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Prediction of Solution Gas - Oil Ratio using Extreme Gradient Boosting Machine Learning Protocol for Niger Delta Region

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Abstract Determination of solution gas–oil ratio (GOR) is a very important requirement that helps in multiple production engineering and reservoir analysis issues. Gas-oil ratio is 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). Before now, some empirical correlations existed that determines the solution gas–oil ratio however, they still prove unreliable due to the applied assumptions and their specification to operate only under a particular range of data. In this research, Extreme gradient boosting (XG Boost) is used to develop an accurate and dependable model to predict gas-oil Niger Delta. 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 qualitative statistical analysis were carried out to compare the performance and reliability of the new developed machining learning models with some selected gas-oil ratio empirical correlations. The proposed Extreme gradient boost model predicted better than the selected empirical models with the best Rank of 1.1062, average absolute percent relative error of 0.115 and a correlation coefficient of 0.986 surpassing the previously studied correlations.

Keywords Artificial Intelligent, Gas – Oil Ratio, Extreme Gradient Boost, Statical Analysis, Niger Delta

1. Introduction

The solution gas–oil ratio (GOR) is defined as the quantity of gas dissolved at reservoir pressures in reservoir fluids [1]. It is also the ratio of the gas volume that comes from the produced oil (or water) 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 [2]. Heavy oil contains higher quantity of solution gas − oil ratio (Rs) when compared to light oil. Gas-oil ratio is one of the important pressure-volume-temperature (PVT) fluid properties that 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 [3]. The phase and volumetric behavior 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 PVT data [4]. 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 [5]. 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.

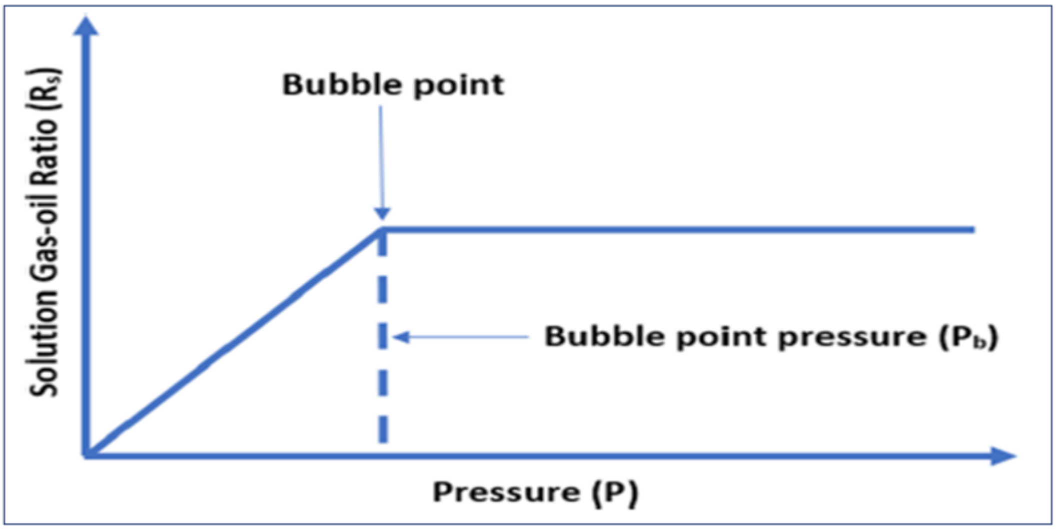

Figure 1: Typical trend of solution GOR versus pressure [6]

The first gas-oil ratio correlation was developed by [7]. Standing utilized 105 laboratory 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 Standing GOR correlations, several authors had tended to improve or proposed new empirical correlations for GOR ([8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18]). [9] developed a correlation for GOR using 45 reservoir fluid samples that were obtained from the North Sea crude. The model depends on API gravity, pressure, temperature, and specific gas. [15] in their study developed two equations for forecasting gas-oil ratio and oil formation volume factor for Nigerian crude oil samples. The authors used 503 data points sets from 100 Nigerian reservoirs in the Niger Delta region. They used [10] bubble-point pressure correlation form in the building the equation. [15] correlation was used in assessing the performance and behavior of the new machine learning models.

