressure and $20.0 < R_s < 1150.7\, scf/stb$ for the gas oil ratio. For all the two machine learning models developed in this study, the data were divided into three set; 70% for training while 15% is for both testing and validation**.** This data will be subjected to further analysis such as normalization, cleaning, preprocessing etc. to make it fit for the model development. Table 1 shows the summary of mean, maximum and minimum values for solution gas oil ratio data used. Tables 2 and 3 show the summary of mean, maximum and minimum values for the Train and test solution gas oil ratio data used.

Table 1. Summary of mean, maximum and minimum values for solution gas oil ratio data used in this study.

PVT Properties	Mean	Minimum	Maximum
Gas gravity	0.760	0.531	1.659
API Gravity	76.60	17.92	240.87
Reservoir Temperature (°F)	175.27	36.50	260.00
Reservoir Pressure (psia)	3065.31	25.00	5000.0
Oil formation Volume factor	0.212	0.175	1.55
Gas-Oil Ratio R_s (scf/stb)	290.98	20.0	2046.0

Table 2. Summary of mean, maximum and minimum values for Train solution gas oil ratio data used in this study.

Parameter	Minimum	Maximum	Mean	Standard Deviation
Gas Gravity	0.531	1.09	0.6547	0.0841
oil API	23.654	84.531	49.861	1.689
Reservoir Temperature (°F)	36.5	255	167.33	27.942
Oil Formation Volume Factor (rb/stb)	1.0074	1.5506	1.843	0.0943
Bubble-Point Pressure (Psia)	815	6560	3106.23	1094.11
Solution Gas-Oil Ratio (Scf/Stb)	15.3	1150.7	284.01	178.83
Reservoir Pressure	95	5000	1335.69	8457.74

Table 3. Summary of mean, maximum and minimum values for Test solution gas oil ratio data used in this study.

Parameter	Minimum	Maximum	Mean	Standard Deviation
Gas Gravity	0.56	1.467	0.6637	0.1555
oil API	18.553	67.515	38.147	11.5446
Reservoir Temperature (°F)	122.3	200	148.75	17.939
Oil Formation Volume Factor (rb/stb)	0.175	1.395	1.1037	0.1107
Bubble-Point Pressure (Psia)	35	3215	896.44	785.56
Solution Gas-Oil Ratio (Scf/Stb)	4	511	151.48	126.493
Reservoir Pressure	67	4415	1954.41	1232.34

B. 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.

C. Modelling Procedure

Two machine learning algorithms (ANN and SVM) were employed in developing the new Gas Oil Ratio 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:

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.

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. 1 and 2.

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

(O) Target data = [GOR] (2)

Data Point Division:The total size of the data pointapplied in this study is 852. The data set was divided into three parts which are training, validation, and testing. The models were trained with 70% (596) of the data points, 15% (127) was used for validating the model and 15% (127) was used for testing the trained models.

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 ofits popularity in high level of accuracy and thecapacity to differentiate everywhere with a positive slope.

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

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

where T is a threshold or transfer value

Method of simulation: The two methods applicable are supervised and unsupervised learning. This work used supervised learning approach for the SVMmodelling. 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 unlabelled 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 [26] and [27].

d. 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 modelled as a constraint optimization problem with the function formulated as;

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

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 [28].

Performance plots were used for qualitative screening. It is a graph of the predicted versus measured gas compressibility data with a 45° 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°.

IV. RESULTS AND DISCUSSION

After the training of the experimental data using ANN and SVM machine learning algorithms, the trained models were tested with 127 (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 models. The predictions and performance of the two new intelligent models were compared with data from the field and the estimations from other gas-oil ratio empirical correlations like [13], [14], [7] and [5]. These empirical correlations were carefully selected having reported by many researchers of their excellent performance in predicting gas-oil ratio. [13] and [14] are gas-oil ratio correlations developed precisely for Niger-Delta Region.

