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Gas Compressibility Factor Prediction Using Machining Learning Algorithmic Protocol for Niger – Delta Gas Reservoir

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ABSTRACT: The gas compressibility factor also known as Z-factor plays an important role in obtaining thermodynamic properties of natural gas reservoir fluid property. Typically, empirical correlations and complex equation of state have been applied to determine this parameter in absence of laboratory measurements. However, high cost of running experimental measurement, poor performance and some limitations associated with these existing correlations have made the researchers to use intelligent models instead. Therefore, this study aimed at adopting support vector machine algorithm to forecast gas compressibility factor and to validate its performance with predictions from Artificial Neural network (ANN) and some existing correlations using statistical and performance plot analysis. A total of 519 data sets from Niger Delta was used in developing the model, out of it, 70 percent was used for training, 20 percent for testing and 10 percent for validation using MATLAB tool. From the statistical analysis result, it was observed that the new developed model did better than other existing methods with numerical value of 0.1997 rank, 0.0009 mean absolute error and 0.98 of coefficient of correlation using the test data. The cross plot of the support vector machine model gave the tightest cloud along 45^{o} reference line. The residual (error) associated with the performance was impressive which was done to observe the distribution and the interval at which the error is minimal.

KEYWORDS: Gas Compressibility Factor; Machining Learning, Niger- Delta, Support Vector Machine; Statistical Analysis.

1. INTRODUCTION

The increasing demand for crude oil as major source of energy, the technological and environmental concerns associated with its production and consumption have drawn attention toward natural gas. The natural gas consumption generates fewer pollutants and greenhouse gases [1]. Critical insight into the behavior of natural gas property is very important in reservoir engineering calculations. Fluid properties are directly involved in all flow and volumetric calculations for both the upstream and downstream zones of the petroleum industry. Some of the natural gas fluid properties are gas compressibility factor, gas density, gas viscosity and gas isothermal compressibility etc. Gas compressibility factor is the focal point in this study.

At low pressure and temperature conditions, gas molecules have fewer interactions and collisions, and behavior can be considered ideal. However, at a higher pressure or temperature, the collision and interaction of the molecules increase, and estimation of reserve and reservoir properties incurs some error hence, the use of gas compressibility factor. Gas compressibility factor is a very useful thermodynamic property of a reservoir fluid which generally adjusts the ideal gas law to account for behavior of real gases. The accurate and reliable estimations of most gas properties, such as formation volume factor, gas viscosity, gas density, and gas compressibility are heavily dependent on the accuracy of the compressibility factor [2]. The standard procedure of acquiring this factor in the industry is to measure it using reservoir samples. The experimental methods of assessing this property at times are very expensive, and consumes time, hence methods such as correlations and equation of state are used to predict this parameter at reservoir pressure and temperature conditions [3].

[4] illustrated a universal compressibility factors chart using concept of pseudo-reduced temperature and pressure properties. The chart predicts gas compressibility factors with negligible quantity of non-hydrocarbons. It is the best chart for compressibility factor used globally by the petroleum industry. Several authors have tried to calculate or represent the Standing and Katz chart [4] in a mathematical form ([5], [6], [7], [8]).

To find relationship between the input and output data gotten from laboratory experiment, a more powerful method than customary empirical equations or complex equation of state are necessary, which is machining learning. Machine learning is a subfield of artificial intelligent which enables machines to learn from past data or experience without being explicitly programmed.

Researchers has documented that the artificial intelligent has the capability to serve petroleum industry to create a more accurate PVT models ([9], [10], [11], [12], [13], [14], [15], [16], [17], [18]). [9] developed an artificial neural network (ANN) for predicting compressibility factors for some pure gases. The artificial neural network model consists of only one hidden layer and an additional input to compute the compressibility factor. In addition, the model cannot compute z-factor for natural hydrocarbon gases model. [12] developed ANN model for gas compressibility factor prediction using Levenberg-Marquardt algorithm backpropagation with sigmoid transfer function. They used four inputs variables of pseudo-reduced temperature, pseudo-reduced pressure, apparent molecular weight, and gas gravity with 30 neurons in the hidden layer. They reported that the ANN model performed better than the existing empirical correlations they evaluated with the best rank of 1.37 and better performance plot.

