Original Research Article

MODELLING THE EFFECTS OF TEMPERATURE AND PRESSURE ON EQUIVALENT CIRCULATING DENSITY (ECD) DURING DRILLING OPERATIONS USING ARTIFICIAL NEURAL NETWORKS.

ABSTRACT

Incorrect evaluationof equivalent circulating density(ECD)whiledrilling oil and gas wells may result in drilling problems such as lost circulation, kicks,differential pipe sticking etc especially in narrow drilling margins (Joel and Oriji, [1], Vajargah et al, [2]).Due to the incompressible nature of liquids, increase inwellbore pressure will only have appreciable effect on the fluid rheology at higher pressures, whereas a small increase in temperature may cause a decrease in the rheology (Ibeh,[3],Oriji, [4]).One thousand and eleven (1,011)field data obtained from high pressure; high temperature (HPHT) wells were used to developartificial neural networks (ANNs)for this study.Training data were used to train the network while validation data were used to guarantee that the network generalizes at the training stage. Test data were used to evaluate the prediction capability of the developed model.Four error metrics, namely R-square (R^2), mean square error (MSE), root mean square error (RMSE) and average absolute percentage error (AAPE) were used to assess the performance of the developed networks. Forecasts from the testing data indicate theoptimizedECD model produced a prediction accuracy; R^2 of 0.9993, MSE of 0.000265, RMSE of 0.01628 and AAPE of 0.337. The optimized ECD model performed better than existing ECD models in terms of the prediction accuracy and the calculated errors.The developed ECD model will help in improving the ECD prediction during thepre-drill design phase which is quite critical in narrow drilling margin wells.

Key Words: Equivalent circulating density;Artificial neural networks (ANNs); Model; Prediction; high pressure high temperature (HPHT);error metrics.

1. INTRODUCTION

1.1 Overview of Artificial Neural Network (ANN)

ANNs are essentially bio-inspired computational systems that are designed to learn and utilize the knowledge gained to estimate the outputs of a complex system. The basic unit of a neural network is the neuron. These neurons are joined together to create a network capable of solving a complex problem (Behnoud far and

Hosseini, [5]). An ANN comprises three layers namely: the input layer, the hidden and the output layer. The input layer neurons represent the number of input parameters to the network. The inputs are the set of values or features in a dataset required to predict the output. The hidden layer neurons are tasked with the responsibility of feature extraction. The manner in which ANN processes information is as follows: First, each of the inputs (I_1, I_2, I_3) are assigned connection weights (w). These weights are the real numbers that are linked with each input that defines the importance of the input in predicting the output. These inputs are then multiplied by their individual connection weights. The weighted sum of the inputs and connection weights are then combined and a bias term (b) is added to the summation. The essence of the bias is to either increase or decrease the input that goes into the activation function. The summation is passed through a transfer or activation function, and the output is then computed and transferred to another neuron. The activation function essentially introduces non-linearity into the ANN model. Sigmoid transfer function and linear activation function (purelin) are recommended for the hidden and output layers respectively (Mekanik*et al*[6]). This process is depicted in Figure 1.

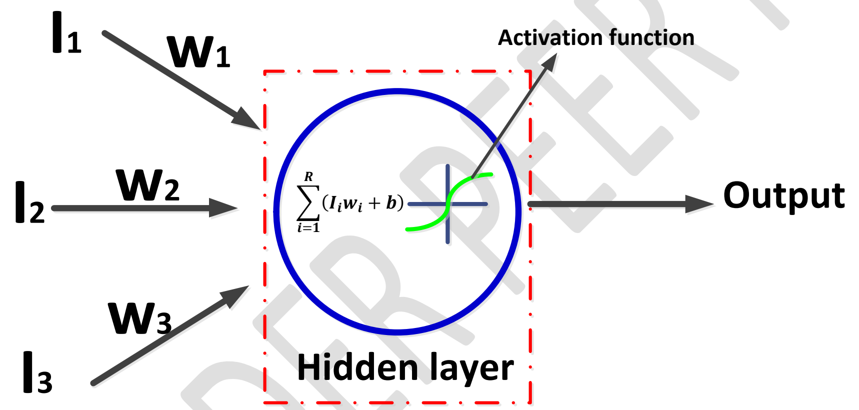

Figure 1: Schematic diagram of an artificial neural network process

The first step of modelling with ANN is the training of the network. Data are processed through the input layer to the hidden layer(s) then all the way to the output layer. In the output layer, the predicted data are compared with the actual data. The difference between the predicted and the actual data is transferred back to the model to update the individual weights between each connection and the biases of each layer. This process is called epoch. In this way, training continues for all the dataset until the average error reduce to certain defined limit (Demuth *et al*., [7]). The performance of the network is equally dependent on the hidden layer neurons; where few neurons lead to under fitting and excessive number of neurons leads to over fitting (Aalst *et al*[8]). The overall correlation between inputs and output for an ANN model is as shown in Equation 1.

$$y_k = f_o\left[\sum_j w_{kj} \cdot f_h\left(\sum_i w_{ji} x_i + b_j\right) + b_k\right] \quad \ldots\ldots 1$$

Where

x is an input vector;

w_{ij} represents the weight from the ith neuron in the input layer to the jth in the hidden layer

b_j represents the bias of jth hidden neuron;

w_{kj} represents the weight from the jth neuron in the hidden layer to the kth neuron in the output layer

b_k represents the bias of kth output neuron

f_h and f_o are the activation functions for the hidden and output neuron respectively.

