Improved Tracking of the Rheological Properties of Max-Bridge Oil-Based Mud Using Artificial Neural Networks

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ABSTRACT: Lab measurements for the rheological properties of mud are critical for monitoring the drilling fluid functions during the drilling operations. However, these measurements take a long time and might need more than one person to be completed. The main objectives of this research are to implement artificial intelligence for predicting the mud rheology from only Marsh funnel ($\mu_f$) and measuring mud density ($\rho_m$) easily and quickly on the rig site. For the first time, an artificial neural network (ANN) was used to build different models for predicting the rheological properties of Max-bridge oil-based mud. The properties included the plastic viscosity ($\mu_p$), yield point ($\gamma$), flow behavior index ($\eta$), and apparent viscosity ($\mu_a$). Field measurements of 383 samples were used to build and optimize the ANN models. The obtained results showed that 32 neurons in the hidden layer and tan sigmoid function transfer function were the best parameters for all ANN models. The training and testing processes of models showed a strong prediction performance with a correlation coefficient ($R$) greater than 0.91 and an average absolute percentage error (AAPE) less than 5.31%. New empirical correlations were developed based on the optimized weights and biases of the ANN models. The developed empirical correlations were compared with the published correlations, and the comparison results confirmed that the ANN-developed correlations outperformed all previous work.

1. INTRODUCTION

Drilling fluid has several functions in the drilling operation as it basically transports cuttings from the bottom of the well to the surface through circulation. Mud is lubricating the drill string and the bit in addition to cooling them. Mud must be designed to form a thin and faster-formed filter cake that can minimize filter loss. One of the most important roles is to control the formation pressure by applying the required overbalance to prevent formation fluids from entering the bottom of the well causing kicks and interruption of the operation.1

According to the base fluid, the drilling fluid has two main categories which are water- or oil-based.1−3 Different chemicals and materials are used for optimizing the drilling fluid properties, such as adding the weighting materials, which are used for regulating the density, and viscosifiers, which are used for tuning the rheological properties (plastic viscosity, yield point, gel strength, etc.) by special chemicals and additives.4

Oil-based mud (OBM) is classified into two main classes, which are all-oil and invert emulsion. All-oil contains oil as a base fluid with no water or with a very little amount, usually less than 5%. Invert emulsion contains oil as the continuous phase with a large volume of water (as high as 60%) as the dispersed phase.5,6

Invert emulsion mud has many advantages such as minimizing corrosion of casing and tubing, efficient in drilling troublesome formations (unstable shale), protecting water-bearing forma-
and lower toxicity compared with the oil-base mud system. It can be stable under extreme conditions of temperature and pressure.\textsuperscript{5}

Max-bridge is one type of oil-based mud with special additives. Max-bridge mud system has bridging agents that consist mainly of resilient graphite and special sealing polymers that effectively seal the pore throats to provide the bridging effect. The advanced bridging materials in this type of mud have been proven to be effective with drilling depleted reservoirs of high permeability to prevent problems such as stuck pipe and losses. Figure 1 shows a schematic diagram of the sealing impact by the mud bridging agents that leads to plugging of the rock pore throats.

1.1. Drilling Fluid Monitoring during Operations. Good monitoring of the mud rheological properties is very critical in the drilling operations as it affected the drilling performance. Improving the drilling performance requires effective cleaning of the hole and optimization of the bit hydraulics.\textsuperscript{10} Drilling hydraulic optimization accounts for pressure losses that rely mainly on the rheological properties of the drilling fluid.\textsuperscript{8} It is also possible to estimate equivalent circulating density (ECD), which reflects the apparent weight of the mud under complex conditions, to compensate for many drilling problems such as loss of circulation, surge and swab pressures,\textsuperscript{9} and instances of well control.