[16] in their study applied different machine learning (ML) techniques like artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS) to forecast the gas compressibility factor for high and low-pressure ranges. The authors extracted empirical equation from the ANN model developed. It was concluded that the ANN-based model outperformed the other models with a correlation coefficient of 0.99 and an average absolute percentage error of 0.159. [17] proposes the use of Support Vector Machine as a new intelligence framework that predicts PVT properties of crude oil systems and solve most of the existing empirical correlations and Neural Networks drawbacks. [18] did a study on natural gas viscosity prediction using support vector machine algorithm (SVM). The authors used MATLAB SVM module in building the model using 332 data set from Niger Delta region of Nigeria. The new model was assessed with both artificial neural network (ANN) and some of the existing empirical correlations as to ascertain its accuracy. The authors showed that support vector machine gave the best prediction from the statistical analysis. [19] did a work on machine learning using three different algorithm of ANN, SVM and Functional networks to forecast Pressure-Volume-Temperature (PVT) properties of crude oil sample. The outcome indicated that SVR and FN are competitive, but SVM gave the best result. Other successful applications of SVM were also found in the prediction of toxic activity with different datasets [20]. Support Victor Machine gave the highest correlation coefficient when compared with artificial neural network. The literature has proven that Support Vector Machine (SVM) is a powerful predictive tool which is more powerful than ANN and the empirical correlations. In this research, Support Vector Machine (SVM) algorithm was used to build a forecasting tool for gas compressibility factor using data from Niger Delta of Nigeria.

2. ARTIFICIAL INTELLIGENCE/ MACHINING LEARNING/ SUPPORT VECTOR MACHINE

Artificial Intelligence (AI) has been described as the division of data science that deals with the ability of machines to simulate the functionalities of the brain but is limited in cognitive abilities like extrapolating knowledge from unprocessed data [21]. Machine learning is a subset of AI which allows a machine to automatically learn from past data without programming explicitly. The application of AI has gained much ground in both engineering and science over the years by the applications of many paradigms such as neural networks, support vector, genetic algorithms, and fuzzy logic [22]. The machine learning technique is categorized as the usability form of an artificial intelligence that mimics the brain completely.

Support Vector Machine (SVM) is a classification and regression prediction tool that uses machine learning theory to maximize predictive accuracy while automatically avoiding over-fit to the data ([23], [24]). They can also be considered a special case of Tichonov Regularization. The generalization ability of SVMs is ensured by the special properties of the optimal hyperplane that maximizes the distance to training examples in a high dimensional feature space. The tool maps out the input vector x to higher dimensional feature space F by nonlinear mapping, to give and solve a linear regression problem in the feature space as it is shown in Fig.1.

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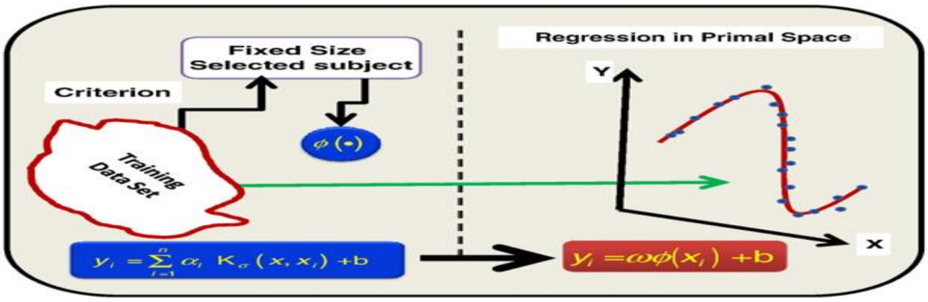

Fig.1. Mapping input space x into high-dimensional feature space [25**]**

The regression approximation estimates a function according to a given data as shown in Equation 1,

$$G = \{(x_i, y_i) : x_i \Re^p\}_i^n = 1 \tag{1}$$

Where,

x_i denotes the input vector. y_i denotes the output (target) value. n denotes the total number of data patterns.