1.2 High Pressure High Temperature (HPHT) WELLS

Drilling of High Pressure and High Temperature (HPHT) wells is comparatively, a new borderlinein the exploration and development of hydrocarbon deposits (Shadravan and Amani [9]). Highoose Limited [10] stated that a greater risk of failure in HPHT wells still exist due to thehigh stress environment (tension and compression), high operating temperatures, high temperature gradients in thesewells, chemicalaction of well fluid constituents enhanced by the elevated temperatureencountered downhole etc.Due to the incompressible nature of drilling fluids (liquids), an increase in the downhole wellbore pressure will only have appreciable effect on the drilling fluid rheology at higher pressures, whereas a smaller increase in temperature may cause a decrease in ECD (Ibeh, [3], Oriji, [4]). Moreover, one of the critical features of HPHT wells is the existence of narrow drilling windows as well as high bottom hole temperature which poses a number of problems to management of drilling muds at HPHT conditions and well control issues (Auwalu [7]). If these challenges are not well managed, it may ultimately result in ECD-related problems such as lost circulation and kick threats, blowout potentials, differential pipe sticking possibilities, poor drilling fluid hydraulics symptoms, inadequate hole cleaning and cuttings bed accumulation risks (Gamal [12]). Hence, understanding the influence of pressure and temperature on rheological properties of drilling fluids is vital to design drilling fluids that can function optimally in the anticipated downhole, operating conditions. (Rommetveit and Bjorkevoll, [13], Ahmadi, [14]).Current methods in oil and gas industry for estimating ECD relies mostly on the use of high-cost, downhole sensors for real-time measurements of ECD. Majority of this equipment have operational challenges such as elevated pressure and temperature, which may hinder the use of these tools in the desired downhole environment (Abdelgawad, et al, [15]). Deep Learning, which is a subdivision of machine learning (Shruti, [16]) was adopted for this study because of its ability to handle big data and intricate algorithms to build a neural network and determine the relationships between complex variables. Moreover, it can execute complicated computations and make more accurate forecasts while eliminating the need for downhole, electronic tools that may have operational limitations in HPHT environment(Agwu [17] and Abdelgawad, et al, [15]). Furthermore, AI's (artificial lift's) cutting-edge speed reduces the time it would have taken to process vast amount of field data and make more accurate predictions (Agwu, [17], West and Allen, [18]). Hence, artificial neural networks technique, which is a form of deep learning, was adopted for this study for the objective of modelling the effects of temperature and pressure on ECD during drilling operations. Table 1 below shows a summary of recent AI based ECD models developed by previous authors and the model's performance.

Table 1: Summary of recent AI based ECD models.

				Performance of model		
Reference	**AI technique**	**No. of data points**	**Inputs**	**R^2**	**AAPE (%)**	**RMSE**
Abdelgawad et al. [15]	ANN [3 – 20 – 1] ANFIS	2376	mud weight, drill pipe pressure, and rate of penetration	0.985	0.224	NA
Alkinani et al. [19]	ANN [7 – 12 – 1]	2000 wells globally	Flow rate (Q), Mud weight (MW), Nozzles total flow area (TFA) in inch2, Plastic viscosity in cp Revolutions per minute (RPM) WOB in Tons, Yield point inIb/100ft	0.982	NA	NA
Alsaihati et al. [20]	SVM, (RF), (FN)	3567	flow rate (Q), hook-load (HL), ROP, rotary speed (RS), SPP, WOB, surface drilling torque (T)	0.95	NA	0.35
Gamal et al. [12]	ANN [6 – 15 – 1] ANFIS	3570	penetration rate, rotating speed, torque, weight on bit, pumping rate, and pressure of standpipe	0.96	0.3	NA

2. MATERIALS AND METHODS

One thousand and eleven (1,011) field data obtained from HPHT wells (that were drilled in the past) were used to develop artificial neural networks (ANNs) for this study. The subsequentmethods or techniqueswerefollowedto develop the ANNmodels for this research.

2.1 Procedure for Modelling Using Artificial Neural Network

In building a predictive model using ANN based on supervised learning, the steps indicated in Figure 2were observed. First, the data upon being fed into the network is normalized and then split in three parts namely training, validation and testing datasets. While the training dataset was used for learning (i.efit the network weights), the validation dataset was used to adjust the network architecture and the test dataset to assess the generalization performance of the trained network. The network is trained by minimizing an appropriate error function. The error function used is the mean square error. The performance of the network is then compared by evaluating the error function using the validation dataset, and the network having the smallest error is selected.

