Development of Efficient Empirical Models for the Prediction of Oil Well Fracture Pressure Gradient

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Abstract: Evaluation of fracture pressure gradient during oil well drilling has been best achieved in the past using the leak-off test. This study however, utilized artificial intelligence techniques involving Hunter Point-Artificial Neural Network (HP-ANN), Multivariate Regression (MVR), and Adaptive Neuro-Fuzzy Inference System (ANFIS) to develop a prediction model for fracture pressure gradient based on the input parameters of pore pressure, vertical depth, fracture pressure, and overburden pressure. The dataset used for training the models were extracted from the works of Akinbinu 2010 and Udo et al. 2020. The three models' prediction performance was compared with existing literature models using RSME, MAE, and R2 error analysis indicators. The HP-ANN model was found to have the highest prediction accuracy for oil well drilling fracture pressure gradient. Using the optimum HP-ANN model weights and the biases, an empirical mathematical equation was extracted for the prediction of Fracture pressure gradient. Along these lines, the created HP-ANN models can be utilized to predict the Fracture pressure inclination of an oil well for practical purposes.

Keywords: *oil well drilling; Fracture pressure gradient; Artificial Neural Network; Artificial Neural Network model equation*

1. INTRODUCTION

Drilling is the creation of holes into the earth's crust such that the capped oil-bearing zone can easily release its confined fluid, the drilled hole likewise create a pathway for the flow of fluid from the oil well reservoir to the surface. According to [1], mud weight control plays an important function in well-drilling technology to prevent mud losses and lost circulation during drilling. [1] noted that one of the ways by which fracture gradient is evaluated during drilling is by measuring the maximum weight of the drilling mud. Also, the oil well fracture gradient is the pressure at which oil-bearing rock formation breaks during the drilling operation. The control of mud weight during oil well drilling, cement weight during well cementing, and CO_2 and formation fluids weight during CO_2 injection and storage contribute greatly to well-drilling technology to prevent losses and even lost circulation.

Determining the fracture pressure gradient of the drilled well is a critical hydrocarbon exploration and development program [2-4].

During drilling operation as the drill bit comes in contact with the oil formation rock, the pressure at which the rock breaks/fractures is indicated as the fracture gradient. Well drilling operation with overpressure causes deterioration in drilling safety and may cause borehole influxes, kicks, and even blowouts [5]. [6] used monte carlo simulation in their study to improve wellbore stability and to minimize the challenges such as pipe sticking, wellbore collapse, fluid loss associated with drilling operation. They also noted that geo-mechanical wellbore integrity problems during drilling can occur due to wellbore shear failure or tensile failure which is due to the loading during boring process. Insitu rock, according to [7] is basically subjected to load which generates stresses that can be resolved into three major stresses. During drilling operation, rock formation definitely undergoes fracturing at the point when the borehole pressure exceeds the minimum stress within the rock gain structure. The prediction of fracture pressure gradient had been attempted by several authors from various input parameters in other to attain maximum safety and economic condition whilst drilling an oil and gas well which includes. [8] work identified two methods for borehole vertical and horizontal fracture gradient prediction. [9] work employed Poisson's ratio as the input variable for developing a suitable prediction model for the estimation of rock fracture gradient. To further improve existing empirical models for evaluating oil formation pressure gradient, [10] adopted the equation developed by [11] to propose an empirical matrix stress coefficient. The proposed model has the advantage of quick calculation and the ability to estimate oil formation breakdown pressure using easy outlay input variables. [12] work focused on an exploration well in the development of a fracture pressure prediction model. To modify the [9] model, [12] uses overburden pressure, Pore pressures, and lithology as the parameters trained for the development of new models. [7] developed empirical model for the prediction of fracture pressure gradient using correlation analysis with stepwise multiple regression statistic techniques. In [7] work, the data set recovered from the oil well log was used as the parameters to develop the new proposed fracture pressure gradients models. The research also examined the relationship existing between oil formation pore pressure and the true formation vertical depth. [7] findings indicated that the oil well overburden pressure has a higher influence on the fracture pressure gradient as compared to the effect of pore pressure. The work reveals that, the vertical depth has no significant relationship with pressure gradient. Understanding the variation status of oil well fracture gradient pressure during oil well drilling is important to support safe operation and efficient drilling with proper balancing of subsurface pressure [13]. Although many attempts had been made by several authors including [14-18] to develop prediction models for pressure gradient prediction and well drilling operation optimization, the lack of significant application of artificial intelligence (AI) techniques requires the application of a good fitting model. [19] noted that artificial neural network is one of the soft computing techniques used for developing accurate multivariable prediction models. Applying this approach to developing a proposed model for fracture pressure gradient gives the study a new ground and is commensurate with previous research works. This study is aim at generating a better accurate predicting model using an artificial neural network to train laboratory test results in a bit to eliminate the need for time-consuming and costly on-site tests and analyses.

