Prediction of Rheological Properties of Recirculating Water-Based Drilling Mud in Geothermal Exploration using Artificial Neural Networks with Tensor Flow

Hillary Mengich, Michael Kabugu, and Mary Nelima Ondiaka

ABSTRACT

Pipe sticking in drilling operations occurs by mechanical and differential forces caused by the loss in circulation of drilling fluids or muds. Rheological properties of recirculating drilling muds (RDMs) determine the drilling hydraulics and hole cleaning effectiveness. Uncertainty in real-time data on the rheological properties of RDMs challenges estimation of potential pipe sticking problems, a problem that can be improved using machine learning methods. This study reports first-time application of a supervised artificial neural networks (ANN) algorithm with TensorFlow to estimate plastic viscosity (PV), apparent viscosity (AV), yield point (YP), flow consistency index (k), and flow behavior index (n), five rheological properties of recirculating water-based drilling mud (R-WBDM). Model input variables were density (MD), marsh funnel viscosity (MFV), and percent solids content (% S) of R-WBDM. Model performance was tested using the root mean square error (RMSE) and coefficient of determination (R²) methods. Sensitivity analysis demonstrated the strength of each predictor variable. Five optimal models showed good generalization capability in estimating the n, k, PV, AV, and YP with RMSE of 0.022, 0.270, 7.890, 8.870, and 10.149, and R² of 0.995, 0.956, 0.756, 0.724, and 0.701 in a similar order, respectively. High sensitivity was observed in PV, AV, YP, and k models, and n-model, to changes in MFV (0.615) and % S (0.067), respectively. Results show the potential use of ANN with TensorFlow to support decision-making in geothermal drilling engineering on pipe sticking problems using easy-to-determine physical properties as predictor variables.

Keywords: Drilling mud, geothermal drilling, mud rheology, neural networks, TensorFlow.

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I. INTRODUCTION

Geothermal energy resource is renewable and involves drilling for steam exploration and development processes. In the East African region, access to electricity is estimated at less than 1% [1], and increasing population, urbanization, and government agenda on rural electrification have necessitated research, exploration, and development of geothermal energy [2]. Subsequently, exploration for geothermal energy is being carried out in Kenya, Uganda, Ethiopia, and Djibouti [3]-[6].

Geothermal power plants are reliable energy sources with minimal environmental impacts [7] but the drilling process is expensive at nearly 25% of the total costs [8]. The drilling process comprises hoisting, rotary, and circulation systems [9], [10]. Drilling fluids or muds are viscous mixtures used in drilling circulation systems to carry rock cuttings to the surface and to cool and lubricate the drill bit [11]. Depending on the internal phase, drilling fluids are water-based, oil-based, or gaseous. Globally, water-based drilling fluids are commonly used [12] since they are low-cost and environmentally friendly [12]. By hydrostatic pressure, the drilling mud helps prevent the collapse of unstable strata into the bore or drill hole as well as aid in preventing the intrusion of water from the water-bearing strata that may be encountered [13].

The rheology of recirculating drilling mud (RDM) is assessed by the hole cleaning capacity of the mud, rate of penetration, torque used, and optimum drilling hydraulics during drilling operation [14], [15]. Physical properties of RDM include density (MD), marsh funnel viscosity (MFV), geological formation, gel strength, and percent solids content (% S) which are frequently measured in the field to establish the reaction to the subsurface environment and formation [16]. Rheological properties of RDM include the plastic viscosity (PV), apparent viscosity (AV), yield point (YP), flow consistency index (k), and flow behavior index (n) [17], which characterize the deformation and flow under applied strain or stress [18]. Changes in geological formations necessitate a continuous assessment of mud rheology during the drilling process to avoid drilling inconsistencies such as plugging as well as damaging the reservoir pores, pipe sticking (or drill string sticking), and lost circulation [17], [19].