The model aim is to build a decision function, where $\hat{y} = f(x)$ that accurately predicts the outputs $\{y_i\}$ corresponding to a new set of input– output examples, $\{(x_i, y_i)\}$.Using mathematical notation, the linear approximation function is approximated using the following function in Equation 2:

$$f(X) = (\omega^T \varphi(x) + b), \varphi: \Re^p \rightarrow F; \text{ and } \omega \in F, \tag{2}$$

Where,

ω and b are coefficients. $\varphi(x)$ denotes the high-dimensional feature space, which is nonlinearly mapped from the input space b. Therefore, the linear relationship in the high-dimensional feature space responds to nonlinear relationship in the low-dimension input space, disregarding the inner product computation between ω and $\varphi(x)$ in the high-dimensional feature space. [25] gives the full detailed descriptions of support vector machine. This project work seeks to utilize the regression model of the support vector machine to establish a relationship between the independent variables (pseudo reduced temperature and pressure in addition to gas specific gravity) and depend variable (gas compressibility factor).

3. METHODOLOGY

3.1 Data Description

The total number of 519 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 Pseudo reduced temperature, Pseudo reduced pressure and gas specific gravity which covers the range of $0.579 \leq \gamma_g \leq 1.152$, $1.372 \leq T_{pr} \leq 1.905$, and $0.196 \leq P_{pr} \leq 8.985$. Tables 1 and 2 show the maximum, minimum, mean, and standard deviation values for both training and test data sets used for this study.

Table 1. Summary of maximum, minimum, mean, and standard deviation for training data used in this study.

Input Parameters	Mean Values	Standard Deviation	Minimum Values	Maximum Values
Gas Specific Gravity (γ_g)	0. 72311	0.083675	0.579144	1.1515
Pseudo Reduced Temperature (T_{pr})	1.6543	0.08367	1.372118	1.905046
Pseudo Reduced pressure (P_{pr})	3.7254	2.0238	0.1959	8.9854

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Measured Gas Compressibility Factor (Z)	0.8939	0.06159	0.716	1.28

Table 2. Summary of maximum, minimum, mean, and standard deviation for test data used in this study.

Input Parameters	Mean Values	Standard Deviation	Minimum Values	Maximum Values
Gas Specific Gravity (γ_g)	0.6928	0.06638	0.5798	0.9155
Pseudo Reduced Temperature (T_{pr})	1.6748	0.06809	1.387	1.8774
Pseudo Reduced pressure (P_{pr})	2.3895	0.8171	0.8321	5.7926
Measured Gas Compressibility Factor (Z)	0.868	0.0497	0.725	1.056

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

Support vector machine regression algorithm was used in development of the new Gas compressibility factor using kernel functions with the Radial Basis function (RBF) procedure using MATLAB 9.11 version. The stages involved are as follows.

Stage1- Importation of the data: The input data which are pseudoreduced temperature, pseudoreduced pressure and gas gravity were imported to the MATLAB platform using the import command.

Stage 2 - Selection of right variables: The input and output vectors are represented in form of matrix P and T respectively. This is to arrange a set "P input" vector and "T output" vectors are organized in columns into first and second matrix in the MATLAB workspace as shown in Equations. 3 and 4.

$$\text{(P) Input data} = [P_r, T_r, \gamma_g] \quad (3)$$

$$\text{(T) Target data} = [\text{Z-Factor}] \quad (4)$$

Stage 3 - Data Point Division: The total size of the data point applied in this study is 519. The data set was divided into three parts which are training, validation, and testing. The model was trained with 70% (363) of the data points, 10% (51) was used for validating the model and 20% (103) was used for testing the trained model.

