A Bio-Inspired Algorithm for Predicting Equivalent Circulating Density of Drilling Muds for Niger Delta Oilfields

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ABSTRACT

Equivalent circulating density (ECD) is a critical parameter in drilling operations that helps to ensure the safety of drilling personnel and equipment. Mud ECD has over time received substantial attention in theoretical analyses, laboratory experiments, field measurements and modelling. This study developed a bio-inspired algorithm based on an artificial neural network to predict mud equivalent circulating density using data obtained from fields in the Niger Delta region of Nigeria. Eleven variables namely: depth, temperature, pore pressure, flow rate, mud weight, average equivalent annular diameter across bottom hole assembly (BHA), average equivalent annular diameter across drill pipe (DP), flow conduit length across BHA, flow conduit length across DP, average annular velocity across BHA and average annular velocity across DP were used as the input parameters to the algorithm. To develop the model, 1011 data points collated from different fields were used to develop the model. To assess the model performance, four statistical error tools namely: the mean square error (MSE), average absolute percentage error (AAPE), root mean square error (RMSE) and determination coefficient (R^2) were adopted. The best performing topology for 11 inputs was: 11–3–1. The results indicate that the model developed by this topology had an R^2 value of 0.9993 and an MSE of 0.000265, AAPE of 0.337 and RMSE of 0.01628. In order to ascertain the parametric importance of the input variables used, the Garson's algorithm was utilized. In this regard, six input parameters had significant effects on ECD namely: mud weight (34%), pore pressure (14%), average equivalent annular diameter across drill pipe (9.2%), average equivalent annular diameter across BHA (9%), temperature (8.1%), depth (7.3%) and average annular velocity across drill pipe (7.04%). In addition, the ANN model was presented in an explicit form that makes it easy to be deployed in software applications, something rarely found in most ANN studies. In comparison with the existing model in literature for Niger Delta oilfield mud equivalent circulating density prediction, the developed model performed better on all the assessment indicators.

1. INTRODUCTION

While drilling an oil well, there are numerous challenges that are related to the drilling mud that arise from time to time. These challenges include but are not limited to lost circulation, kicks, formation fracture and in some rare cases well blowout. To prevent these issues, it is necessary to precisely determine the effective circulating density operating at the bottom of the well. By definition, equivalent circulating density (ECD) is defined as the sum of the mud hydrostatic pressure and the annulus pressure loss acting on the formation (Haciislamoglu 1994). These challenges become more pronounced in deepwater and high-pressure high-temperature (HPHT) wells where the difference between the formation pore pressure and the formation fracture pressure (drilling window) tends to be small (Alsaihati et al., 2021). For formations with a narrow drilling window, the ECD has to be accurately determined. Neglecting temperature and pressure in such situations gives rise to a greater chance of kicks occurring due to well underbalance (Osisanya and Harris, 2005).

Several factors were found by various researchers to have an impact on the ECD and among them were the annular pressure losses, wellbore geometry, mud properties such as density, viscosity, mud pumping rate, downhole pressure and temperature, and concentration of cuttings (Rommeveit, 1997). A detailed discussion of factors affecting ECD is provided by Skalle (2010). Due to the multiplicity of factors affecting ECD, accurately measuring it downhole remains a daunting challenge.

To measure ECD in the oilfield, downhole sensors are utilized. The main tools used now are measurement while drilling (MWD) and pressure while drilling (PWD) tools (Lapierre et al., 2006; Abdelgawad et al., 2019). These downhole sensors are expensive, have operational limitations such as high pressure and high temperature which affects their output at downhole conditions and are susceptible to wear and tear (Roy et al., 2022).

Conventional computer programs estimate ECD using several rheological data inputs along with a user-defined rheological model (Gamal et al., 2021). The rheological input parameters are calculated from the laboratory experiments. Even after this, it has been seen that a notable difference exists between the calculated and field data (Maglione et al., 1996). This can be attributed to the fact that the assumptions of these models do not apply to most of the drilling sites.

ECD can also be estimated while drilling using hydraulics. Nevertheless, correlations are utilized to predict ECD prior to drilling. According to Aljubran et al. (2021), the main goal of developing and using an ECD model is to ensure that the applied static/dynamic mud pressure is within the drilling margin. This implies that in order to prevent wellbore instability, a drilling mud must have enough mud weight, but it must not be larger than the fracture pressure that would cause formation cracks.

Many correlations are available in the literature to predict ECD. However, most of those correlations did not use enough data, and/or the model is only applicable in a specific area (Alkinani et al., 2019). In recent times, there has been an upsurge in the use of machine learning techniques such as support vector machines, artificial neural networks, fuzzy logic and hybrid intelligent systems to develop predictive models for estimating different parameters in the oilfield. In these applications, these techniques have proven their ability to solve complicated problems that cannot be solved analytically. Therefore this study aims to use the artificial neural network technique to develop a robust model for predicting downhole ECD using data from Niger Delta oilfields.