Pipe (or drill string) sticking is a major hurdle in geothermal energy exploration [20], [21]. A stuck string...
requires recovery since sticking is risky, and increases the rig’s productive time and drilling costs, thus an expensive problem in drilling operations [8], [20], [22]-[24]. Stuck pipes account for nearly half of the total drilling costs estimated at over $250 million per year globally [25]. The delays in the overall productivity of drilling operations and abandonment of some wells in Menengai and Olkaria geothermal drilling sites in Kenya have been attributed to the pipe sticking problems [20], [26]. Preventing pipe sticking is more economical than the best freeing or fishing methods, thus the need to expect, understand, and plan for prevention [27].

Differential sticking arises when the drilling mud’s hydrostatic pressure is higher than the formation pressure at permeable zones leading to the caking formation that increases the overall friction coefficient on one side of the drilling string or pipe [28]. Mechanical pipe sticking is caused by insufficient hole cleaning, the presence of junk materials in the wellbore, and poor drilling operations [28] that have been attributed to the lack of real-time data on the rheological properties of drilling mud [21]. The complete measurement of rheological properties takes a long time, hence expensive since only two (2) to five (5) measurements can be carried out in a day [17], [21], which delays decision-making by drilling engineers on drilling inconsistencies [21], [23]. Mechanical pipe sticking is common in geothermal drilling [20], thus the main subject of this study.

Researchers have used mathematical [29]-[33] and machine learning (ML) [16], [34] models to investigate event detection, fluid properties, hole cleaning, and hydraulics aspects in drilling engineering. Models can address the limitations of scientific experiments and enhance the understanding of the performance of drilling fluids during drilling operations. Mathematical models provide empirical and deterministic solutions to yield variable correlation equations and simulations of actual systems, respectively [32]. Though applied widely, Pitt’s model [30] approximated AV using marsh funnel time and density with a low accuracy of 64%. Moreover, the marsh funnel height was correlated with PV, AV, and YP where the shear rate and shear stress on the walls of the marsh funnel are determined but temporal variations and consistency plots failed to correct the shear rate equation that affected marsh funnel results [35].

The ML methods applied in drilling fluid engineering have been reviewed [16]. The ML models include artificial neural networks (ANN), adaptive neuro-fuzzy inference system (ANFIS), extreme gradient boosting (XGBoost), Naïve Bayes, K-nearest neighbors (KNN), Markov decision process (MDP), random forest (RF), and support vector machine (SVM) [16], [17], [19], [36]-[40].

The ML algorithms differ in their learning approaches subject to data types [41] including supervised, unsupervised, and reinforcement learning paradigms [42]. Supervised learning use labelled data suitable for regression and classification learning [43]. Unsupervised learning uses unlabelled data applicable in feature extraction such as clustering [44]. In reinforcement learning, exact model development is infeasible, thus learning trial and error techniques yield the best model output [45].

The three learning paradigms apply in the ANN modeling approach. The application of ANN to solving complex engineering problems exceeds the computational capacity of classical mathematical procedures [43],[45]-[47]. Few researchers have effectively used the ANN approach to estimate the rheological properties of water-based drilling mud with good generalization ability [17], [38]-[40]. Using mud weight (MW) and MFV as input variables, the ANN model performance based on the coefficients of determination (R²) of 0.970 - 0.990 with absolute average percentage errors (AAPE) of 2.4-6.1% in estimating the PV, AV, YP, n, and k [38]. Similar ANN model input variables were used to predict AV with R² = 0.981 and an average absolute error (AAE) of 0.109 [39].

An ANN model [17] effectively predicted PV, AV, YP, n, viscometer 300 (R300), and 600 (R600) using MD and MFV as the input variables. The model performance showed high R² (0.910-0.970), and < 10% estimation errors with AAPE lying in the range of 2.5-7.7%, for all variables estimated (PV, AV, YP, n, R300, and R600). The R300 and R600 are viscometer readings measured at 300 and 600 revolutions per minute, respectively [17], [19].

Reference [40] used an Adaptive Neuro-Fuzzy Inference System (ANFIS), a kind of ANN model, to predict PV, AV, YP, n, k, and R600 using mud weight (MW) and MFV as the input variables. The model performance was R² (0.910-0.970) with AAPE of 1.69-5.66%, for all estimated variables (PV, AV, YP, n, k, and R600). With the successful application of ANN [17], [38]-[40], this study reports the application of the ANN modeling method in predicting the rheological properties of R-WBDM used in drilling for geothermal energy exploration.