The results of the statistical assessment adopted in this research are presented in Table 3 and Fig. 3 for all gas-oil ratio 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 0.1391, mean absolute error of 0.141 and best correlation coefficient of 0.98. The support vector machines regression algorithm predicted the gas-oil ratio with the rank value of 0.1616, mean absolute error of 0.158 and correlation coefficient of 0.95 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 [13] and [14] which are indigenous correlations performed better than the foreign ones which are [7] and [5]. The trend of the locally developed correlations is expected because correlations performed better in region of their originality. [13] performed better than other evaluated correlations with the rank value of 0.1751, mean absolute error 0.231 and correlation coefficient 0.95 followed by [14] with the rank value of 0.190, mean absoluteerror of 0.263 and correlation coefficient of 0.961. This study recommends [13] correlation to be used in predicting gas-oil in absence of machining learning model developed in this study for Niger Delta region.

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 gas-oil ratio for Niger Delta region in terms of root mean squared error, absolute average percent error, standard deviation, correlation coefficient and Rank.

TABLE 3. Statistical Accuracy of Gas-Oil Ratio for Different Machining Learning Algorithm and Empirical Correlations Using Niger-Delta Data

AUTHORS	%MSE	%MAE	%SRE	%SAE	R	Rank
ANN	0.183	0.141	0.241	0.162	0.98	0.139
SVM	0.163	0.158	0.215	0.271	0.95	0.162
Obomanu and Okpobiri (1987)	0.159	0.231	0.192	0.192	0.95	0.175
Ikensikimama and Ajienka (2012)	0.193	0.263	0.194	0.192	0.96	0.190
Glaso (1980)	0.297	0.240	0.201	0.204	0.94	0.199
Standing (1947)	0.213	0.264	0.286	0.237	0.94	0.217

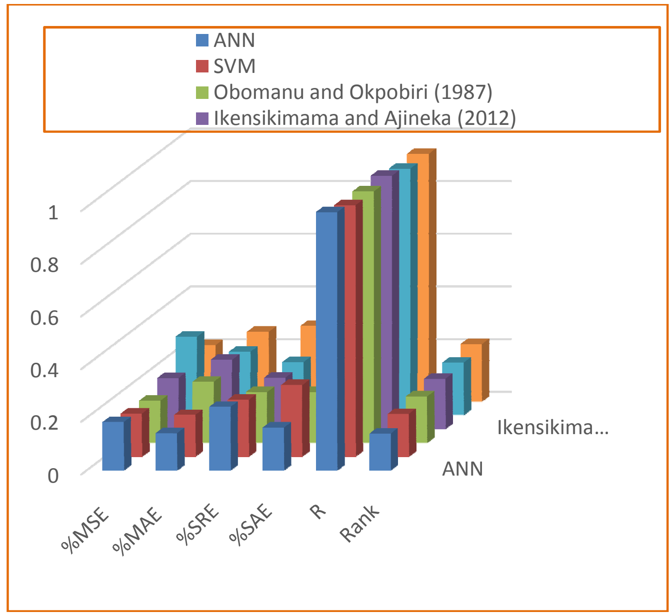

Fig. 3. Comparison of the Statistical Accuracy for Different Machine learning and correlations using GOR Niger -Delta Data

Figs. 4 to 7 illustrate cross plots of the predicted versus experimental gas-oil ratio values for training and test data for the two 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 gas-oil ratio for Niger-Delta region of Nigeria.