2. REVIEW OF RELATED LITERATURE

2.1 Definition of Equivalent Circulating Density (ECD)

Equivalent circulating density abbreviated as ECD is essentially the effective density of a circulating fluid in the wellbore arising from the sum total of the hydrostatic pressure imposed by the static fluid column and the frictional pressure (Raabe and Jortner, 2022). According to Rehm *et al.* (2008) when mud is circulated in a well, there is an increase in friction that increases the wellbore pressure over the when the mud is in static condition. The ECD at any point of interest, the dynamic equivalent density, ECD, is substantially greater than the equivalent static density (ESD). Prevention of kicks and loss of circulation requires that downhole ECD remains within the given boundaries. ECD provides the information required to determine how close the drilling operation is within given safety margins usually obtained by geological or offset well data.

The ECD is calculated using Equation 1.

$$ECD = ESD + \frac{\Delta P}{K * TVD} \qquad \text{Equation 1}$$

Where ESD is the equivalent static density of mud; ΔP is the pressure loss due to friction; TVD is the true vertical depth of the well and K is a constant equal to 0.052. The ECD formula in Equation 2.1 is a simple, however when the changes in mud viscosity with pressure and temperature are accounted for, then computation of ECD becomes more complex especially in high temperature, high pressure wells (Rehm et al., 2008). ECD is equivalent to the bottomhole pressure equation expressed as a mud-density gradient (Sarbini, 2012).

The formula for estimating the pressure loss during flow as a consequence of the contact between the mud and the wellbore walls is given in Equation 2

$$\Delta P_f = \frac{2 f \rho v^2}{d} \Delta L \qquad \text{Equation 2}$$

Where ρ = mud density; v is mud velocity; ΔL is length of flow conduit; d is pipe diameter and f is the fanning friction factor.

According to Samuel (2010), in directional wellbores, vertical depth should be used and the formula for the multiple sections of the well is shown in Equation 3.

$$ECD = \rho_m + \left(\frac{\sum_{i=1}^{n} \Delta P_a}{0.052 * \sum_{i=1}^{n} \Delta L_{tvd}} \right) ppg \qquad \text{Equation 3}$$

Where ρ_m = mud density, ΔP_a = annular pressure loss, ΔL_{tvd} = true vertical depth of each section and n = the number of wellbore sections.

2.2 Distinction Between Equivalent Circulating Density (ECD) and Equivalent Static Density (ESD)

Equivalent static density is essentially the mud weight when the mud is not flowing or is not being circulated. Instances when the mud is not circulated include when the pumps are turned off to make a connection (Grace, 2017) whereas equivalent circulating density is the mud weight when the mud is being pumped or circulated into the well through the drill pipe and is the summation of ESD and pressure losses in the annulus due to mud flow to the surface. The greater the pressure loss, the greater the ECD would be. The pressure loss is essentially a function of the frictional pressure loss arising from the contact made between the mud and the borehole wall as it flows upwards to the surface. This contact creates some sort of "drag" because of friction and the mud loses some of the pressure supplied by the mud pump in order to overcome this frictional drag due to contact. This pressure loss is absorbed by the formation. Therefore, this pressure loss when converted to density and added to ESD gives the ECD. Thus, the numerical value of ECD is always greater than ESD. The pressure loss due to friction is determined by the mud rheological properties, the geometry of the wellbore and the mud flow rate (Osisanya and Harris, 2005). According to Dokhani et al. (2016), the commonly used term for calculating downhole pressure in hydrostatic pressure calculations is equivalent static density (ESD) while the equivalent circulating density (ECD) is the necessary input for hydraulic calculations, though, when there is circulation.

2.3 Models for Estimating ECD

ECD can be predicted using various methods, including analytical, numerical, and empirical methods. Some of these methods are described in this section.

2.3.1 Analytical models for ECD estimation

An analytical model represents the system using a set of mathematical equations that specify parametric relationships and the parameter values associated with those relationships as a function of time, space, and/or other system parameters. Analytical models are primarily quantitative or computational in nature.