II. MATERIALS AND METHODS

A. Learning Dataset

A labelled learning dataset comprising three (3) input variables, five (5) output variables, and five hundred and fifty-seven (557) data values was used to train artificial neural networks (ANN) models. Physical properties (density (MD), marsh funnel viscosity (MFV), and percent solids content (% S)) and rheological properties (plastic viscosity (PV), apparent viscosity (AV), yield point (YP), flow consistency index (k), and flow behavior index (n)) of recirculating water-based drilling mud (R-WBDM) were the input and output variables, respectively. The data were obtained from the field (physical properties) and laboratory (rheological properties) experiments conducted at the Olkaria geothermal steam exploration site in Nakuru County, Kenya during geothermal drilling operations following the American Petroleum Institute (API) 13 A Section-11 Oil Company Materials Association (OCMA) Standard (unpublished work). All data are continuous. Fig. 1 presents pair plots and Pearson correlations among the input and output variables.
Fig. 1. Pair plots and Pearson’s correlation of input versus output variables.

B. Artificial Neural Networks

The artificial neural networks (ANN) modeling method is inspired by biological neural networks, hence artificial neurons (or nodes) are the elementary units [17]. The ANN is historically linked to Walter Pitts and Warren McCulloch [48] from 1943, though the concepts precede 1900, paving way for improvement and modern research applications [47], [49]-[52]. The multilayer perceptron (MLP) structure of ANN comprises the input, hidden and output layers (Fig. 2).

Fig. 1. Schematic representation of the architecture of a neural network.

The nodes in the input layer are assigned input variables from external data sources, nodes in the hidden layer are assigned specific transfer functions between the input and output layer, and nodes in the output layer provide the feedback (or prediction) from the network functions [52]. The three layers adequately describe the nature of the learning problem, and the weights and biases (represented by \( w \) and \( b \) in Fig. 2, respectively) are the model’s learning parameters. The weights increase the steepness of the activation functions used while the biases delay the triggering of the activation functions.

The MLP is an ANN approximator that learns from labelled data using feed-forward learning and error backpropagation in the transfer procedures. The backpropagation is fast, simple, and easy to develop and implement [53], thus widely used in supervised learning using a gradient descent optimization approach [54]. In this study, the MLP learning and adaptive moment estimation (Adam) optimizing algorithm in TensorFlow [55], [56] will be used for supervised regression learning.

C. TensorFlow

TensorFlow is an open-source software developed and released by Google in 2015. TensorFlow has multiple libraries that support deep learning [57] and is widely used for differentiable and dataflow programming for various tasks such as production and research [58]. Developed in 2015, TensorFlow has been used in text-based applications, voice search, image recognition, regression analysis, and classification predictions [41], [58]-[61]. In drilling engineering, TensorFlow has been applied in sequence mining and pattern analysis [62], and permanent downhole gauge data interpretations [63] with promising results. Thus, this study reports the application of TensorFlow in predicting the rheological properties of recirculating water-based drilling mud for the first time.

D. Structure and Development of Artificial Neural Networks Models

A dense ANN architecture as shown in Fig. 3 was developed in this study. The input layer comprises three neurons representing the three input variables (MD, MFV, and % S). The number of hidden layers and neurons were varied and tuned using trial and error techniques expounded in subsequent Section F. The output layer comprises five neurons representing the five output variables (PV, AV, YP, k, and n).

Fig. 2. The architecture of the dense artificial neural networks model.

E. Data Preprocessing

A filtration process was used to clean the data. The cleaned data were normalized using the MinMaxScaler in the Scikit-Learn package. The Minimum-Maximum scaling ensured that all the input and output variables acquired the same range of values lying between 0 and 1 through scale shifting and rescaling techniques. The MinMaxScaler subtracted the minimum value from each data record divided by the difference between the maximum and the minimum values (1) [64].

\[
\text{x}_{\text{sc}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \quad (1)
\]

Where \( x_{\text{sc}} \) is the scaled value of the variable, \( x \) is the data record of the variable to be scaled, \( x_{\text{min}} \) and \( x_{\text{max}} \) are the minimum and maximum values of the variables, respectively.
The data were randomly split into training (72%) and testing (28%) datasets [65]. A 10-fold resampling procedure [66], [67] was used to split the training dataset into learning (90%) and validation (10%) sets [68].