ANN technique follows the human brain operation principle as it mimics brain capabilities and analysis approach. [19] indicated that atificial neural network models are mathematical models with interconnected processing nodes under pre-specified layers. One basic characteristic of the ANN modeling technique is the ability to perform massively parallel computation on input stimulus (data) and process the data to enable the network to identify an existing relationship, learns and mimics the data relationship by adjusting the strength of the links between neurons which then generalize and give estimates for uncertainty conditions (like frocks) or even incomplete data [20].

According to [21], the successful training of the ANN model requires three intrinsic mathematical components which are the network architecture, activation functions, and learning algorithm.

Fig. 1 shows a typical ANN structure with k layers of input parameters, h number of hidden layers, and a single output layer. In each layer, Pj neurons exist in each hidden layer, with j = 1, 2, 3, n. The neural network initial must be prepared by countless input patterns; this gives an assurance of yielding results in view of the input information pattern. Training neural network models are performed by either supervised or unsupervised learning approaches depending on the developers' adopted techniques [21].

In this study, both approaches were adopted to train the dataset to minimize overfitting and improve the model performance.

Subsequent to preparing the fitting model, the dataset was validated with a portion of the testing datasets. After which the model was tested with new dataset from the first dataset that has not been used initially during the training.

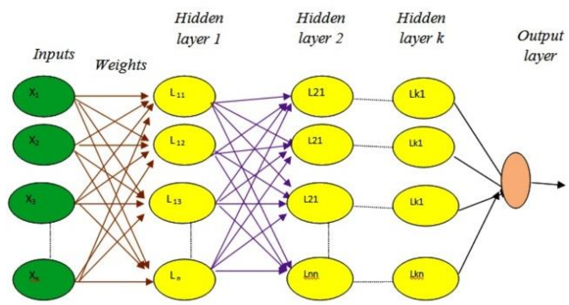

Fig.1: General representation of a typical ANN architecture

Developing a good model basically aims to provide a suitable model equation that expresses an accurate connection between extremely complex input and target datasets by changing the loads and predispositions utilizing a back-proliferation calculation. These datasets are generally arbitrarily separated into three sections at a specific rate.

Onshore drilling operation and well monitoring data on depth (TVD), pore pressure, and overburden pressure were gathered to examine the proximate pressure gradient of the selected well. The results of the monitored depth (TVD), pore pressure, and overburden pressure were used as the input parameters in the proposed models and the pressure gradient as the target output. Several Model architectures and algorithms were adopted for the model development and the optimum model was identified.

Various models' architectures were compared with the existing models and the model with the best prediction performance was proposed in this study for the estimation of oil well fracture pressure gradient.

2. Experimental Investigation

Data used to develop the fracture pressure gradient model were collected from [7] work and additional datasets were gotten from log data. The collected log data from [7] work were evaluated using various standard equations to obtain the equivalent fracture pressure gradient. From the collected log data, the normal compaction observed trend with the overburden stress was measured, and the source rock (shale) velocity trend (Vp) was evaluated and used to calculate the formation pore pressure. To generate values for the pore pressure, the Modified Eaton's equation with e5 was employed as shown in Eq. 1.

The adopted Eaton's Formula for calculating formation pore pressure is given in Eq.1.

$$W_p = P_v - (P_v - S_n)\ (V_{pobs} / V_{pnorm})^5 \qquad (1)$$

The designated parameters are; Pv which denotes the total vertical stress; Vpobs is the observed sonic velocity at varying altitude; Wp is the oil formation pore pressure; Sn represents the hydrostatic pressure; Vpnorm is the drilling sonic velocity when pore pressure is normal. The formation poison ratio was calculated using Eq. 2.

$$\gamma = 12(Npv)/2-1\ (Npvs)/2-1 \qquad (2)$$

Where, γ is the Poisson's ratio, Npv denotes the compression wave velocity from sonic log and Npvs represents the sonic log shear wave velocities.