Therefore, continuous measurements for the mud properties are needed and performed on the rig site using the mud lab that is equipped with the needed testing instruments like a Marsh funnel and a mud balance. Marsh funnel viscosity is just a time recorded for a volume of 930 cm\textsuperscript{3} to flow through the funnel orifice as described by Marsh.\textsuperscript{13} Some other lab devices are existing only on the mini-lab on rig site like a rotating viscometer for measuring the mud rheological properties, and an API filter press is required for measuring filtration properties. Mud weight has particular significance concerning pressure management inside the well.\textsuperscript{17} During the drilling process, mud density and Marsh funnel viscosity are assessed three to four times per hour. The two measurements provide an indication of the mud properties changes that reflect the interaction between the mud and the drilled rock. These lab measurements will help for better monitoring of the mud performance and quick actions for optimizing the mud properties by mud reformulation.\textsuperscript{15}

The traditional way of such measurements is time-consuming and prone to human errors; hence, automating this process is a need for the drilling industry to overcome the difficulties in measuring rheology at a higher frequency. A few studies were conducted for addressing this issue.\textsuperscript{18–20} A patented device has been conducted for addressing this issue.\textsuperscript{21} They claimed that normal rheology lab measurements are outdated, but they could not explain the disparity between the continuous flowing measurement of rheology and the static old-fashioned lab tests.

Apparent viscosity (\(\mu_a\)) (cP) was related to Marsh funnel viscosity (\(\mu_f\)) (s) and mud weight (\(\rho_m\)) (gm/cm\textsuperscript{3}) by Pitt\textsuperscript{21} as per eq 1. The same parameters were used in another study by Almahdawi et al.\textsuperscript{22} to get apparent viscosity, but the constant was different as in eq 2.

\[
\mu_a = \rho_m \times (\mu_f - 25) \tag{1}
\]

\[
\mu_a = \frac{\rho_m}{18} \times (\mu_f - 28) \tag{2}
\]

1.2. Petroleum Engineering Utilization of Artificial Intelligence. The artificial intelligence (AI) technology helped to manage a process in which the machine starts to learn about the data patterns and how different parameters could affect each other to find a description of the relations.\textsuperscript{23} The implementation of AI tools contributed to solving many technical problems such as estimation and optimization of drilling parameters\textsuperscript{14,24–28} and prediction and monitoring of the drilling fluids properties,\textsuperscript{25–34} reservoir fluid properties,\textsuperscript{35–40} rock permeability,\textsuperscript{41,42} and rock strength and geomechanical properties.\textsuperscript{43–47} This is reflecting the trust in the AI models generated and the need for such applications in the drilling industry.

The main objective of this research is to build artificial neural network (ANN) models that can be used to predict the rheological properties of Max-bridge in real time using only two inputs, which are mud density (\(\rho_m\)) and Marsh funnel viscosity (\(\mu_f\)). These models were optimized, and empirical equations were developed to overcome the traditional measurement technique for the mud properties and enhance the automation technique for better monitoring of the mud characteristics.

Section 2 describes the data description, statistical analysis, and the ANN approach and optimization, followed by Section 3 that represents the results obtained from the model training and testing, Section 4 for in-depth discussion and analysis of the results, and finally Section 5 that summarizes the study findings.

2. MATERIALS AND METHODS

The mud rheological properties are determined according to the model that best describes the mud behavior. Those mathematical models that may describe mud rheology are like the Bingham plastic model, which is a two-parameter model. The design of the rotational rheometer was conducted basically for the fluids following the Bingham plastic model. Another rheological model is the power-law model, which is also a two-parameter model, but it describes pseudoplastic fluids that show a decrease in viscosity with increasing shear rate.\textsuperscript{14} The most accurate model considered for describing the rheological properties changes is considering the Bingham plastic model. Another rheological model is the power-law model, which is also a two-parameter model, but it describes pseudoplastic fluids that show a decrease in viscosity with increasing shear rate.\textsuperscript{14} The most accurate model considered for describing the rheological properties changes is considering the Bingham plastic model.
behavior of drilling fluids is the Herschel–Bulkley model, which is a three-parameter model.

2.1. Data Description and Statistics. The recorded data for this study were the mud weight and Marsh funnel viscosity that were measured for the same mud samples. The plastic viscosity, yield point, apparent viscosity, and behavior index of the same samples were calculated from the viscometer readings at 300 and 600 rpm. All of the recorded data were for the same mud type but from several drilling sites. The data collected were of a wide range that was essential to have reliable general models.

The data used for building the artificial intelligence models contained mud weight for each sample of a total of 383 samples with a wide range starting from 76 to 120 pcf. The Marsh funnel viscosity was measured and recorded for each sample with very low values starting from only 44 s to 120 s. The plastic viscosity values ranged from 12 to 73 cP, while the yield point ranged from 14 lb/100ft² to 39 lb/100ft². The apparent viscosity ranges from 20 to 89 cP. The behavior index was calculated and shows a range of 0.51–0.82. Table 1 summarizes the statistical analysis of the model data.