F. Setting and Optimizing Hyperparameters

The number of hidden layers was set starting at 1 followed by 2, 3, 4, 5 to 10 with the optimized model from the training and validation experiments selected. The number of neurons in each hidden layer was set starting with 16 and followed in subsequent multiples of 2, thus 32 then 64, 128, 256, 512, and 1024. The optimum number was selected based on model performance concerning the error factor, or mean square error (MSE) function, of the models, developed.

A batch size of one and the number of epochs were set at 500, followed by 1000, 2000, and 3000 with a learning rate set between 0.01 to 0.5. The number of epochs and batch size were optimized by assessing the predictive capabilities of the models built during validation.

The hyper-parameters were tuned to avoid overfitting or underfitting the models. Softsign, tanh, and sigmoid activation functions (Equations 4 to 6) were assigned between the hidden layers while a rectified linear unit (ReLU) function was assigned between the hidden and output layers (3), all of which enhanced the network structure in model building. These nonlinear activations functions (2 to 6) are essential in learning complex data and allow the models to create complex mappings between the network’s inputs and outputs.

\[
Z_i = \sum_j W_{ij} x + b_i
\]  
(2)

\[
y = \text{ReLU} = \max(0, Z_i) \quad [0, \infty]
\]  
(3)

\[
y = \text{softsign}(Z_i) = \frac{Z_i}{1 + ||Z||} \quad [-1,1]
\]  
(4)

\[
y = \text{tanh}(Z_i) = \frac{e^{Z_i} - e^{-Z_i}}{e^{Z_i} + e^{-Z_i}} \quad [-1,1]
\]  
(5)

\[
y = \text{sigmoid}(Z_i) = \frac{1}{1 + e^{-Z_i}} \quad [0,1]
\]  
(6)

Where \(Z_i\) is the transfer function, \(W_{ij}\) are the weights, \(x\) is the layer input, \(y\) is the layer output, and \(b_i\) is the bias.

Adaptive moment estimation (Adam) Optimizer in Keras, a stochastic gradient descent optimization technique described elsewhere [69], [70] was used to optimize the models’ biases and weights during the model training whose performance was based on the MSE.

G. Model Performance and Accuracy

The accuracy of ANN models is measured by their ability to minimize bias [71], thus reducing error functions. Using the testing dataset, the models’ performance and accuracy markers were the root mean square error (RMSE) (7) and coefficient of determination \(R^2\) (8).

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\hat{x}_i - x_i)^2}{N}}
\]  
(7)

\[
R^2 = 1 - \frac{RSS}{TSS}
\]  
(8)

Where \(R^2\) is coefficient of determination, \(RSS\) is the residual sum of squares (9), and \(TSS\) is the total sum of squares (10) [72].

\[
RSS = \sum_{i=1}^{N} (y_i - f(x_i))^2
\]  
(9)

\[
TSS = \sum_{i=1}^{N} (y_i - \bar{y})^2
\]  
(10)

Where; \(N\) is the number of observations, \(y_i\) is value in a sample, and \(\bar{y}\) is the mean value of the sample.

The \(R^2\) measures the strength of linear correlations or associations between two variables, hence indicating how far away the estimated data points are from the line of best fit [73]. A plot of actual versus predicted observations of rheological properties of R-WBDM was produced and the \(R^2\) determined.