2.3.2 Empirical Models

The empirical model provides explicit empirically derived equations for estimating mud density at various temperature-pressure conditions. The compositional model on the other hand, takes into account the volumetric behaviour of each of the individual mud constituents in response to variations in temperature and pressure (Micah, 2011). And therefore, prior knowledge of the composition (oil, water and solids) of the drilling fluid is required in order to employ the use of these compositional models. Generally, these models can be assigned into three categories.

i. Category 1: composite models, represented by the model of Hoberock. . In this category, drilling fluid is considered as a mixture of salt water, base oil, and solid materials. The property of each component of the mixture varies with temperature and pressure. When the change rule of a component at high temperature and high pressure is determined, separate experiments must be carried out to test other components of the drilling fluid, thus understanding their change rules before using. Therefore, this category of models is greatly limited in application.

ii. Category 2: semi- empirical models, represented by those of Sorelle, Harris, and Guan Zhichuan. In this category, a mechanical relationship among drilling fluid density, pressure (characterized by elastic compression coefficient Cp), and temperature (characterized by thermal expansion coefficient Cr) is established and the empirical formula using temperature, pressure, Cp, and Cr is obtained through fitting with a certain amount of experimental data. However, the pressure and temperature of drilling fluids affect the drilling fluid density in actual practices.

iii. Category 3: empirical models, represented by those of Yan Jienian and Wang Haige. This category of model is obtained through fitting the laboratory experimental data of a certain number of samples after multivariate nonlinear regression. This model can be expressed in different forms and its precision depends on the selected mathematical formulas and sample quantity.

2.3.3 Machine learning based models for ECD prediction

Some of the commonly used ML methods for ECD prediction include:

i. Artificial Neural Networks (ANNs): ANNs are commonly used for ECD prediction due to their ability to model complex relationships between input and output variables. ANNs are trained on historical drilling data, including drilling parameters such as flow rate, mud weight, and pump pressure, to predict ECD.

ii. Support Vector Machines (SVMs): SVMs are another popular ML method for ECD prediction. SVMs work by finding the hyperplane that best separates the data into different classes. In ECD prediction, SVMs are trained on a dataset of drilling parameters and their corresponding ECD values, and the resulting model can then be used to predict ECD for new drilling scenarios.

iii. Decision Trees: Decision trees are a type of ML algorithm that can be used for ECD prediction. Decision trees work by partitioning the data based on the values of input variables and constructing a tree-like model to predict the output variable. In ECD prediction, decision trees are trained on a dataset of drilling parameters and their corresponding ECD values, and the resulting model can be used to predict ECD for new drilling scenarios.

iv. Random Forests: Random forests are an ensemble learning method that combines multiple decision trees to improve prediction accuracy. In ECD prediction, random forests can be trained on a dataset of drilling parameters and their corresponding ECD values, and the resulting model can be used to predict ECD for new drilling scenarios.

Overall, machine learning methods can provide accurate and efficient ECD predictions, which can help drilling engineers optimize drilling operations and improve safety.

A summary of these methods and their application in ECD prediction is summarized in Table 1.

Table 1: **Summary of researches on mud ECD prediction using artificial intelligence**

Reference	AI technique	Input variables	R^2	AAPE (%)
Elzenary et al. (2018).	ANN ANFIS	ROP, mud weight, drill pipe pressure	0.9982 0.9982	0.2237 0.2262
Alkinani et al. (2019)	ANN [7 – 12 – 1]	Flow rate (Q) in L/min Mud weight in gm/cc, Nozzles total flow area in inch^2, Plastic viscosity, Revolutions per minute (RPM), Weight on bit (WOB) in Tons, Yield point	0.98	NA
Han et al. (2019)	Autoregressive integrated moving	Not available	Not available	Mean absolute

	average (ARIMA BPNN) hybrid			deviation = 0.0008
Abdelgawad et al. (2019)	ANN [3 – 20 – 1] ANFIS	Rate of penetration (ROP) in m/h, mud weight in lb/gal & the drill pipe pressure (DPP)	0.9964	0.2237
Gamal et al. (2021)	ANN ANFIS	penetration rate, rotating speed, torque, weight on bit, pumping rate, and pressure of standpipe	0.99	0.32
Alsaihati et al., (2021a)	SVM, Random forest & functional network (FN)	Flow rate (Q), hook-load (HL), ROP, rotary speed, SPP, WOB, surface drilling torque (T)	SVM: 0.97 FN: 0.99 RF: 0.99	
Alsaihati et al. (2021b)	PCA-based SVM	flow rate (Q), hook-load (HL), ROP, rotary speed (RS), SPP and surface drilling torque (T)	0.95	Not available
Roy et al. (2022)	Random Forest, SVM, XGBoost, Decision Tree, Elastic net regression	Rate of penetration, Weight on a bit, mud density, torque, pump pressure	RF: 0.992 SVM: 0.987 DT: 0.984 XGBoost: 0.982 Elastic Net: 0.991	
Robinson et al. (2022)	Deep neural network	Standpipe pressure, mud density in, mud flow in, bit depth, surface rotary speed, and the rate of penetration (ROP)	Not available	MAE = 0.326

3. MATERIALS AND METHODS

The focus of this section is to showcase the data sources and strategies necessary to develop the models outlined in the objectives of this study. Furthermore, this chapter would include the details of the modelling parameters and process.