[16] developed two PVT correlations, one is for predicting bubble point oil formation volume factor and the other for bubble point solution gas–oil ratio using MATLAB and Excel Solver platform. They used 250 data set from Niger-Delta in developing the new models. Ikiensikimama and Ajienka 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. [18] did evaluation study on GOR and oil formation volume factor for correlations on a regional basis. The region they researched are Middle East, Central and South America, North America, Africa, and Asia. The results showed that [7] and [9] gave better performance than every other GOR correlations evaluated based on average absolute error for data range used. The authors also developed universal new empirical correlation for the GOR. [18] presented the list of gas- oil ratio correlations and their main features as they appeared in open literature.

In this recent time, Artificial intelligent (AL) based models have become very attractive topic in engineering applications and are efficiently applied in many Petroleum and Gas engineering calculations. Random forest (RF), lightgbm, Extreme Gradient boost, artificial neural network, Support Vector machine, Super Learner and neuro-fuzzy inference system are some of the examples of Artificial intelligent models. Lately, researchers like [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29] and [30] have adopted the use of artificial intelligent/machine learning in predicting the PVT reservoir properties. [19] applied artificial neural network backward propagation methods in addition to Levenberg-Marquardt algorithm to predict oil viscosity in Nigeria. They applied 1750 data points to optimize the oil viscosity models for dead and bubble point pressure oil viscosity. [23] used three machine learning of Artificial Neural Network (ANN) model, Functional Networks (FNs) and Support Vector Machines (SVMs) to predict the oil–gas ratio for volatile oil and gas condensate reservoirs. They models were developed based on 17,941 data points at the ratio of 70% for training, 15% for validation, and 15% for testing. The results obtained reveals that using these techniques showed that the ANN model performed better than Functional Networks (FNs) and Support Vector Machines (SVMs).

Through the literature, it can be found that Artificial Neural Network (ANN) model has gained ground but recently, some authors have started investigating other artificial intelligent as to address the shortcomings of ANN tool in predicting PVT properties. Lately, some researchers have started to investigate new machine learning algorithm such as XG Boosts, Neuro-Fuzzy Inference System (ANFIS), random Forest, Supper learn and Lightgbm etc rather than Artificial Neural Network. [24] used 2247 PVT data points both from light and heavy oil to forecast viscosity of the dead oil. The authors 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 revealed that the Super-Learner algorithm showed high performance compared to other used algorithms. [25] used adaptive neuro-fuzzy inference system (ANFIS) machine learning approach to develop a model that predicts gas-oil ratio below the bubble point. Mohammed and his team used a total number of 376 data points from Sudanese oil fields. They reported their 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. [26] 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). The authors reported that the best functional parameter for dead oil viscosity are temperature and API gravity and for the bubble point oil viscosity, API gravity, dead oil viscosity 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 reported that among all the empirical oil viscosity accessed their new ensemble SVR model gave better prediction than other existing oil viscosity model evaluated by the statistical parameters adopted. They also reported that error margin associated with dead oil viscosity is high.

[27] 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. [28] 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 with a 17.17 average absolute per cent error. [29] utilized Extreme Gradient Boosting (XG boost) intelligent tool to estimate dead oil viscosity for Niger Delta Region. A total number of 263 data set was obtained from PVT report from the region, out of which, 70% were used to training, 15% for testing and 15% for validation. They carried out quantitative and qualitative analysis as to compare the performance and reliability of the new developed XG Boost algorithim with some selected empirical correlations. The result showed that the new developed machine learning model outperformed some selected common dead oil viscosity correlations with the best rank of 0.127, highest correlation coefficient of 0.98, mean absolute error (Ea) of 0.151 and with a better performance plot. [30] adopted two machine learning procedures of Artificial Neural Network (ANN) and Support Vector Machine (SVM) to predict GOR for Niger Delta region. The authors used a total number of 852 data set which was obtained from PVT report from Niger-Delta. From the statistical analysis carried out, Mbachu and Peter revealed that the Artificial Neural Network performed better than the Support Vector Machine (SVM) as well as some common selected GOR correlations examined. ANN performed better than other evaluated tool with the best rank of 0.139 with the highest correlation coefficient of 0.98. It can be shown from the open literature that oil and gas industry still have an interest to develop models that can predict gas-oil ratio for proper reservoir fluid management and monitoring. Considering these points, the main aim of this study is to use XG Boosts machine learning algorithm to predict gas-oil ratio using Niger Delta data.