H. Sensitivity Analysis of the Models

The significance or importance of each input variable in estimating the rheological properties of R-WBDM was assessed using the Sobol library to measure. Equations 11 to 13 define the variance-based sensitivity analysis used in this study [74]. In the analyses, the first-order effect (S1) computed the first-order indices while the total order effect (ST) computed the total order indices [75]. The algorithm stored the corresponding confidence intervals, typically 0.95 (or 95%).

\[
Y = W_1X_1 + W_2X_2 \pm \cdots \pm W_{n-1}X_{n-1} + W_nX_n
\]  
(11)

\[
\text{Var} (Y) = E[\text{Var}(X_i)] + \text{Var}(E[Y|X]) \text{ for } i = 1, ..., n
\]  
(12)

\[
S_i = \frac{\text{Var}(E[Y|X_i])}{\text{Var} (Y)}
\]  
(13)

Where \(X_i\) is the random input variable, \(S_i\) is the sensitivity index, \(\text{Var}\) is the variance, \(E\) is the expected value operators, and \(W\) are the weights.

I. Model Implementation

The models were implemented by initializing the entire hyper-parameters, training, and assessing the performance and accuracy of retained models. The models were independently built through repeated training, validation, and testing exercises to yield an optimum predictive model for each rheological property of the R-WBDM. During model training, indices of training and validation sets were printed to assess the K-fold cross-validation process after each iteration, and five (5) optimum models were retained after each experiment. The mean of error metrics, that is the RMSE and \(R^2\), were computed for the optimum models to determine the overall performance of each model. The sklearn library ensured that the models’ training and testing
datasets did not interact. All models were built using the TensorFlow library in Python software (Version 3.7) installed on a 64-bit Intel i5 Lenovo ThinkPad laptop.

III. RESULTS AND DISCUSSION

A. Optimum Neural Networks Models

Five (5) optimum artificial neural networks (ANN) models were developed to estimate the plastic viscosity (PV), apparent viscosity (AV), yield point (YP), flow consistency index (k), and flow behavior index (n), the rheological properties of recirculated water-based drilling mud (R-WBDM). The optimal hyper-parameters were 1 batch size, 1,000 epochs, and a learning rate of 0.01 with a seven-layered structure having one input layer, five hidden layers, and one output layer. Each hidden layer had 512 neurons. Hence, the models completed 1,000 passes using a batch size of one. The high number of 512 neurons in the hidden layer can be attributed to the use of different combinations of activations functions and the manual tuning of the models’ hyper-parameters [74]. The input and output variables in this study exhibited low Pearson’s correlations (refer to Fig. 1) necessitating the development of a deep neural network model to ensure robust predictive models, hence the combination of different activations functions could have contributed to a large number of neurons in the hidden layer.

Similar studies have reported different ANN model structures. Three-layer ANN models (one input, hidden, and output layer) with 30 neurons for plastic viscosity and flow consistency index and 29 for apparent viscosity, yield point, and flow behavior index [19], and 10 neurons in the hidden layer and 10,000 epochs [39] have been reported. The difference between the number of neurons and layers reported in this study and those reported in the published literature [19],[39] can be attributed to the use of different activation functions, that is Elliot symmetric sigmoid (elliotsig) [19] and tansig [39] in the models. In this study, a combination of activation functions described in Section F was adopted, which could have influenced the ANN architecture, thus the performance of the models developed.

Also, the choice of optimization algorithms that determine the global convergence of ANN solutions can influence model performance. Researchers used modified self-adaptive differential evolution (MSaDE) [19], Broyden–Fletcher–Goldfarb–Shanno (BFGS) [39], and adaptive moment estimation (Adam) in this study and optimizing algorithms. The SaDE allows users to train models without adjusting the control parameters [75] while the BFGS attempts to solve nonlinear optimization problems without any constraints [76]. But the Adam Optimizer in TensorFlow defines and optimizes the expressed complex system or problem easily with the use of multi-dimensional arrays or tensors, thus able to solve extremely complex problems [55].