3.1 Data Collected and its Features

The data used for this work was obtained from the field. The dataset contains 1011 data points and consist 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). The minimum and maximum of each parameter as well as their units of measurement is shown in Table 2.

Table 2: Inputs and output parameters of ECD model and their respective values

Database parameter	Minimum	Maximum	Unit
Depth	131	15173.7	Ft
Temperature	77.67	368.6023	°F
Pore pressure	65.58735	15116.67	Psi
Flow rate	64.92451	1225.46	gpm
Mud weight	8.5799	18.326	Ppg
Average equivalent annular diameter across BHA	1.17	20.8905	Inches
Average equivalent annular diameter across DP	1.92	23.75	Inches
Flow conduit length across BHA	31.82376	3899.887	Ft
Flow conduit length across drillpipe	62.02	17458.53	ft
Average annular velocity across BHA	0.122264	12.64414	ft/s
Average annular velocity across drill pipe	0.157697	13.05758	ft/s
Equivalent circulating density (ECD)	8.72235	20.30857	Ppg

3.2. Overview of Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are a type of machine learning algorithm inspired by the structure and function of the human brain. ANNs consist of layers of interconnected nodes (also known as artificial neurons) that process information and learn to make predictions or decisions (Behnoud far and Hosseini, 2017). The basic structure of an ANN includes an input layer, one or more hidden layers, and an output layer. Each node in the input layer represents a feature or attribute of the input data, while the nodes in the hidden layers process the input data using mathematical operations, and the nodes in the output layer produce the final prediction or decision. 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 basically the real numbers that are linked with each input which 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*., 2013). These layers are depicted in Figure 3.1.

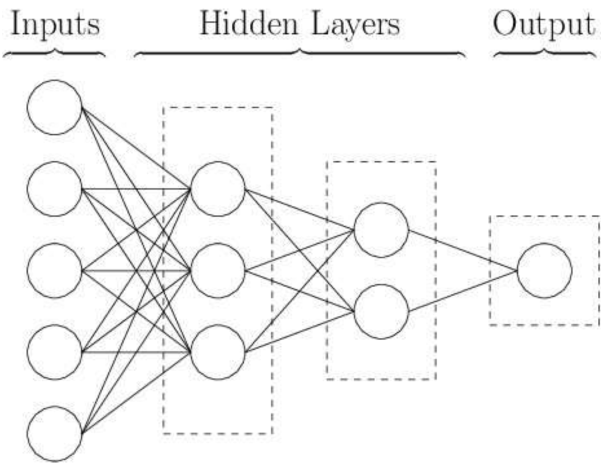

Figure 3.1: Schematic diagram of the layers of an artificial neural network

The first step of modelling with ANN is the training of the network. The training process of an ANN involves adjusting the weights and biases of the nodes in the network to minimize the difference between the predicted output and the actual output. This is achieved by feeding the network with a large amount of training data, and using backpropagation algorithm to propagate the error back through the network and adjust the weights and biases accordingly. (Demuth *et al*., 2009). 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*., 2010). The overall correlation between inputs and output for an ANN model is as shown in Equation 3.1.

$$y_k = f_o\left[\sum_j w_{kj} \cdot f_h\left(\sum_i w_{ji} x_i + b_j\right) + b_k\right] \qquad \text{Equation 3.1}$$

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 and f_h and f_o are the activation functions for the hidden and output neuron respectively. For more details on the ANN technique, the work of Mekanik *et al*.(2013) is recommended.

3.3 Model development

Modelling is essentially the process by which a simplified mathematical reality is constructed from a more complex physical reality (Barbour and Krahn, 2004). In the case of modelling with ANN, the following has to be taken into consideration.

3.3.1 Data Normalization

Data normalization is a technique used in data pre-processing to transform data into a common scale and range. The main purpose of data normalization is to remove inconsistencies and improve the accuracy of the machine learning models by bringing the features onto a similar scale. The normalization technique adopted used in this study is the min – max normalization technique. A short description of this approach is as follows: Min-max normalization as shown in Equation 3.2 performs a linear alteration on the original data. The values are normalised within the given range. For mapping a value of an attribute X from range [minX, maxX] to a new range [new_minX, new_maxX], the computation is given by:

$$Y = 2\frac{(X - X_{min})}{(X_{max} - X_{min})} - 1 \qquad \text{Equation 3.2}$$

where X_{min} and X_{max} are the minimum and maximum values of X, where X is the set of observed values of X and Y is the normalised value of X. This normalization technique reduces the values to fall between -1 and 1.

When the ANN network training is completed, since the value of the network output is normalised, it needs denormalization to transform it into the actual value. Equation 3.3 is used for the denormalization.

$$X = 0.5(Y + 1)(X_{max} - X_{min}) + X_{min} \qquad \text{Equation 3.3}$$

where X_{min} and X_{max} are the minimum and maximum values in X, where X is the set of observed values of X and Y is the normalised value of X.