To calculate the drill well fracture pressure gradient at different depths using Eaton's proposed method, two main parameters used are the computed formation pressure and the poison ration values. Eq. 3 presents Eaton's equation used for calculating fracture pressure gradient.

$$PG = \gamma\ (1-\gamma)\ (Pv - W_p \times Z) + W_p \times Z \qquad (3)$$

Where Pv is the measured formation overburden stress in psi, Wp represents the formation pore pressure in psi, Z is the drilling depth in ft, PG is the calculated fracture pressure gradient in psi/ft and γ denotes the estimated poison ratio from Eq.2.

Eaton's method of fracture pressure estimation was used in this study because of the ability of the model to take into consideration the effect of variation information lithology as the drilling advances. The model achieves this lithology change adjustment through the inclusion of the poisson ratio in the proposed Eq.3 for fracture pressure calculation. The parameters needed for the computation were extracted from several months drilling log records. The required normal compaction trends data and other parameters utilized in calculating formation pore pressure for each drilling operation attempt and fracture pressure gradients were all extracted from the collected well log information. Eqs. 1–3 were used to calculate the pore pressure and formation drilling fracture pressure for each oil well log data. The computer pore pressure value and fracture pressure.

To enable the general application of the proposed models, the dataset was trained and validated using ANN, MVR, and ANFIS and compared with one another.

3 MODEL DEVELOPMENT

3.1 Artificial Neural Network Modeling

ANN modeling processes involve training specific machine architecture to learn from real-life operation datasets in order to simulate the network prediction efficiency. Normally, different training procedures are utilized to track down the appropriate values of weights and biases of the ANN. In this work, optimum training of the network was obtained through Hunter Point ANN techniques. The ANN model was developed on MATLAB© software.

Fifty-Nine (59) gathered datasets were utilized for this project's ANN preparation process. During the training process, datasets obtained from real-life operations are adopted to simulate the machine behavior based on the selected transfer function and learning algorithms. To improve the training efficiency, each generated training weight and bias from each successful simulation is readjusted through backpropagation algorithms.

In preparing the dataset utilized for the development of ANN models proposed in this study, overfitting was avoided through normalization of all the datasets using Eq.4 as proposed in [22].

After every successful training rounds, the developed model was tested with the testing dataset to establish the model prediction performance (Fig. 2).

$$Yi = \frac{2(Di - Dmin)}{(Dmax - Dmin)} - 1 \qquad (4)$$

Where Dmin is the minimum input value in the input dataset, Dmax is the maximum input value in the input dataset, Di is the input value to be normalized, and Yi is the normalized input value result [22].

For each dataset, Total Vertical Depth (TVD), Pore Pressure (PP), and Overburden Pressure (BP) were used as input variables whereas, the corresponding output data (target data) of the input feature data is the Fracture Pressure gradient.

In training the proposed ANN model in this study, 80% of the total Fifty-nine (59) dataset was used as the training data, and 10% were used for validating and testing the ANN model respectively. Therefore, in this research, out of the 59 datasets, 47 data samples were randomly chosen for model development, six (6) data samples were used for validation, while the remaining 6 data samples were used to evaluate the developed ANN models' performance after successive data training. To find a precise ANN model, great boundaries setting was utilized for training and testing the ANN models after propagation training. The parameters setting adopted for the proposed ANN model after the initial weights and biases have been updated after some preliminary experiments are shown in Table 1.

Table 1 Parameter setting for the best ANN model

Parameter	Value
Input layer Neuron	3
Hidden layer Neuron	8
Output layer Neuron	1
Number of Iteration	1000

Two-layer feed-forward network training technique with a linear transfer function in a single hidden layer and a sigmoid activation function in the output layer was adopted for the ANN model training. The model was built with three input layers, the hidden neurons were set to be eight (8) while the neurons in the output layer were one (1) which is the Fracture Pressure gradient that is to be predicted.

After the necessary parameters have been set, the MATLAB© program was launched to train, validate and test the network. Fig. 3 shows the ANN model training structure. For optimization, two ANN training algorithms were considered for this study, the Levenberg-Marquardt (trainlm) and Bayesian Regularization (trainbr) ANN algorithms. These two adopted training algorithms are often known as the fastest ANN backpropagation algorithms. During training, the algorithms often update the weight and bias values according to the Bayesian Regularization and Levenberg-Marquardt optimization respectively.