Stage 4 - Function Selection: Imbedded in the support vector machine is a function that is design to estimate the model parameters. This function is called the kernel function. Different kernel function exists, (Linear, Polynomial, Radial Basis, and Sigmoid Functions) (Equations 5 – 8) but Radial Basis Function (RBF) has been the most popular choice of kernel types used in SVM because of its high level of accuracy. This is mainly because of their localized and finite responses across the entire range of the real independent variables. These functions are defined below:

Linear function: $$K(x_i, x_j) = x_i x_j \quad (5)$$

Polynomial function: $$K(x_i, x_j) = (\gamma x_i x_j + coefficient)^n \quad (6)$$

The RBF function: $$K(x_i, x_j) = e^{-\gamma |x_i - x_j|^2} \quad (7)$$

Sigmoid function: $$K(x_i, x_j) = tanh(\gamma x_i x_j + coefficient) \quad (8)$$

Stage 5 - Model Parameters Estimation: The function contains parameters which must be estimated from modelling and simulating the SVM. These constants are Capacity (C) and epsilon (ε). The SVM was modelled such that a search for the model parameters were initiated between the interval of 1 to 100 for capacity (C) and 0.1 to 1.5 for epsilon(ε).

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Stage 6 -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 criteria.

Stage 7- Choosing stopping criteria/Determination of model accuracy: The SVM simulates until a stopping criterion is met, this stopping criterion is chosen based on two factors; Number of iterations (N) and Tolerance (t). Several parameters were used to measure the performance of the model.
Stage 8 - Simulation of support vector machine model: This allows performing additional tests on the model or putting it to work on new inputs.

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;

$$Min\ Rank = \sum_{j=1}^{m} S_{i,j} q_{1,j} \tag{10}$$

Subject to
$$\sum_{i=1}^{n} S_{i,j} \tag{11}$$

With
$$0 \le S_{ij} \le 1 \tag{12}$$

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 10 to 12 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 [26].

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

4.1 Statistical Accuracy Result

The trained support vector predictive machine was tested with 103 data points that was not previously used during training and validation processes. The test data set was selected randomly by the tool to show the accuracy and stability of the new developed model. The performance and accuracy of the newly developed support vector machine model tool was tested and compared with predictions from Artificial Neural Network, equation of state and some selected empirical models like [7,8,12]. The selected correlations have been reported by many authors of their good prediction of gas compressibility factor. [27] correlation was used to correct the presence of impurity for all the correlation investigated.

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MatLab. 2020 version was used to simulate [12] ANN model based on their architectural design of four inputs variables of pseudo-reduced temperature, pseudo-reduced pressure, apparent molecular weight, and gas gravity with 30 neurons hidden layer. The algorithm for the ANN gas compressibility factor model was Levenberg-Marquardt, backpropagation with sigmoid as the transfer function. The support vector machine model performed better than other evaluated models with the best rank of 0.1997, Mean Absolute Error (E_a) of 0.0009 and correlation coefficient (R) of 0.98 (Table 3). Table 3 shows the numerical values of all the models investigated in this study.

Table 3: Statistical Accuracy of Gas Compressibility Factor

Authors	MRE	MAE	SER	SAE	R	Rank
Dranchuk and Abou-Kassem (1975)	0.0153	0.098	0.032	0.074	0.91	0.2386
Azubuike et al. (2020)	0.0064	0.0739	0.0302	0.0892	0.93	0.234
Beggs and Brills (1973)	0.0032	0.0628	0.0247	0.0451	0.95	0.2259
Artificial Neural Intelligent (ANN)	0.0013	0.0364	0.0301	0.0152	0.95	0.2114
This Study (SVM)	0.0019	0.0009	0.02	0.0011	0.98	0.1997