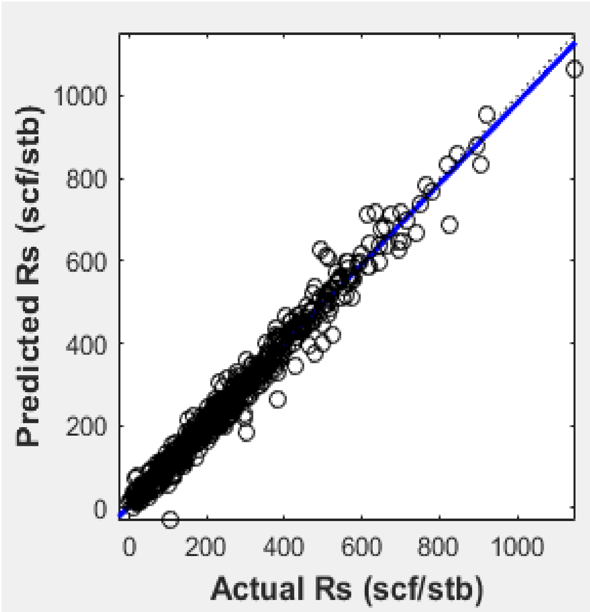

Fig. 4. Artificial Neural Network Cross-Plot for the Train Data

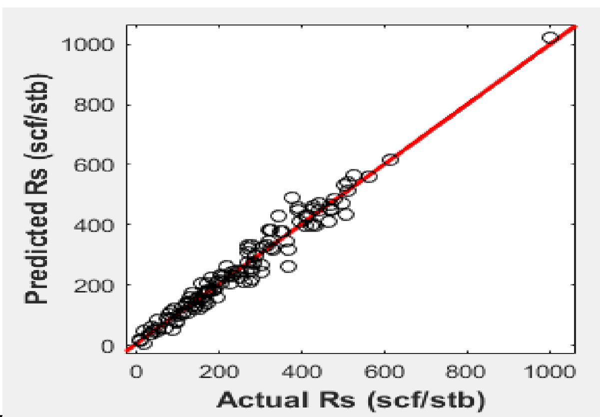

Fig. 5. Artificial Neural Network Cross-Plot for the Test Data

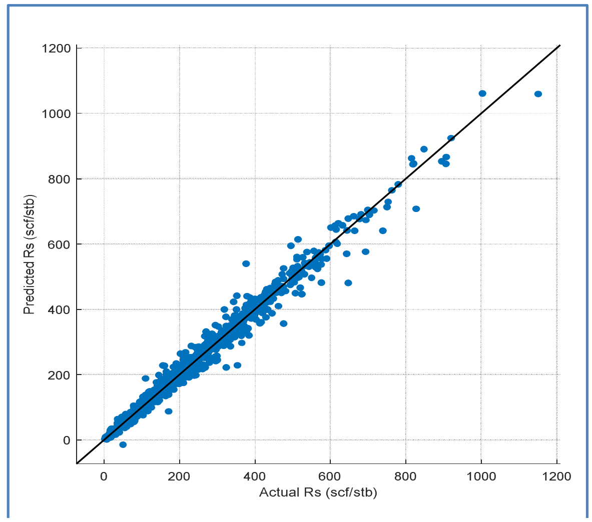

Fig. 6. Support Vector Machine Cross-Plot for the Train Data

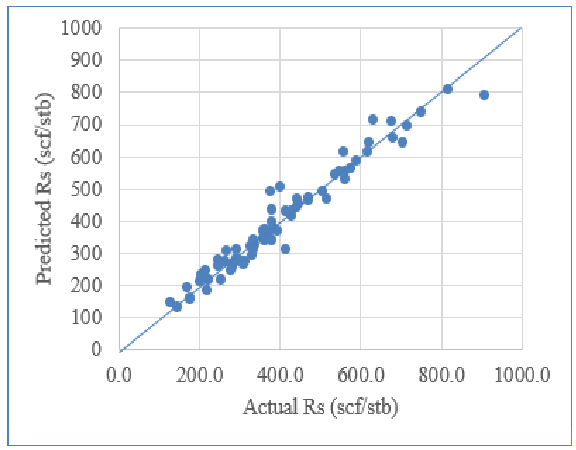

Fig. 7. Support Vector Machine Cross-Plot for the Test Data

IV. CONCLUSIONS

This study demonstrates the application of two machine learning algorithms Artificial Neural Network (ANN) and Support Vector Machine (SVM) to forecast solution gas-oil ratio using 852 data set from Niger Delta Region. The study showed that ANN is a good promising tool that can predictsolution gas-oil ratio followed by support vector machine for the data set used. Two machine learning algorithms developed in this study performed better than the empirical correlations developed for Niger Delta and two of the best foreign GOR equation for the statistical parameter used. The adoption of Machine learning procedures in predicting PVT properties is very important because it increases the accuracy as well as to reduce the cost of experimental measurements.

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