The Maximum iteration is 1000 but the training process was closed at the 1000th iteration when the validation criteria were met. The training reached the 1000th iteration because over-fitting did not occur during the training process. The datasets for validation were used throughout the learning process to serve as training evaluators and help to terminate the training process once the validation error is minimized

The hunter point training approach was adopted in training the proposed ANN model. To obtain the optimum ANN model, the training process was repeatedly trained with different ANN algorithms and architectures. The predicted accuracy of the five model architectures was examined using MSE and correlation coefficient (R^2) [23].

ANN model weights data and biases are assessed as a vector of factors for the proposed model. The state of every selected ANN training algorithm was assessed using the Root Mean Square Error (MSE) and Coefficient of Correlation (R^2), to evaluate the prediction accuracy of any developed model.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(G_i - P_i)^2 \quad (5)$$

$$R^2 = \frac{\left(n\sum G_iP_i - \sum G_i \sum P_i\right)^2}{\left(n\sum G_i^2 - (\sum G_i)^2\right)\left(n\sum P_i^2 - (\sum P_i)^2\right)} \quad (6)$$

Eqs. 5-6 show the equation for computing RMSE and R^2 respectively, where Pi denotes the predicted value from the ANN and Gi represents the target output. A low RSME value indicates a better model prediction, while a high RSME value indicates a poor model performance. Models giving a high value of R^2 indicate a better accuracy model prediction. Table 2 present the training performance of various ANN algorithms and architectures adopted in developing the proposed ANN models. The Bayesian regularization training algorithm with 3-8-1 architecture had the lowest mean square error (MSE) and the highest R^2 value. The training regression and error histogram of the best ANN architecture is shown in Fig.4.

Table 2 Hunter-Point ANN training performance Assessment Result

Neurons	MSE	R^2	Algorithm
4	0.00248	0.993	Trainslm
4	0.000062	0.998	Trainbr
5	0.00003	0.999	Trainslm
5	0.000088	0.997	Trainbr
10	0.000067	0.998	Trainslm
10	0.000063	0.998	Trainbr
8	0.000177	0.999	Trainslm
8	0.000007	0.99998	Trainbr (Optimum model)

The optimum model was extracted into a mathematical equation using the approach adopted in [22] Eqs. (7-8). Validating the extracted ANN mathematical equation, an additional twenty datasets were utilized and the prediction result was compared with the output of the developed ANN models. The predicted values from the ANN model were compared with the predicted value obtained from Eqs 7-8 to evaluate the accuracy of the mathematically transformed ANN formulas. Fig. 3 shows the comparison of the ANN mathematical equation prediction with the direct ANN model outputs. From Fig.3, it was revealed that the optimum ANN models prediction and that of the extracted mathematical equations are the same.