3.3.2 Procedure for Modelling Using Artificial Neural Network

In building a predictive model using ANN based on supervised learning, the steps below are followed. 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 is used for learning (to fit the network weights), the validation dataset is used to adjust the network architecture and the test dataset assesses 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.

3.4 Parameter Settings for Model Training, Testing and Validation

The settings used for the ANN model is presented in Table 3.3. 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 are used to adjust the weight of the neurons. Validation data are 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 3.3: Parameter settings for ANN 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, 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.

3.5 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 the ANN 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.

3.6 Model Performance Assessment Methods

To assess the performance and effectiveness of the proposed ANN model, four error analysis benchmarks 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).

The mathematical descriptions of the four statistical metrics are shown in Equations 3.4 – 3.7.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_{actual} - y_{predicted}\right)^2}{\sum_{i=1}^{N}\left(y_{actual} - \bar{y}\right)^2} \qquad \text{Equation 3.4}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_{actual} - y_{predicted}\right)^2 \qquad \text{Equation 3.5}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_{actual} - y_{predicted}\right)^2} \qquad \text{Equation 3.6}$$

$$AAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_{actual} - y_{predicted}}{y_{actual}}\right| * 100 \qquad \text{Equation 3.7}$$

For Equations 3.4 – 3.7, 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.

4. RESULTS AND DISCUSSION

This section presents the results obtained in the course of developing the ANN model for the prediction of ECD. First, the result from the method used for selecting the model architecture is presented. The results from the performance of the proposed models are presented next while the mathematical representation of the models comes thereafter. The results from the parametric importance of the input variables, the models computational burden analysis would be highlighted.

4.1 Optimal Number of Neurons in Hidden Layer

The number of neurons in the network's hidden layer influences the generalisation ability of the ANN model. In order to find the appropriate architecture for the networks, the trial-and-error approach was adopted. In this regard, numerous network topologies were evaluated, wherein the number of neurons in the hidden layer was varied between 1 and 20. The error function chosen was the MSE. Decision on the optimum topology was based on the minimum error of the testing data. Each topology was tried for 25 times in order to get the best network from that topology. At the end of the trials, it was observed that a network having 3 neurons in the hidden layer gave the optimal performance for ECD prediction. The optimal architecture of the ANN network for the model with 11 input parameters is shown in Figure 4.2.