2. Extreme Gradient Boosting (Xg Boost)

Extreme Gradient Boosting also known as XG Boost is the machine learning algorithm adopted in this study. Machine learning is major aspect of Artificial Intelligence (AI) that gives it capability to learn a pattern. Extreme Gradient Boost is scalable, distributed gradient-boosted decision tree (GBDT) machine learning library that helps to understand data and make better decisions [31]. The learning process is achieved by using algorithms to discover patterns and generate insights from the original or measured data they are exposed to (Fig. 2). It provides parallel tree boosting and is the leading machine learning library for regression, classification, and ranking problems.

The XG Boost algorithms builds on supervised machine learning, decision trees, ensemble learning, and gradient boosting.

Supervised machine learning uses algorithms to train a model to find patterns in a dataset with labels and features and then uses the trained model to predict the labels on a new dataset's features Fig. 2

Decision trees create a model that predicts the label by evaluating a tree of if-then-else true/false feature questions and estimating the minimum number of questions needed to assess the probability of making a correct decision. Decision trees can be used for classification to predict a category, or regression to predict a continuous numeric value.

A Gradient Boosting Decision Trees (GBDT) is a decision tree ensemble learning algorithm similar to random forest, for classification and regression. Ensemble learning algorithms combine multiple machine learning algorithms to obtain a better model. Both random forest and GBDT build a model consisting of multiple decision trees. The difference is in how the trees are built and combined. The term "gradient boosting" comes from the idea of "boosting" or improving a single weak model by combining it with several other weak models to generate a collectively strong model. Gradient boosting is an extension of boosting where the process of additively generating weak models is formalized as a gradient descent algorithm over an objective function. Gradient boosting sets targeted outcomes for the next model to minimize errors. Targeted outcomes for each case are based on the gradient of the error (hence the name gradient boosting) with respect to the prediction. GBDTs iteratively train an ensemble of shallow decision trees, with each iteration using the error residuals of the previous model to fit the next model. The final prediction is a weighted sum of all the tree predictions. Random forest "bagging" minimizes the variance and overfitting, while GBDT "boosting" minimizes the bias and underfitting.

XG Boost is a scalable and highly accurate implementation of gradient boosting that pushes the limits of computing power for boosted tree algorithms, being built largely for energizing machine learning model performance and computational speed. With XG Boost, trees are built in parallel, instead of sequentially like GBDT. It follows a level-wise strategy, scanning across gradient values and using these partial sums to evaluate the quality of splits at every possible split in the training set.

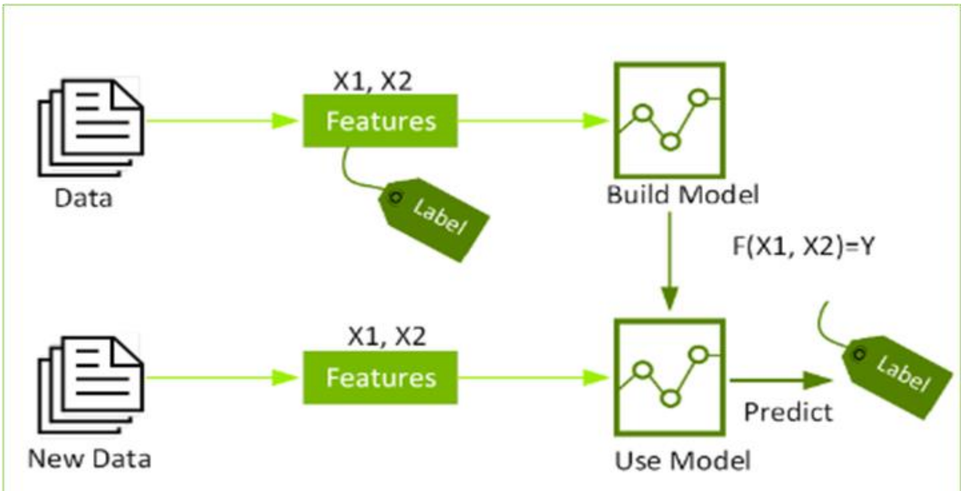

Figure 2: Machine learning Process

3. Methodology

3.1 Data Description

The data used in this study was the same data set used by Mbachu and Peter (2024). The good performance of gas-oil ratio with other parameters using machine learning method requires data points that is large. These data points include natural gas gravity, API gravity, reservoir temperature, reservoir pressure, formation volume factor, 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, $67 < P_b < 6560\, psia$ 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 training 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	84.53
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 Training solution gas oil ratio data used in this study