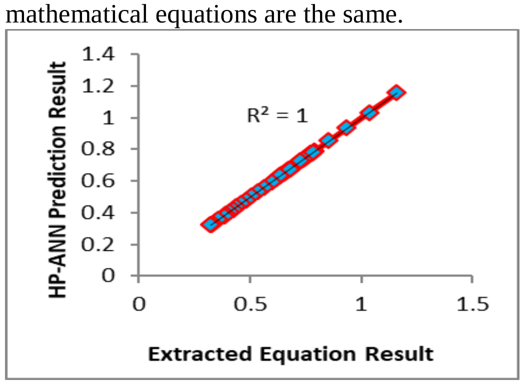

Fig. 3: Relationship between the prediction result of the

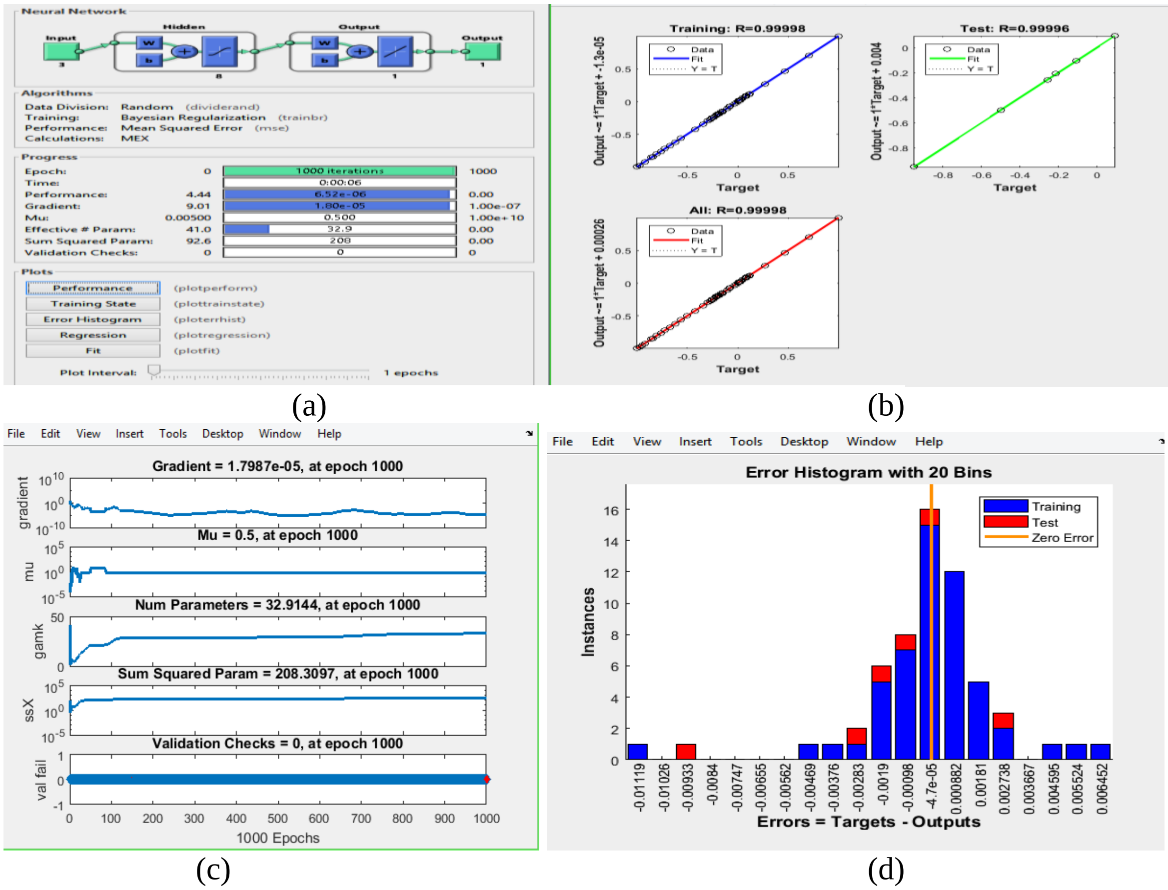

Fig. 2: Optimum model developed: a) Neural Network Training Process, b) regression graph for the optimum ANN model, c) Training state curve, and d) Model error histogram

Table 3 Weights and biases from the ANN model

Weights				Biases; bo=0.7399
w_1			w_2	b_1
3.3298	2.2012	-0.9432	1.2409	0.676
-1.1197	-2.0325	-0.2985	2.9314	-1.287
-0.0344	2.7842	-0.9474	-1.2029	-0.6833
-3.1658	3.8262	0.3553	0.9835	0.9057
7.5982	-3.1848	-4.1789	-3.2171	1.4254
-0.1770	0.54519	1.4954	2.933	1.6912
-1.8754	-2.3814	1.5757	-1.797	0.6740
0.7565	3.4462	-1.1896	-1.3762	-0.207

ANN mathematical equation and the direct ANN model outputs. The weight and bias of the optimum model were extracted and transformed into mathematical equations. Table 3 shows the weights and biases of the most suitable ANN architecture which was then transformed into a mathematical formula as presented in Eqs. (7-8).

$$PG = 0.4178 \tanh (D1+\ldots..+ D8 + 1.533) + 0.7399 \qquad (7)$$

Where; PG is the ANN output (Fracture Pressure Gradient) and D1 to D8 are the output from the hidden layer going into the output layer.