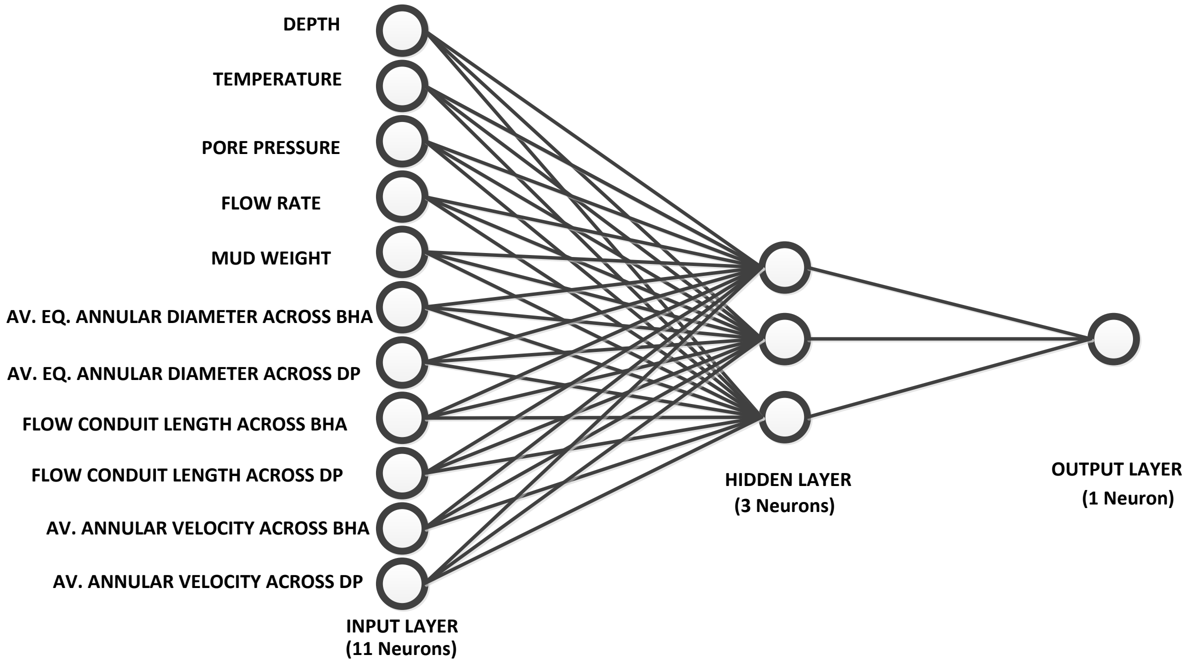

Figure 4.2: Optimal architecture of the neural network for ECD prediction

Figure 4.3 presents the scatter plots of the proposed model predicted ECD versus actual results for the training, validation and testing datasets respectively. The predicted model results are in agreement with the field values for the training, testing and validation sets as seen in their correlation coefficients (R). The reason for this assertion is that the closer the correlation coefficient is to 1, the better the model. However, using only the correlation coefficients as the basis for determining the predictive capability of an ANN model is not always recommended. This is because a model may have a good correlation coefficient but predicts poorly when subjected to new data sets that were not used during the ANN training process.

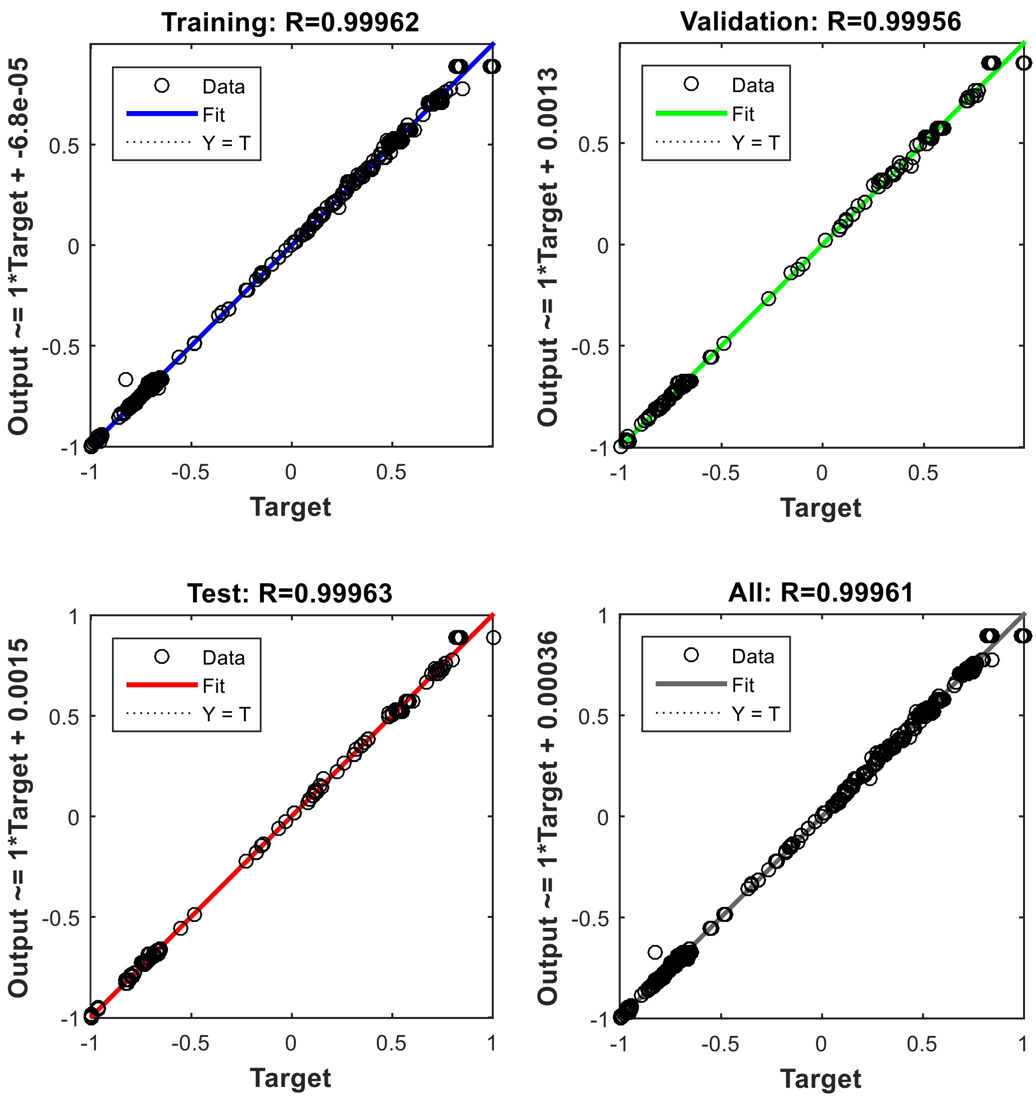

Figure 4.3: Scatter plots of ANN model for ECD

4.2 Performance Evaluation of Developed ANN Model for ECD prediction

4.2.1 Performance Plot

From Figure 4.4, there exist 4 lines representing the training, validation, test and best lines. The line for the best 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 3 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.