Fig. 2 presents the graphical statistical evaluation result for all the gas compressibility factor correlations and ANN model investigated for quick assessment. The results show that the support vector machines regression algorithm has proved reliability and efficient performance as to compare with other existing correlations and ANN model. For all the correlations assessed, the statistical indices show that [8] has the best rank with MRE and MAE of 0.0032 and 0.0628 respectively, which agrees with the study of ([12], [28]). [7] correlation has the second-best prediction of gas compressibility with MRE and MAE of 0.0153 and 0.098 respectively. The overall evaluation with the artificial intelligence shows that support vector machine algorithm has the best prediction of the gas compressibility factor with highest rank followed by ANN model of [12]. The order of the statistical accuracy in predicting gas compressibility for the correlation follows ([8], [7], [28]) (Fig. 2).

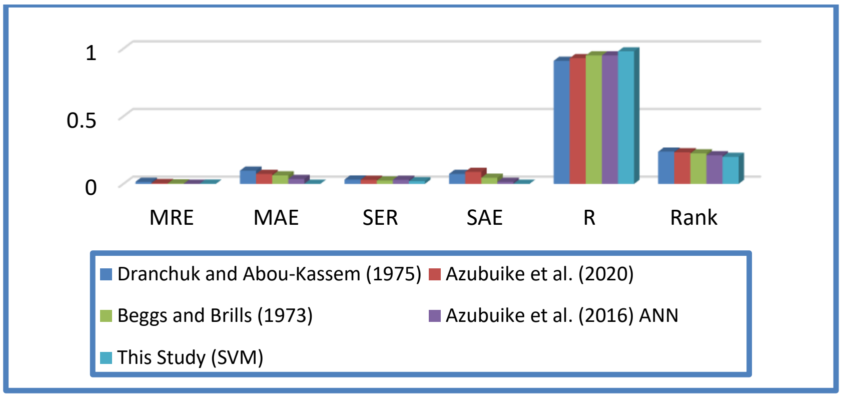

Fig. 2 Statistical Accuracy for the Different Empirical, ANN Models and Support Vector Machine

4.2 Performance Plot Results

Performance plots for all the correlations investigated were obtained to ascertain the behavior of the correlations in predicting the measured gas compressibility factor (Figs. 5 to 6). Fig. 6 shows the closeness of the point to the perfect line or 45º line, followed by prediction from ANN (Fig. 3.) Indicating that Support vector machine model gives good prediction among the correlations studied.

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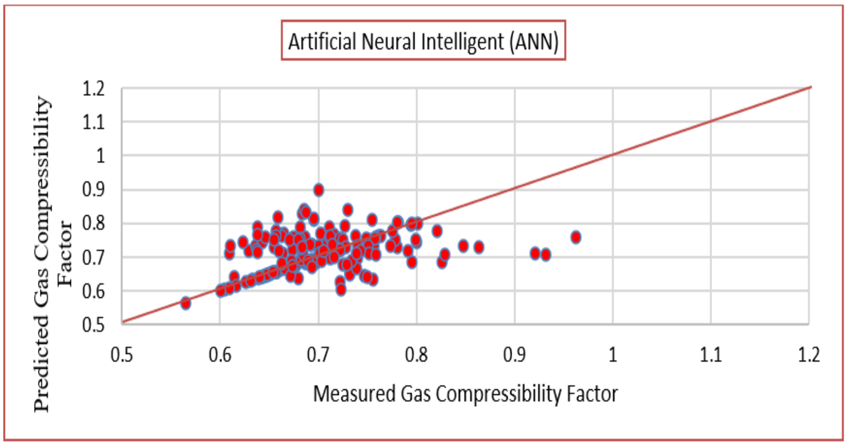

Fig. 3. Performance Plot for Artificial Neural intelligent Gas Compressibility Factor correlation