$$D1 = 1.2409 \tanh(3.3299TVD + 2.2012PP - 0.9423BP + 0.6759)$$

$$D2 = 2.9314 \tanh(-1.1198TVD - 2.0314PP - 0.2985BP - 1.2868)$$

$$D3 = -1.2029 \tanh(-0.0344TVD + 2.7843PP - 0.9475BP - 0.6833)$$

$$D4 = 0.9835\tanh (-3.1658TVD + 3.826PP + 0.3554BP + 0.9057)$$

$$D5 = -3.2171\tanh (7.5982TVD - 3.1849PP - 4.1789BP + 1.4254)$$

$$D6 = 2.933\tanh (-0.1771TVD + 0.5452PP + 1.4954BP + 1.6912)$$

D7= -1.797tanh (-1.8754TVD - 2.3814PP + 1.5757BP + 0.6740) –.(8)

3.2 Multivariate Regression (MVR)

As demonstrated by [24], multivariate regression modeling is one of the previous procedures utilized for creating a relationship model for single output variable and multiple-output variable as utilized by [25] for the forecast of fuel elemental composition and by [22] for the prediction of the elemental composition of coal and biomass.

Eq. 9 shows the general Equation used for developing the MVR model.

$$X=K_0 + K_1P_1+ K_1P_1+ K_1P_1+\ldots+ K_nP_n \qquad (9)$$

Where, K0, K1,….., Kn is the model constant, X is the dependent variable, and P1,……, Pn is the independent variable. The MVR model developed in this study comprises three independent variables (Drill depth, pore pressure, and overburden pressure). Eq. 10 shows the MVR model equation developed for predicting fracture pressure gradient.

$$PF=0.00009102PP+0.00006173VP+0.000001D+0.7\quad 7 \qquad (10)$$

3.3 Adaptive Neuro-Fuzzy Inference System

According to [22] and [26] definitions, ANFIS is a soft computing method used for model creation, his system adopts the principle of Fuzzy logic in neural networks. Referring to [27] work, [22] indicate that ANFIS as a fuzzy logic system functions with the concept of a Fuzzy mapping algorithm that replicates and estimates independent and dependent data values through a hybrid learning to develop an optimal distribution of membership function using Tagaki-Sugeno-Kang system.

In this study, to develop a suitable model, a 3-3-3 grid partitioning structure with a five-layer consisting of input, inputtmf, rule, outputtmf, and output layer was created.

A total of Eighty-one rules were created in the developed fracture pressure model as shown in Fig.4. The ANFIS model prediction performance was tested with twenty new datasets. The exactness of the model was contrasted to that of ANN and MVR models.

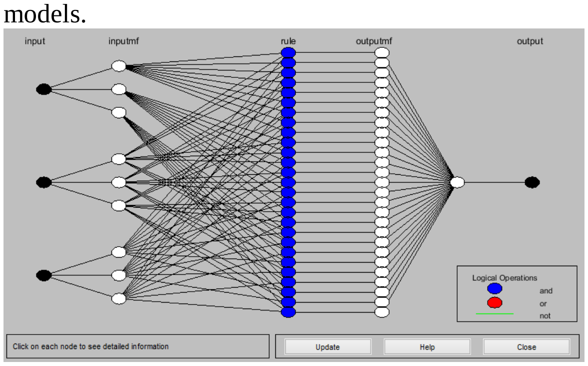

Fig.4: Fracture Pressure Gradient ANFIS prediction model with 3-3-3 grid Structure

4. Model comparison

The three models developed from ANN, MVR, and ANFIS for the prediction of fracture pressure gradient were compared with [4] model as shown in Fig. 5. The R^2 of the model proposed by [4] was 0.705 while the R^2 values of the proposed ANN, MVR, and ANFIS for the prediction fracture pressure gradient are 0.958, 0.675, and 0.757 respectively. Based on this comparison, the proposed models give better predictions than the [4] model except for the MVR.

To decide the performance of the three proposed models, the Root mean square error (RMSE), Pearson relationship coefficient (R^2), and mean average error (MAE) were used to survey the effectiveness of the created models.

As indicated by [22] RMSE is an applied statistical index that shows the model fitness standard deviation of the variation between the predicted and measured values obtained from different models; it is calculated using Eq.11.