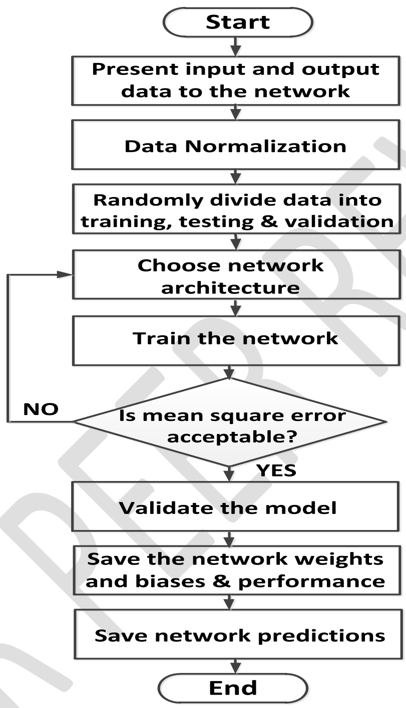

Figure 2: Steps involved in predictive modelling using ANN(Chang et al, 2019)

2.2 Data Normalization

Normalization brings the data sets to fall within the same range of values, helps the process of training to run smoothly, and increases the network's performance. The normalization technique adopted used in this study is the min – max normalization technique.

2.3 Data Collation and Its Features

The data used for this work was obtained from oil and gas wells that had been drilled in the field. The field data comprises 1011 datasets. This dataset consists of eleven input parameters namely;depth, temperature, pore pressure, flow rate, mud weight, average equivalent annular diameter across BHA, average equivalent annular diameter across DP, flow conduit length across BHA, flow conduit length across drillpipe, average annular velocity across BHA and average annular velocity across drill pipe. The output parameter considered is the equivalent circulating density (ECD). Table 2 below shows the nature of the collected data. It gives a statistical description of the input and output variables using statistical measures such as mean, standard deviation, and range.

Table 2: Descriptive statistics of the input and output variables used in modelling ECD.

Database parameter	**Mean**	**Range**	**Standard Deviation**
Depth	11402.7	15042.7	3639.466
Temperature	284.6912	290.9323	67.8557
Pore pressure	8972.161	15051.08	3755.655
Flow rate	472.9805	1160.535	252.1641
Mud weight	13.62774	9.7461	3.318229
Average equivalent annular diameter across BHA	4.453021	19.7205	4.530027
Average equivalent annular diameter across DP	5.950322	21.83	4.948064
Flow conduit length across BHA	469.1674	3868.063	762.1241
Flow conduit length across drill pipe	11271.02	17396.51	4462.084
Average annular velocity across BHA	4.486683	12.52187	3.384304
Average annular velocity across drill pipe	3.345555	12.89989	2.009544
Equivalent circulating density (ECD)	14.23982	11.58622	3.574859

2.4 Parameter Settings for Model Training, Testing and Validation

The settings used for the ANN model is presented in Table 3. By default, the MATLAB software partitions the data into three sets: the training data set (70%), test data set (15%) and validation data set (15%). Training data were used to adjust the weight of the neurons. Validation data were used to guarantee that the network generalizes at the training stage, the testing data is used to evaluate the network after being developed. The stopping criteria are usually established by the preset error indices e.g. mean square error (MSE) or when the number of epochs reaches 1000. For the ANN model, the lowest MSE was used.

Table 3: Parameter settings adopted from Deep Learning (MATLAB) Softwareto develop theANN models.

Parameters	**Value**
Training data set	707 (70% of dataset)
Testing data set	152 (15% of dataset)
Validation data set	152 (15% of dataset)
Number of hidden layers	1
Number of neurons in hidden layer	1 – 20
Activation function (hidden layer)	Tansig
Activation function (output layer)	Purelin

Number of epochs	1000
Architecture selection	Trial and error
Target goal mean square error	10^{-5}
Minimum performance gradient	10^{-5}

In this study, the ANN architecture used to build the model is the feed-forward back propagation method with adaptive weights. In this method approach, data flows in a forward manner from the input to the output layer and the graphs have no loops. Some of the benefits of this gradient-based technique include its efficient implementations, good fine-tuning and faster convergence when compared with other methods.

2.4 Determining the Number of Neurons in the Hidden Layer

Ascertaining the number of neurons in the hidden layer of an ANN is very crucial and has a dominant effect on theANN learning and performance. However, up until now, there has been no universally accepted method for determining it. Although, the universal approximation theorem, states that for any input-output mapping function in supervised learning, there exists a multilayer perceptron with a given number of hidden layer neurons, which is approximately correct. Unfortunately, the theorem gives one no clue on how to find this number. Therefore, the trial-and-error method was employed to find this number.