Parameter	Minimum	Maximum	Mean	Standard Deviation
Gas Gravity	0.5650	1.290	0.6647	0.0845
oil API	28.750	85.86	49.623	1.721
Reservoir Temperature (ºF)	36.50	255.00	167.33	27.942
Oil Formation Volume Factor (rb/stb)	1.0074	1.5506	1.843	0.0943
Bubble-Point Pressure (Psia)	67.00	6560.0	3106.23	1094.11
Solution Gas-Oil Ratio (Scf/Stb)	15.30	1150.70	284.01	178.83
Reservoir Pressure (Psia)	95.00	5000.0	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	0.5660	1.668	0.6686	0.1595
oil API	18.553	82.25	38.147	11.5446
Reservoir Temperature (ºF)	122.30	200.00	148.75	17.939
Oil Formation Volume Factor (rb/stb)	0.1750	1.3950	1.1037	0.1107
Bubble-Point Pressure (Psia)	35.000	3215.0	896.44	785.56
Solution Gas-Oil Ratio (Scf/Stb)	4.000	511.00	151.48	126.493
Reservoir Pressure	67.00	4415.0	1954.41	1232.34

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 Modeling Technique

Extreme gradient Boost (XGBoost) was used to predict the gas-oil ratio using the quadratic extreme gradient function procedure with MATLAB (2021) version.

The procedure involves the importation of input and output data into the MATLAB environment using the import command. The input parameters are gas gravity, oil formation volume factor, API, Reservoir temperature and pressure, oil formation volume factor and bubble-point pressure while output parameter is gas-oil ratio (GOR).

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;

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

Subject to

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

With

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

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 the rank (Z), (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. 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 [32].

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 experimental data using XG Boosts machine learning algorithms, the trained model was 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 trained model. The predictions and performance of the new artificial intelligent tool was compared with data from the field and the estimations from other gas-oil ratio empirical correlations like [7], [9], [14], [15], [16] [18]. These empirical correlations were carefully selected having reported by some researchers of their excellent performance in predicting gas-oil ratio. [15] and [16] are gas-oil ratio correlations developed precisely for Niger-Delta Region.

4.1 Statistical Analysis Result

The results of the statistical assessment as presented in Fig. 3 gives the statistical accuracies for all the gas-oil ratio correlations and XG boost model investigated. The results show that the XG boost algorithm is reliable and efficient in predicting gas-oil ratio as to compare to other existing correlations with the best rank of 0.1063, mean absolute error of 0.115, standard deviation absolute error of 0.112 and the highest coefficient of correlation of 0.986. Table 4 shows the statistical numerical values of all the models accessed with XG boost algorithm. The two indigenous correlations performed better than other evaluated empirical correlations. The trend is expected because correlations performed better in their region of originality. [15] outperformed all other empirical correlations evaluated with the best Rank of 0.1554 with Mean absolute Error (MAE) of 0.201 and correlation coefficient (R) of 0.964 followed by [16] which gave the rank of 0.1633, Mean absolute Error

(MAE) of 0.205 and correlation coefficient of 0.952. This study recommends [15] as a good predictive model for gas-oil ratio for Niger Delta region in absence of the machine learning algorithm developed in this study.
[7], [9], [14] and [18] are foreign correlations accessed. Among these foreign correlations, [9] performed better than other evaluated equations with a rank of 0.1922, followed by [18] and finally [7]. [15] correlation can be used to forecast gas-oil ratio for Niger Delta region in absence of the newly developed intelligent model. This study showed again the supremacy of machining learning in predicting reservoir PVT properties particularly in applying XG Boosts algorithm.

Table 4: Statistical Accuracy of Oil Formation Volume Factor Using Niger-Delta Data

Authors	%MRE	%MAE	%SRE	%SAE	R	Rank
Extreme Gradient	0.236	0.115	0.106	0.112	0.986	0.1063
Obomanu and Okpobiri (1987)	0.161	0.201	0.183	0.183	0.964	0.1554
Ikiensikimama and Ajienka (2012)	0.197	0.205	0.192	0.192	0.952	0.1633
Glaso (1980)	0.277	0.25	0.2	0.203	0.94	0.19215
Slieti et al. (2022)	0.310	0.253	0.221	0.232	0.931	0.20415
Standing (1947)	0.212	0.253	0.277	0.249	0.94	0.2053
Dindoruk and Christman (2004)	0.222	0.271	0.289	0.251	0.91	0.2156