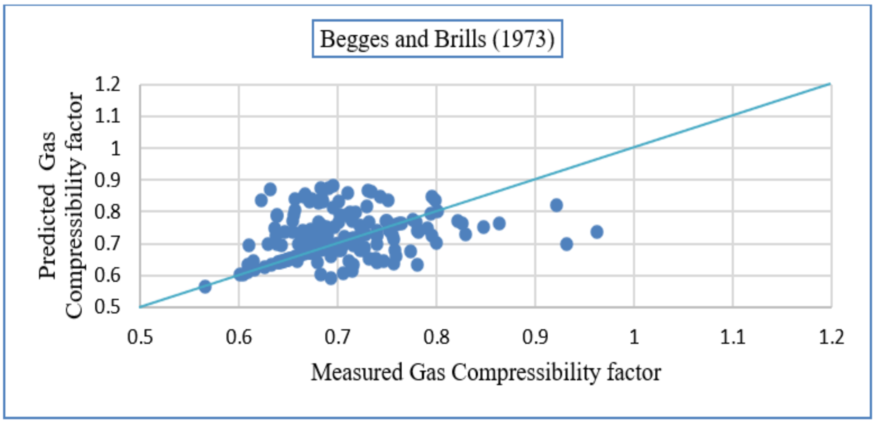

Fig.4 Performance Plot for Beggs and Brill (1973) Gas Compressibility Factor correlation

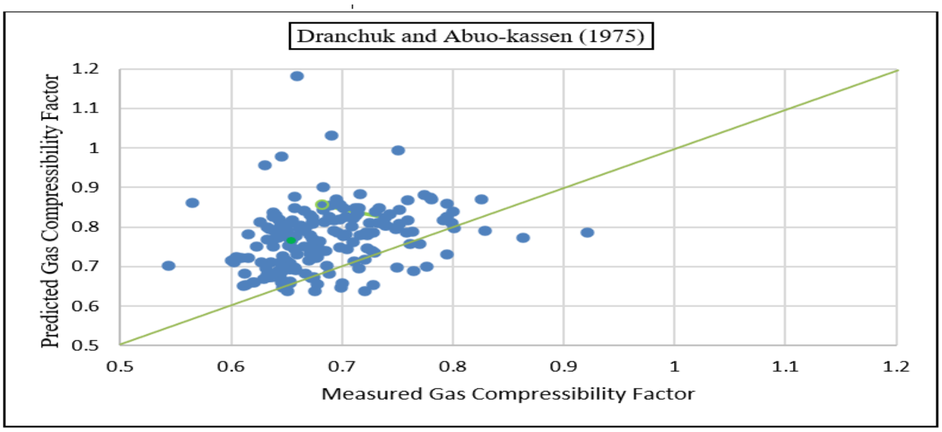

Fig. 5. Performance Plot for Dranchuk and Abuo- Kassen (1975) Gas Compressibility Factor Correlation

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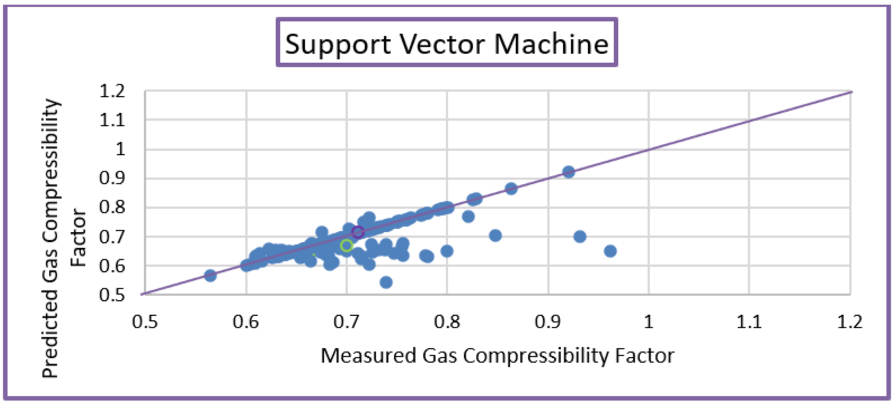