2.5 Relative Importance of Input Parameters in the Developed ANN model

A viable means of getting insight into a model is to assess its behaviour as one or more of its parameters are varied. This gives an idea as to the importance of the variable to the output of the model. The contribution of each input parameter to the output's prediction defines the relative importance of that variable. Garson's algorithm was used to extract the relative importance of the input parameters from the developed model. To determine whether each input variable in the ECD model developed had significant contribution to its predictive capability, the Garson's algorithm was employed to ascertain this. Increasing numbers of input variables were eliminated (due to the low contribution they have to the predictive capability of the developed model) to build the most optimized ANN models with fewer input variables. The four neural network models developed in this study are the 11-3-1, 7-6-1, 5-3-1 and 3-5-1 ANN architectures. The relative importance of a given input variable can be defined as shown in Equation 2. The Garson's algorithm is a weight-based method, which is used to calculate the input relevance. Equation 2 shows the Garson's algorithm.

$$R_{ik} = \sum_{j=1}^{nh} \left(\frac{|\omega_{ij}||\omega_{jk}|}{\sum_{i'=1}^{ni} \left(|\omega_{i'j}||\omega_{jk}| \right)} \right) = \sum_{j=1}^{nh} \left(\frac{|\omega_{ij}|}{\sum_{i'=1}^{ni} |\omega_{i'j}|} \right) \qquad \text{......} 2$$

Where

n_i and n_h are the number of inputs and hidden units respectively.

ω_{ij} is the weight between input i and hidden units j.

ω_{jk} is the weight between hidden unit j and the output k.

2.6 Model Performance Assessment Methods

To assess the performance and effectiveness of the proposed ANN model, four error analysis benchmarks or error metrics are employed to evaluate the proposed models. The error analysis metrics include: coefficient of determination (R^2), mean square error (MSE), root mean square error (RMSE) and Average Absolute Percentage Error (AAPE). It has to be stated that the R^2 value shows the discrepancy between the actual and predicted data and indicates how close the points are to the bisector in the scatter plot of two variables. RMSE is a statistical measure of the variance of predicted data values around actual data values. The RMSE is said to be a good statistical criterion for model evaluation because the unit of the error is the same as the unit of the measured value. The MSE is the average squared difference between actual values and predicted values (Adamowski *et al.*, [22]). A perfect model is described by an R^2 of 1 and an RSME and MSE of 0. The mathematical descriptions of the four statistical metrics are shown in Equations 3 to 6.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_{actual} - y_{predicted}\right)^2}{\sum_{i=1}^{N}\left(y_{actual} - \bar{y}\right)^2} \quad \ldots\ldots 3$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_{actual} - y_{predicted}\right)^2 \quad \ldots\ldots 4$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_{actual} - y_{predicted}\right)^2} \quad \ldots\ldots 5$$

$$AAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_{actual} - y_{predicted}}{y_{actual}}\right| * 100 \quad \ldots\ldots 6$$

For Equations 3 to 6,

N = number of data samples,

y_{actual} = the actual or experimental values,

$y_{predicted}$ = values predicted by the developed model

$\bar{y}$ = average of the actual or experimental values.

3. RESULTS AND DISCUSSION

3.1 Outcome of the Assessment of Relative Importance of Input Parameters

The results from the parametric importance of the input variables using Garson's method are shown in Figure 3 below. As seen in the Figure, mud weight has the highest effect on ECD estimation while flow conduit length of drill pipe has the least effect on it. This is in accord with the findings by Badrouchi et al. [22] wherein they posited that mud density is a vital parameter necessary for ECD computation. From Figure 3, six other input parameters had significant effects on ECD namely: depth, temperature, pore pressure, average equivalent annular diameter across drill pipe and average equivalent annular diameter across BHA and average annular velocity across drill pipe. This is in harmony with the observations made by Galliano [23] wherein he posited that flow geometry, fluid resistance to flow, pressure of flow, fluid density, fluid temperature and acquired solids are the main factors that affect ECD. The true vertical depth (TVD) of the well affects the equivalent circulating density (ECD) as well. The pressure drop and ECD increase with the vertical distance that the drilling mud must travel before reaching the surface.