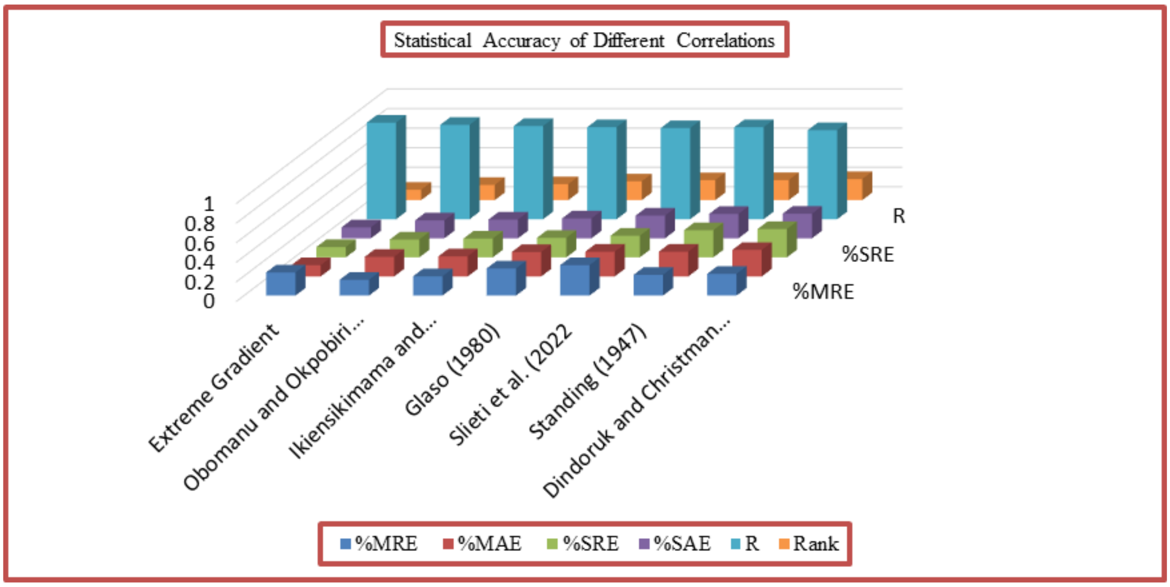

Figure 3: Comparison of the Statistical Accuracy for Different correlations using Niger - Delta Data

4.2 Cross Plot Result

Cross plots of the training, test and validating data as randomly selected by the XG algorithm are illustrated in Figs. 4 to 6. It is a plot of predicted versus measured properties with a 45° reference line to readily ascertain the correlation's fitness and accuracy

Fig. 5 shows the cross plots done using the test data selected by the GX Boost. It shows the tightest cloud of points around the 45° line with very good clusters at low band, indicating the good agreement between the training and test data values. Fig. 6 which is the validation data cross plot indicates that the Extreme Gradient Boost intelligent model does not over fit the data, which implies that it was successfully trained.