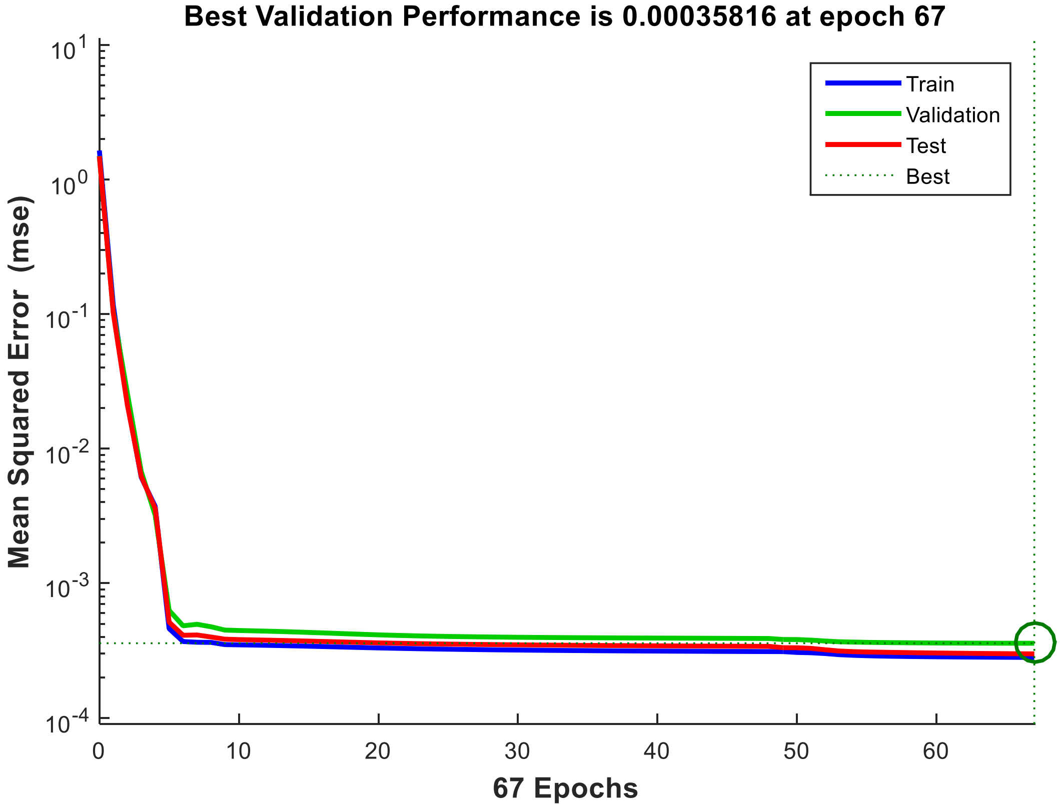

Figure 4.4: Performance plot for developed ANN model with 11 inputs

The network was trained using data that was split into training, validation, and test data. Efforts were made to ensure that the performance curves were as similar as possible. Having the curves in a similar fashion is an indicator of how well the network performed and reduces the chances of overfitting (Beale, 2014). Figure 4.4 displays the performance curves for the selected network using the Levenberg Marquadt (LM)-learning algorithm and three hidden neurons.

4.2.2 Model Performance

The performance of the models after being evaluated using three statistical error metrics is summarized in Table 4.1. From the Table, the value for the coefficient of determination for the ANN model developed was 0.99926 indicating that 99% of the data fit the regression model. According to a categorization of R-values by Taylor (1990), a weak or low correlation has a value $R \leq 0.35$; a moderate correlation ranges between $0.36 \leq R \leq 0.67$ and high correlation ranges between $0.68 < R < 1.0$ values.

A small value of the MSE and RMSE indicates that it is close to finding the line of best fit. For a perfect model, the MSE and RMSE should have a numerical value of 0. In the case of the ECD data used in developing the ANN models, it was easy obtaining a small value for the MSE and RMSE. Therefore a test MSE value of 0.000298 for the model is acceptable.

Table 4.1: Summary of ANN model performance for ECD prediction

	R^2	MSE	RMSE	AAPE
Training	0.9992	0.000280986	0.01676	0.322
Testing	0.99926	0.000298655	0.01728	0.369

Validation	0.99911	0.000358158	0.01892	0.424

It is generally assumed that the RMSE for the training and test sets should be similar in numerical value for the model to be deemed “good”. However, if the RMSE value obtained for the test dataset is much higher than that of the training dataset, it signifies that data overfitting has occurred. This means that the developed model that tests well in the sample dataset used to develop it but would have little or no predictive value when subjected to new data sets. The reverse is the case with when the RMSE of the test data is much smaller than the training dataset RMSE. In this scenario, the data is said to be underfitted. In the case of the model developed in this work, it is clear from Table 4.1 that the RMSE value for the test data is very similar to the training RMSE, thus the model is generalizable.