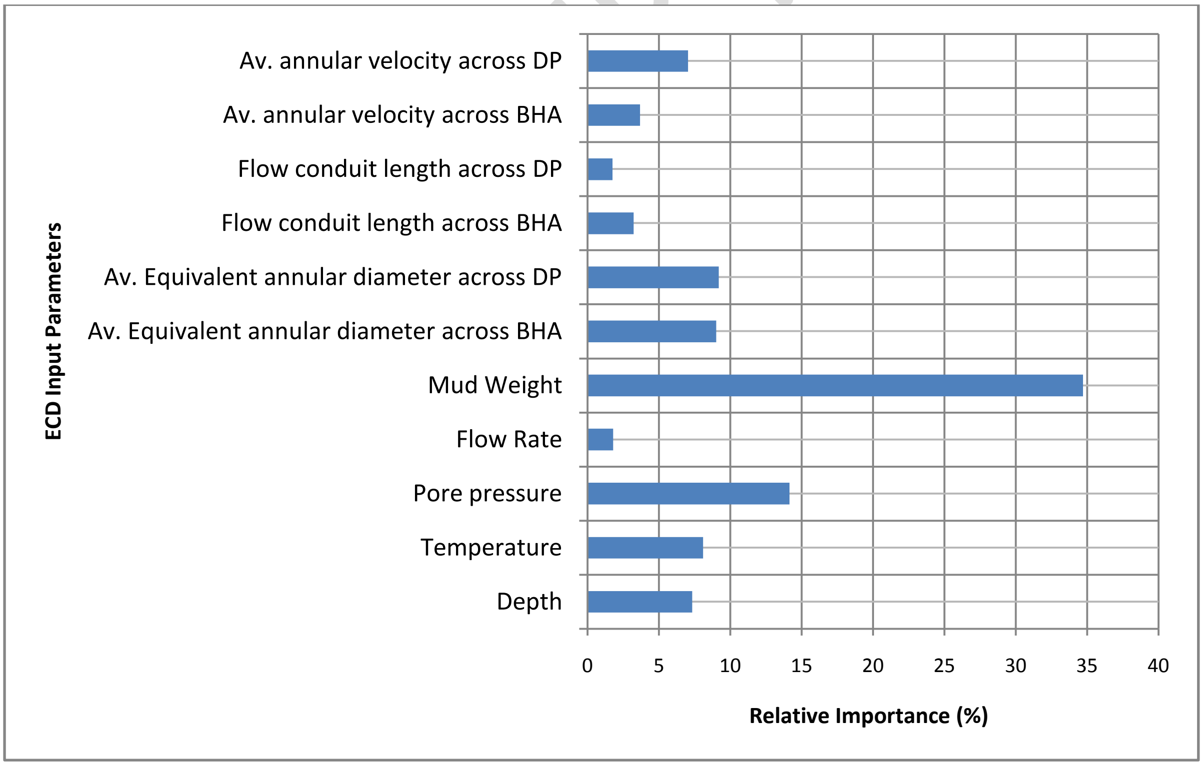

Figure 3: Relative importance of input variables in the ANN model for ECD prediction

3.2 Performance Evaluation of the Developed ANN Models

The performances of these ANN models were compared in terms of their correlation coefficient and error metrics.Figure 4(A, B, C, D) presents the normalized scatter plots of the proposed model (predicted ECDs values versus actual ECDs values in normalized forms, hence both axes were not represented in ppg) for the training, validation, test, and combined datasets respectively for the 11-3-1 ANN architecture (i.e with 11 inputs). Similarly, Figures 5, 6 and 7 below represents the cross-plots (predicted ECDs values versus actual ECDs values in normalized forms) for the training, validation, test, and combined datasets respectively for the 7-6-1, 5-3-1 and 3-5-1 ANN architectures. In each of the Figures, A, B, C, D represents the normalized scatter plots of the proposed model (predicted ECDs values versus actual ECDs values in normalized form, hence both axes were not represented in ppg units) for the training, validation, test and combined datasets respectively for that particular ANN architecture.