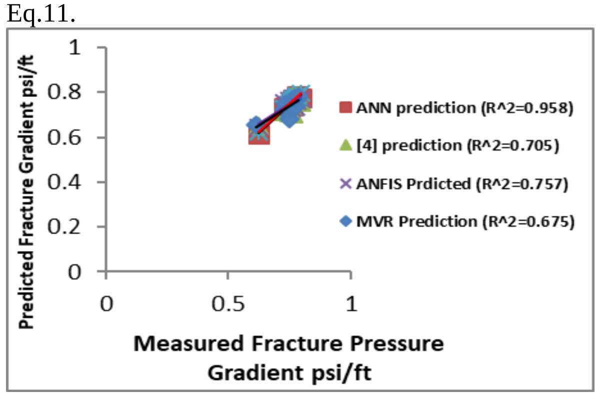

Fig.5: Examination of both measure and the model predicted fracture pressure Gradient

$$RMSE=\sqrt{\frac{\sum_{i=1}^{N}(PVi-MVi)^{\wedge}2}{N}} \qquad 11$$

According to [28], R^2 depicts a quantity index used to evaluate how strong the correlation is between two variables, as shown in Eq. 12.

$$R^2 = [1-\frac{\sum_{i=1}^{N}(MVi-PVi)^2}{\sum_{i=1}^{N}(MVi-Me)^2}] \qquad 12$$

MAE is another broadly embraced indicator measure for model assessments; it expresses the mean of the absolute error, which gives a close impression of the specific prescient value relationship with the actual value. It is determined utilizing Eq.13.

$$MAE=\frac{\sum_{i=1}^{N}(/Me-PVi/)}{N} \qquad 13$$

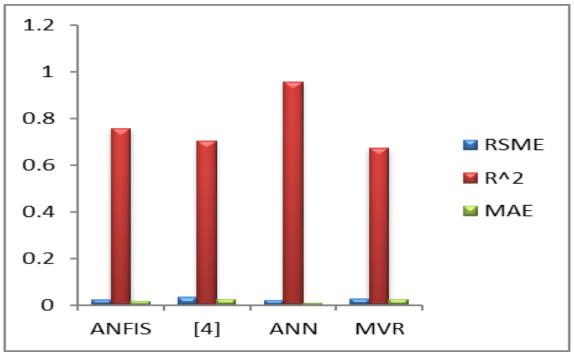

Fig.6 Error analysis of the predicted pressure Gradient with the measured pressure Gradient

The RSME and MAE give a clear level of error between the predicted value and the estimated value. Also, R^2 demonstrates the pace of model prediction accuracy [29]. The consequence of the model exhibition examination is presented in Fig.6. For the RSME examination, ANN has the least value followed by the ANFIS model while the [4] model has the most noteworthy value. The ANN model likewise has the least MAE value while MVR has the most noteworthy value.

In the case of R^2, ANN has the highest while the MVR model has the least. Also, ANN rose had the lowest value as compared to others, with [4] model giving the highest value.

Based on the models performance (error) analysis, it can be inferred that ANN has the highest prediction accuracy and is more suitable for the prediction of oil well pressure gradient.

5. CONCLUSION

The time-consuming and capital-intensive nature of the onsite test approach for fracture pressure gradient measurement is the bottleneck of this method. In view of the difficulty associated with onsite test and measurement of fracture pressure gradient can't at times be gotten by direct estimation, particularly while considering small to medium-size exploration drilling. In an attempt to defeat this constraint, three proposed (ANN, MVR, and ANFIS) models were developed by using onshore drilling activity and well-monitoring data on depth (TVD), pore pressure, and overburden pressure. For the ANN model development, five ANN model architectures with two training algorithms were embraced for the model development. The Bayesian regularization model with a 3:8:1 structure was identified to be optimum. Additional two models were developed with ANFIS and MVR. Error analyses were performed to evaluate the prediction accuracy of all the models, and also to compare them with existing models in the literature using RSME, MAE, and R^2 as the performance evaluation indicator.

The analysis reveal ANN model to have the highest accuracy prediction capacities and can be utilized to appraise fracture pressure gradient for practical purpose. The author's future work will possibly focus on predicting well fracture pressure by artificial intelligence optimization algorithms such as Grey wolf algorithm, and particle swarm optimization algorithm. Besides, some other influential parameters will be added to the independent variables such as rock characteristics and drilling equipments factors.

6. Acknowledgments

The authors wish to express their deep appreciation to Engr. Victor of the Federal University of Technology, Mining Department for fruitful discussions and for reading the early version of the draft.

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