Fig. 6. Performance Plot for Support Vector Machine (This Study)

4.3 Residual and Performance

The residual (error) associated with the performance of the RSVM model were also determine from the simulation. It was done to observe the distribution and the interval at which the error is minimal. Figs. 7 and 8 show the residual in the performance of the model for the observed and predicted values. The error values associated with observed values (Fig. 7) is very low within the range of -0.05 to 0.02 for Z factors values of 0.8 to 0.98 which is impressive considering the mean values for both test (0.868) and training (0.8939) data. It was observed form Fig. 8 that the residual values are scattered around the zero line for the predicted Z factor values from 0.83 to 1.05, indicating that the RSVM model will predict very well for all values of the input parameters since the test data has the maximum value 1.056.

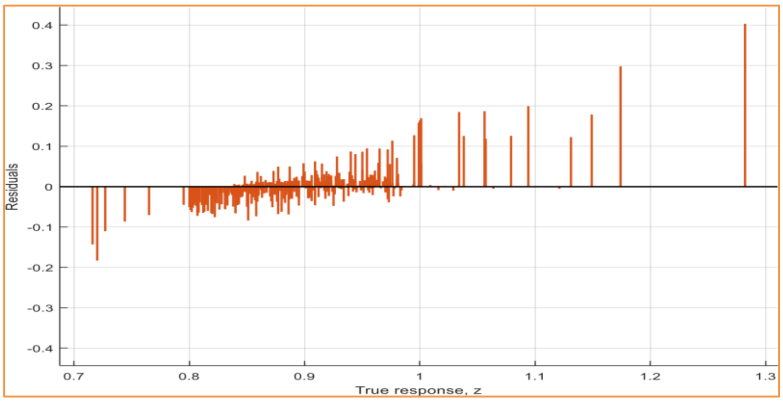

Fig. 7. Residual of the RSVM Model with Experimental Values

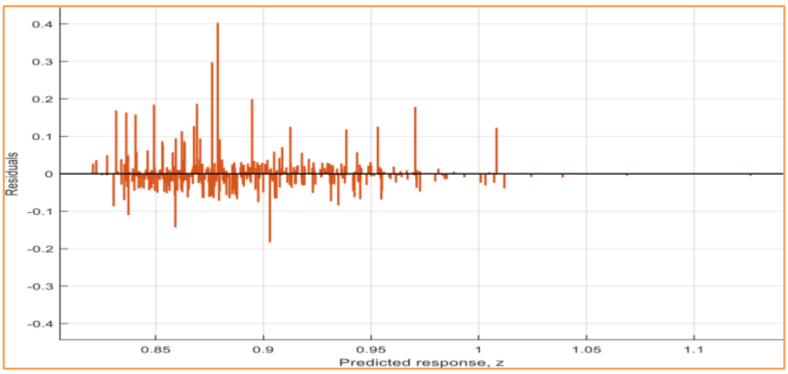

Fig. 8. Residual of the RSVM Model with Predicted Values

5. CONCLUSION

The development of the predictive model in this work was done using regression support vector machine (RSVM) which is a subclass of artificial intelligence. All the algorithm in the RSVM were simulated with their different kernel function, but cubic SVM algorithm and cubic kernel function was found to be far better than the other algorithm in predicting gas compressibility factor for this study. The new model utilized an advantage of using extra input parameter of specific gravity, which helps in enhancing its accuracy rather than the normal use of pseudoreduced temperature and pressure. The support vector machine model is valid at these input parameter ranges of $0.579 \le \gamma_g \le 1.152$, $1.372 \le T_{pr} \le 1.905$, and $0.196 \le P_{pr} \le 8.985$. The performance of the model can also be improved when more data is available.

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