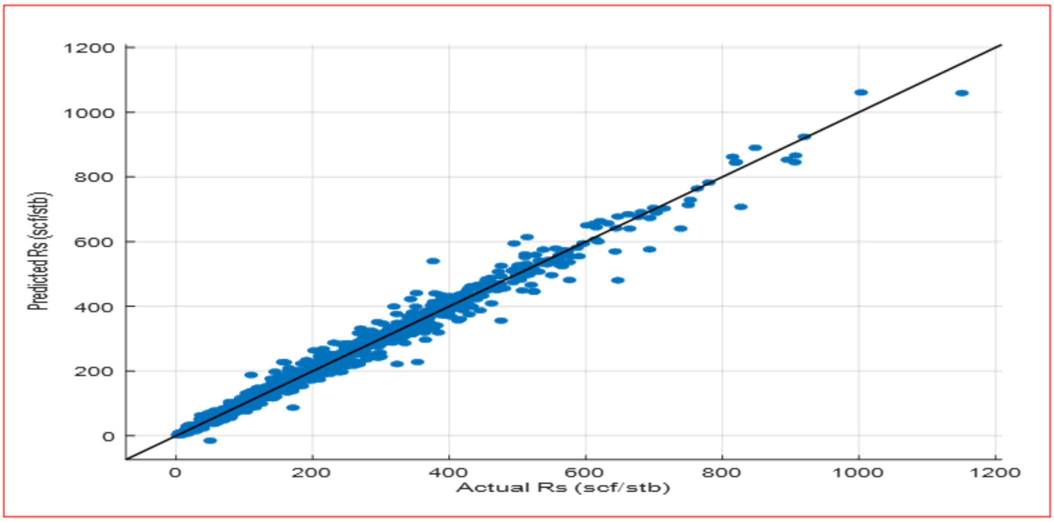

Figure 4: Cross Plot of Extreme Boost (XG) using Training data for GOR

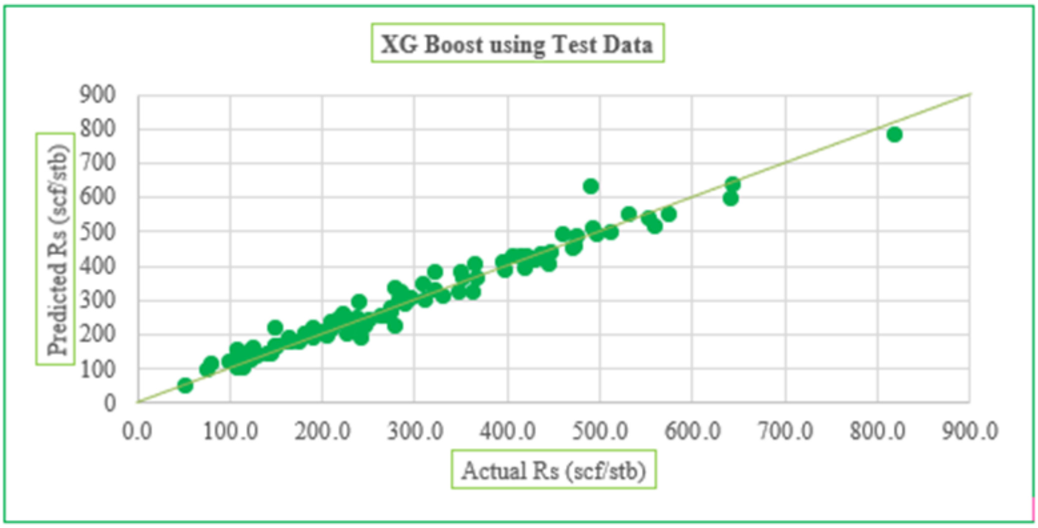

Figure 5: Cross Plot of Extreme Boost (XG) using Test data Model for GOR

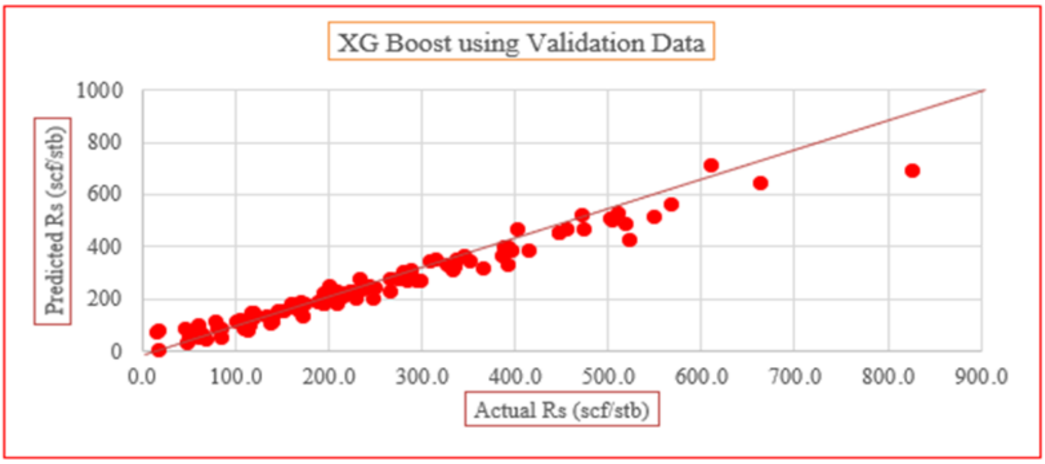

Figure 6: Cross Plot of Extreme Boost (XG) using Validation data Model for GOR

5. Conclusion

The newly developed XG Boots model for predicting crude gas-oil ratio for Niger-Delta region was developed in this study using MATLAB Version 2021. The quadratic extreme imbedded in the Extreme Gradient boost was used to estimate the model parameters. The new intelligent tool outperformed the existing correlations by the statistical parameters used. It shows a best rank with a numerical value of 0.1063, correlation coefficient of 0.986 and superior performance plot as compared to the existing empirical correlations for those regions where the data set was used. This reveals the supremacy of machine learning model that will assist petroleum engineers to predict various reservoir and fluids properties with better accuracy, leading to better a forecasting tool.

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