Fig. 4 shows the ability of the developed models to fit the data. In increasing order, the RMSE in estimating the flow consistency index (k), flow behavior index (n), apparent viscosity (AV), yield point (YP), and plastic viscosity (PV) is 0.12, 0.201, 0.630, 0.870, and 0.900, respectively. Low and high error terms indicate accurate model fitting of data and high residual errors in model fitting, respectively [77]. Thus, based on the error functions, the application of density (MD), marsh funnel viscosity (MFV), and percent (%) solids content (%S) of the R-WBDM would best fit the k and n data, moderately fit AV data, and least fit YP and PV data of the R-WBDM during drilling operations. Similar studies report training coefficients of determination (R²) and mean absolute percentage errors (MAPEs) of 0.970 and 7.8% [19] and 0.993 and 7.3% [39], respectively, to predict AV using MD and MFV as input variables. Thus, the findings in this study are comparable to those reported in published literature.

![Plastic Viscosity, PV-Training](image1)

![Apparent Viscosity, AV-Training](image2)

![Yield Point, YP-Training](image3)

![Flow Consistency Index, k-Training](image4)

![Flow Behavior Index Prediction, n-Training](image5)

Fig. 4. Learning ability of neural networks models.
B. Performance of the Models

Fig. 5 shows the prediction ability of the developed models when tested with new data. In decreasing order of model performance, the RMSE in estimating the k, n, PV, AV, and YP is 0.022, 0.2703, 7.890, 8.870, and 10.149, respectively. The small RMSE values indicate a good model fit of observed data characterized by a small noise and while the large RMSE values demonstrate failure by the model to account for some important features in the data, hence lower accuracy [77]. Comparatively, the performance of the ANN models in estimating the k and n properties of R-WBDM was consistently good during training and testing showing low errors, indicating potential reliability in estimating the rheological properties assessed in this study. Moreover, the order of error functions during training and testing the models in estimating the PV, AV, and YP properties was not consistent, which implies that the RMSE may not be an absolute measure of a good model because of the intuitive penalization of large errors [77].

In a similar order of rheological properties, the $R^2$ of 0.995, 0.956, 0.756, 0.724, and 0.701 indicate good generalization capability of the models above 70% (Fig. 4). The higher the $R^2$ the higher the predictive ability of the model [78]. Thus, the models demonstrate the potential application of MD, MFV, and %S of R-WBDM as predictor variables to estimate the rheological properties of the mud during drilling operations.

C. Sensitivity of the Models to Variable Changes

Table I presents the sensitivity of the models in estimating the rheological properties of R-WBDM to changes in the input variables, thus their importance in estimating the output variables. The results show that the PV, AV, YP, and k models are highly sensitive (sensitivity index = 0.615) to variations in the order of error functions during training and testing the models in estimating the PV, AV, and YP properties was not consistent, which implies that the RMSE may not be an absolute measure of a good model because of the intuitive penalization of large errors [77].

In a similar order of rheological properties, the $R^2$ of 0.995, 0.956, 0.756, 0.724, and 0.701 indicate good generalization capability of the models above 70% (Fig. 4). The higher the $R^2$ the higher the predictive ability of the model [78]. Thus, the models demonstrate the potential application of MD, MFV, and %S of R-WBDM as predictor variables to estimate the rheological properties of the mud during drilling operations.

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Fig. 5: Cross-plot of the actual and predicted values of the rheological properties of the mud.
The artificial neural networks (ANN) algorithm in TensorFlow has effectively estimated the plastic viscosity (PV), apparent viscosity (AV), yield point (YP), flow consistency index (k), and flow behavior index (n). Five rheological properties of recirculating water-based drilling mud (R-WBDM) used in geothermal drilling for exploration. Five optimal models were retained, one for each rheological property. Three model input variables used to develop the models: the density (MD), mass funnel viscosity (MFV), and percent solids content (%S) of the mud. The findings demonstrate the potential to use MD, MFV, and %S as model prediction features, which are physical properties of the mud frequently measured in the field during drilling operations using inexpensive instruments. All models show good generalization ability with R^2 > 0.70. The PV, AV, YP, and k model predictions were sensitive to variations in the MFV of the mud while the n model prediction was influenced by changes in the %S. There is potential in using ANN models and TensorFlow machine learning libraries in drilling engineering to assist in solving pipe sticking problems under uncertain flow characteristics of drilling mud, which could save time and costs of experiments.

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### CONFLICT OF INTEREST

Authors declare that they do not have any conflict of interest.

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