4.3 Model Weights and Biases

The weights and biases of a neural network are essentially the most important parts of its development and functionality. The essence of including the crucial details (the weights and biases) of the models developed is to ensure that the models are reproducible (ability to recreate a model without the original code). Legendi *et al.* (2013) posited that model reproduction is scarcely carried out since successful reproductions do not seem to deliver new scientific results and the reasons of failed reproduction may be hard to discern. Table 4.2 lists the weights and the biases of the developed empirical correlation that can be used to predict ECD.

Table 4.2: Weights and biases for ANN Model for ECD prediction

Input layer weight matrix											Input layer bias vector	Hidden layer weight vector	Output layer bias vector
J=1	J=2	J=3	J=4	J=5	J=6	J=7	J=8	J=9	J=10	J=11	b1	LW2	b2
1.49	0.75	-4.69	-0.45	1.94	-0.70	0.51	-0.61	-0.12	0.56	1.18	-1.66	0.11	-0.25
-1.09	2.02	-0.76	-0.12	-2.46	-2.92	3.06	-0.14	-0.22	0.31	-0.39	1.33	-0.17	
-0.03	0.04	0.01	0.01	-0.71	0.00	0.01	-0.04	-0.03	0.05	-0.09	-0.38	-1.18	

4.4 Mathematical Representation of Developed Model

For the ANN model to be explicitly presented, the weights and biases for the network were presented. These biases and weights are presented in Table 4.2. With these weights and biases, the model can be replicated and the results obtained therefrom can be reproduced. Equation 4.2 is the explicit representations of the model for ECD prediction. This explicit nature makes it easy for the models to be deployed in software and also makes them explainable.

The explicit ANN model for ECD prediction using the weights and biases of the network is given by Equation 4.2:

$$\mathrm{ECD} = 5.595\mathrm{ECD}_n + 14.515 \qquad \text{Equation 4.2}$$

Where the denormalized value of the ECD_n = [A + B + C– 0.25]

and

$$A = 0.11 \left[tanh\,(1.49x_1 + 0.75x_2 - 4.694x_3 - 0.45x_4 + 1.94x_5 - 0.7x_6 + 0.51x_7 - 0.61x_8 - 0.12x_9 + 0.56x_{10} + 1.18x_{11} - 1.66)\right]$$

$$B = -0.17\left[tanh\,(-1.09x_1 + 2.02x_2 - 0.76x_3 - 0.12x_4 - 2.46x_5 - 2.92x_6 + 3.06x_7 - 0.14x_8 - 0.22x_9 + 0.31x_{10} - 0.39x_{11} + 1.33)\right]$$

$$C = -1.18\left[tanh\,(-0.03x_1 + 0.04x_2 + 0.01x_3 + 0.01x_4 - 0.71x_5 + 0.00058x_6 + 0.01x_7 - 0.04x_8 - 0.03x_9 + 0.05x_{10} - 0.09x_{11} - 0.38)\right]$$

Where x_1 = depth, x_2 = temperature, x_3 = pore pressure, x_4 = flow rate, x_5 = mud weight, x_6 = average equivalent annular diameter across BHA, x_7 = average equivalent annular diameter across DP, x_8 = flow conduit length across BHA, x_9 = flow conduit length across DP, x_{10} = average annular velocity across BHA and x_{11} = average annular velocity across DP

5.1 Conclusion

This work presents an ANN approach to modelling ECD by using field data. Eleven field inputs were used to build the model. On the basis of the results obtained in this study, the following are the main conclusions:

i. The vast majority of the correlations that have been developed to forecast mud ECD are founded on information gathered from fields outside the Niger Delta. In comparison to field values from the Niger Delta region, their predictions either produce lower or higher values.

ii. Previous efforts also neglected to take into account model reproducibility and replicability. For instance, the authors did not reveal the weights and biases of the models. Due to this, it is challenging to reproduce the models.

iii. Unlike the existing ANN models, which are black boxes, the ANN model proposed in this work is clear, making it deployable in software applications.

5.2 Suggestions for Further Studies

Notwithstanding the study's innovative conclusions, there are also other factors to take into account. These include:

i. In this study, ANN was the only method employed to forecast mud ECD. The predictive power of the model can be increased by combining ANN with evolutionary techniques.

There are other more evolutionary algorithms with which one might experiment. Artificial bee colonies and ant colony optimization are two of the most intriguing. Another area that needs investigation is which of them would be better suited for mud ECD optimization from oil wells during drilling based on a thorough analysis of all of them.

ii. How to change evolutionary algorithms to handle a stream of continuously changing training data rather than fixed training data is a second issue that merits investigation.

iii. Several datasets must be used to test the effectiveness of models. To assure data availability for the testing, extensive experiments and/or numerical simulations should be run under diverse scenarios.

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