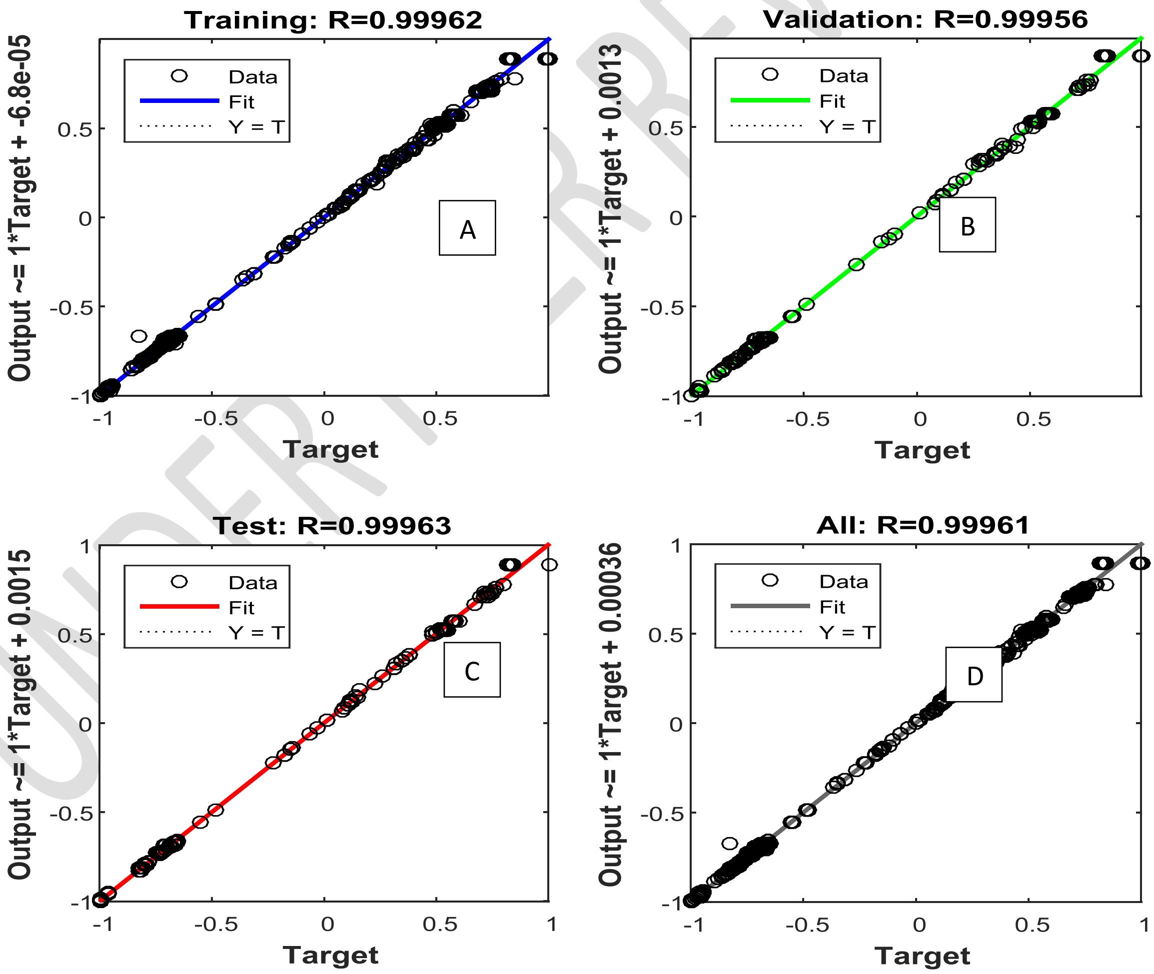

Figure 4: Normalized Scatter plots of 11-3-1 ANN architecture for ECD prediction

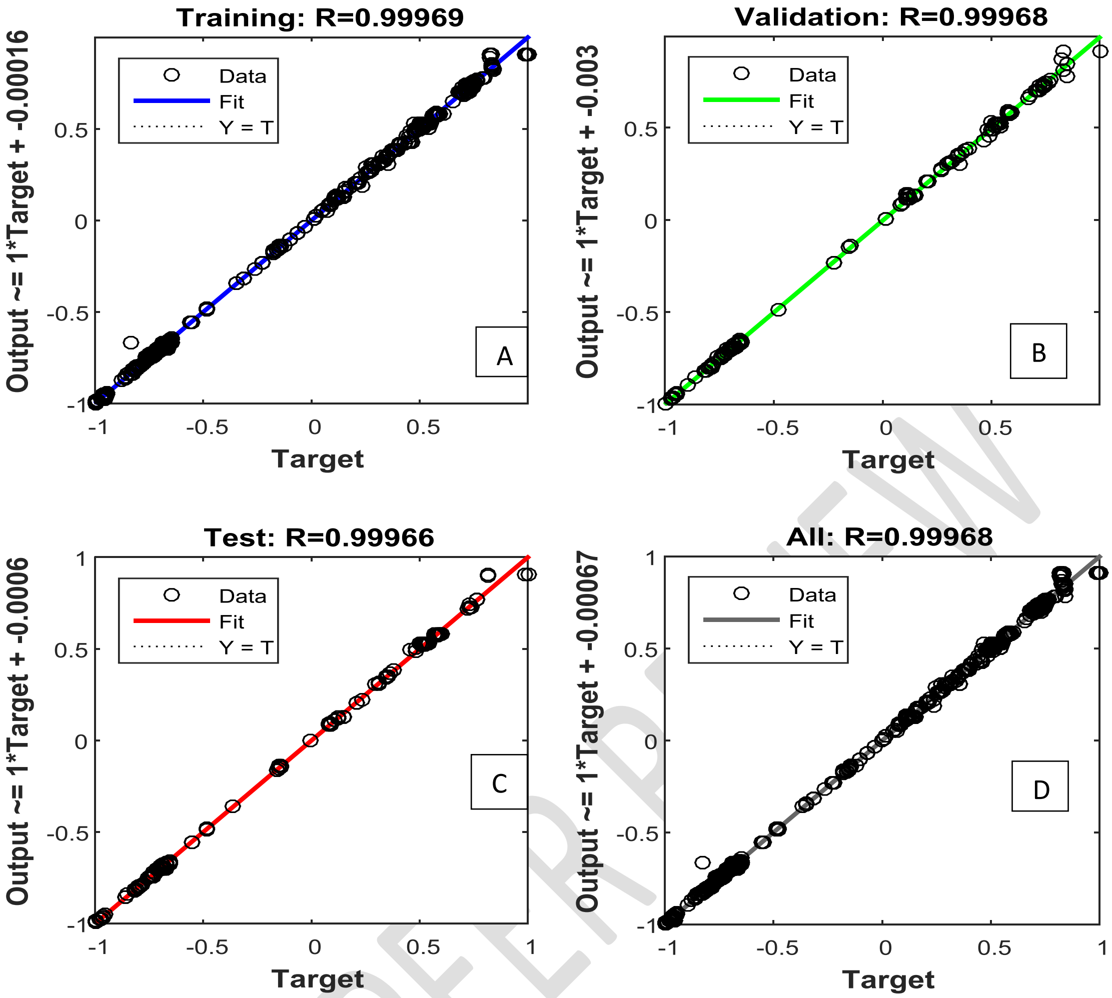

Figure 5: Normalized Scatter plots of 7-6-1 ANN architecture for ECD prediction

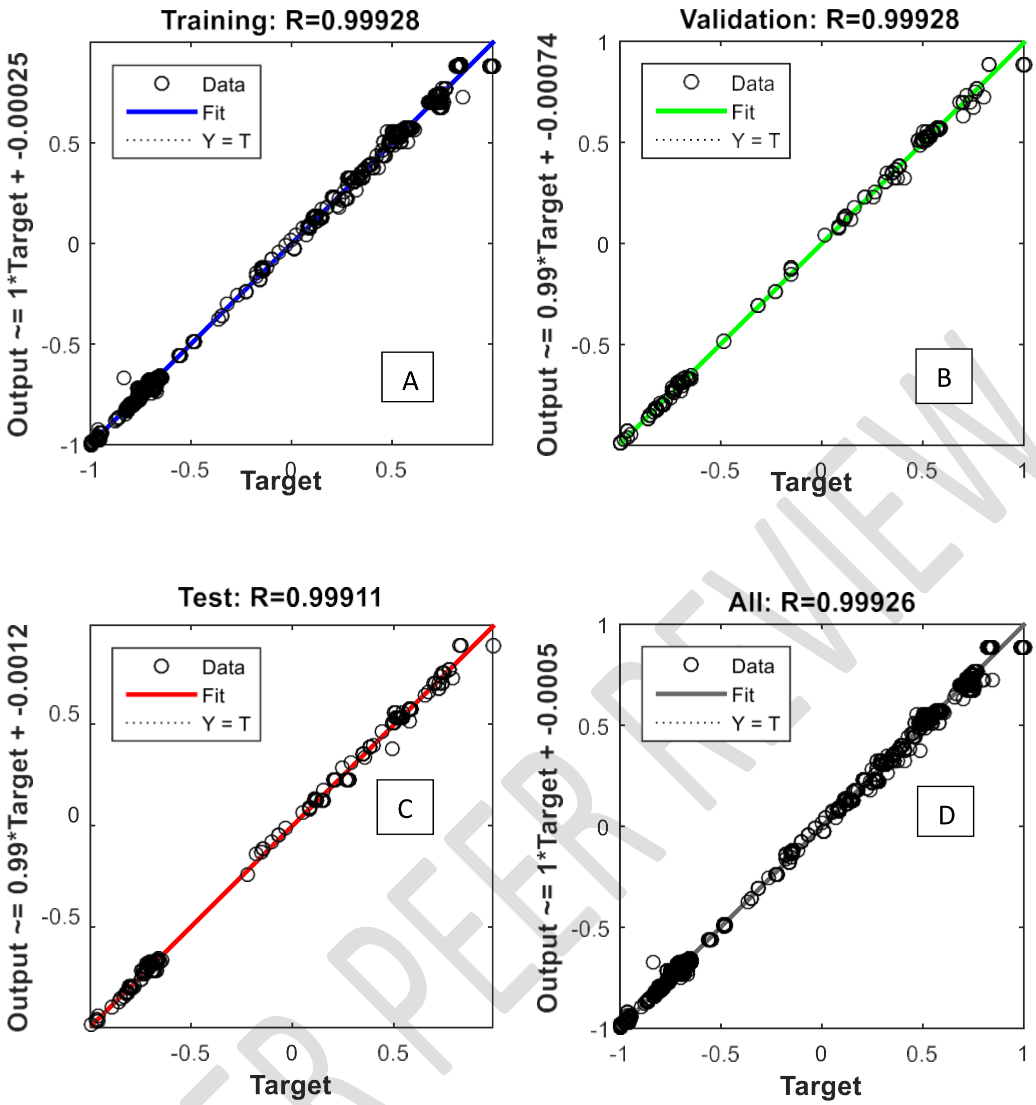

Figure 6: Normalized Scatter plots of 5-3-1 ANN architecture for ECD prediction

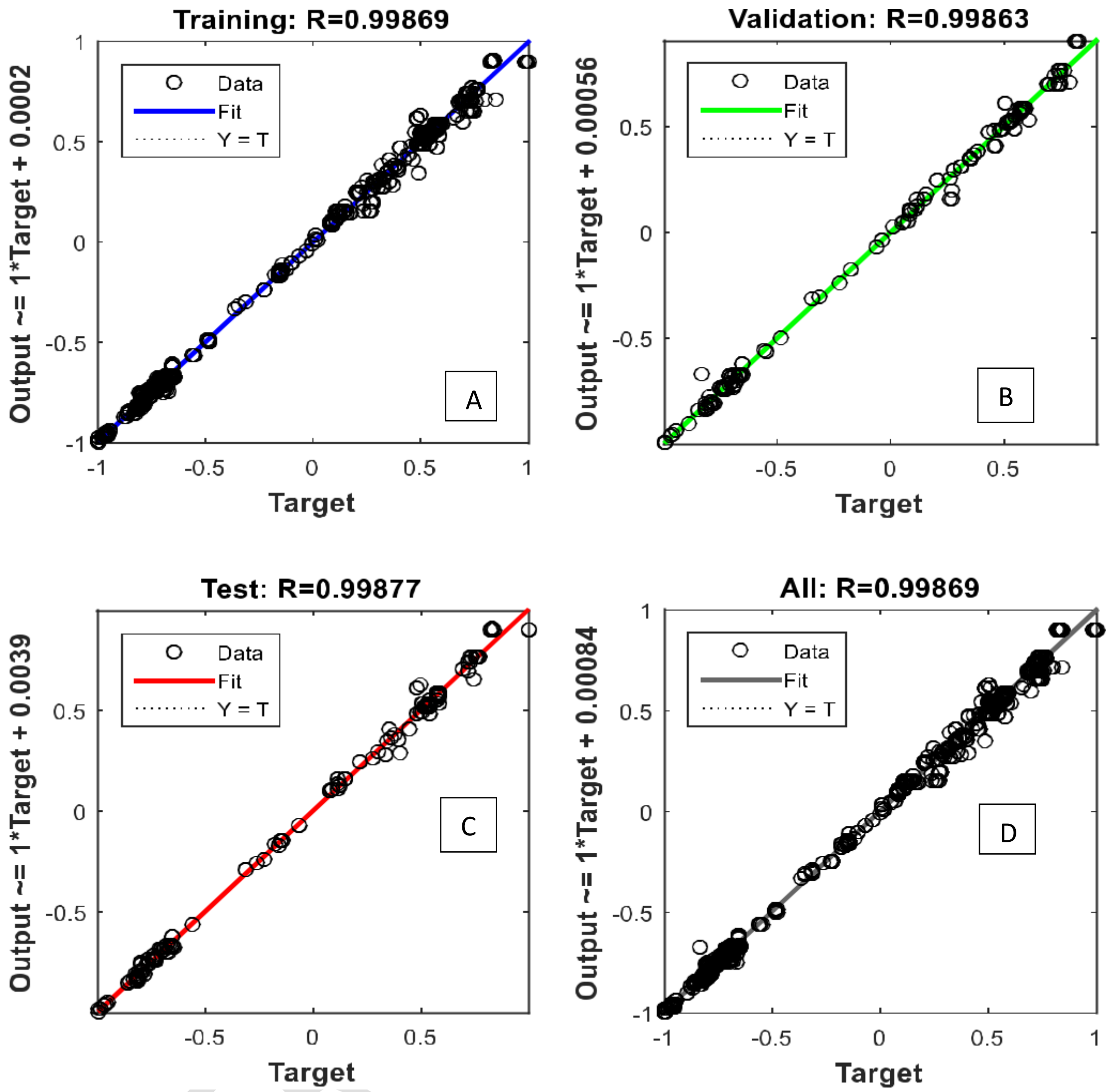

Figure 7: Normalized Scatter plots of 3-5-1 ANN architecture for ECD prediction

From Figure 4 to 7, there exist four lines representing the training, validation, test and best lines.The line for the best fit is dotted. This means that the other lines (training, testing and validation lines) should lie on or close to it. If this happens, it signifies that the network was trained successfully. Generally, if any of the other three lines (training, testing and validation) meet or are in close proximity to the best line, it signifies that convergence has been achieved, and if it goes otherwise, then a retraining of the network is necessary.

Table 4 below shows the outcome of the error metrics or performance of all the ANN models (with reducing number of inputs variables) that were developed for this study.

Table 4: Summary of ANN model performances with reducing number of inputs variables.

ANN Architectures				
Metric	**11 – 3 – 1**	**7 – 6 – 1**	**5 – 3 – 1**	**3 – 5 – 1**
AAPE	0.369	0.337	0.626	0.8
MSE	0.0002986	0.000265	0.000638	0.0009998
RMSE	0.01728	0.01628	0.025	0.0316
R^2	0.99926	0.9993	0.9982	0.9975

4. CONCLUSION

Comparing the performance of the developed model with existing ECD models or recent AI models by previous authors for estimating equivalent circulating density showed that the optimized ECD model developed in this work performed better than existing models in terms of the prediction accuracy. Whereas existing models have an average R-Square value of 0.98, the optimized model(7-6-1 ANN architecture) developed for this work had higher R-square values and lesser error measurements (R^2 of 0.9993, MSE of 0.000265, RMSE of 0.01628 and AAPE of 0.337). The established empirical correlations for the ANN models can be used during well design to select appropriate mud weight to safely drill the well based on the expected temperatures and pressures condition and other relevant input variables with a reduced risk of occurrence of poor drilling fluid rheological issues and ECD related problems. The model developed in this study is not complex and can be easily deployed in software applications for quick ECD computation in the field. In addition to improving the drilling efficiency of the process, this modelling method will save cost when compared to the use of expensive and sophisticated downhole pressure monitoring tools.

Contributions to Knowledge

i. The model developed in this study made use of input parameters that can be easily obtained at the surface or from downhole sensors; making it possible to be deployed in software applications for quick ECD computation in the field.

ii. Unlike ANN models, the model developed in this study is not complex and has been explicitly presented with all the vital details (weights and biases) of the model such that it can be easily used in softwares.

iii. Whereas most ECD models found in the literature subjected their model performance evaluation to two error metrics, this study utilized four error metrics to better evaluate the performance or prediction accuracy of the model.

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