2.2. Data Preprocessing and Analysis. The approach that was employed in this study included purification of the data before using simple Matlab codes from invalid, unrealistic, and/or missed portions of data that were removed to have a good quality data set of 383 lines. This process was implemented to remove the data outliers to improve the data quality.48,49

The next step was to verify that there is a relation between inputs and outputs by checking the correlation coefficient (R) between inputs and outputs.

Strong relations between the parameters were shown as per the correlation coefficients (Figure 2). Mud weight increase has a direct relationship with viscosity, and the data used in this study showed the highest correlation coefficient with apparent viscosity, which is logical and natural. Mud weight had a slightly less correlation coefficient with plastic viscosity (0.67) and with apparent viscosity (0.68). Numbers are pushing toward the fact that high-quality data are available for developing accurate models with mud weight with a correlation coefficient of 0.43 with behavior index. The least correlation coefficient was with yield point. The correlation coefficient between mud weight and yield point was 0.29, which is still good. This low R might be attributed to the nonlinear relations between the parameters.

The correlation coefficient between the other input that was Marsh funnel viscosity and apparent viscosity was also the highest among all of the rheological parameters, i.e., 0.59, followed by plastic viscosity, 0.57, which is still a high correlation coefficient. The n parameter had the lowest correlation coefficient of 0.30, while the yield point had a correlation coefficient of 0.34 with Marsh funnel viscosity.

2.3. Optimization Tool and Approach. The technique of artificial neural networks is widely used for its efficacy and reliability in the petroleum industry disciplines such as fluid properties modeling50–52 reservoir flooding,53–55 and rock properties estimation.56,57 It can imitate various complex issues that cannot be dealt with using simple nonlinear regression techniques.58 Artificial neural networks provide an efficient way for analyzing the problem characteristics and the interrelations of parameters based on data analytics.59 It was originally designed to mimic the performance characteristics of neurons.60

The elementary units of artificial neural networks are artificial neurons. The required layers of the artificial neural network structure are known as the input, hidden, and output layers. In addition to the appropriate transfer function that represents the nature of the problem, the network also contains a training algorithm.60 In each layer, neurons are connected with other neurons by constant parameters called weights and biases in the next layer.61 For regression tasks, the (pure linear) transfer function used in the output layer, in addition to log-sigmoid and tan-sigmoidal, is a common type of transfer function.60

AI has recently been widely used in the field of fluids for drilling. Some of these applications involve optimizing drilling,63 optimizing hydraulics,64 and predicting rheological characteristics of invert emulsion mud65 water-based KCl mud66 drilling liquid CaCl267 and water-based NaCl drill-in fluid.31

After data purification and quality checks, the next step is to choose the artificial intelligence technique that would approximate functions for predicting the rheological parameters from mud weight and Marsh funnel viscosity. The neural networks technique was chosen that helped us to derive ANN-based equations in this study to make them available for usage in automated systems or simple comparison with other research. The data set was prepared for the training process within the code developed using the Matlab program. The data set was used for predicting a single rheological parameter in time.

Several trials were made to obtain the optimum parameters for the neural network used for the prediction of each rheological parameter and tuning of the artificial neural network parameters. Each rheological property, including plastic viscosity and yield point, was considered as a separate problem that needed to be defined in a separate neural network. A file containing the inputs, which were mud weight and Marsh funnel viscosity, and the output, which was a single rheological property, was loaded and the parameters were defined.

To have an improved generalization of the developed models, the data set was divided into a training set, which would be used in training, and a testing set, which is separate from training and will not be seen by the neural network while training. The testing set is used to check the strength of the trained model.

A feedforward neural network was used with a single hidden layer, which was powerful enough to have excellent accuracy. Training function of a network updates weights and bias values according to certain optimization. A backpropagation Levenberg–Marquardt algorithm was used, which is the fastest method with medium-sized networks, and it is the most efficient when used with Matlab software. For each rheological parameter, the number of neurons in the hidden layer had a significant effect on the accuracy of the trained model and was considered to be the main hyperparameter. Other hyperparameters were selected and tested for their results. Not only the trained model was evaluated with the accuracy of training, but also the testing stage was included in the evaluation. The correlation coefficient between the values obtained for the
output from the developed artificial neural networks model and the measured values was used as an indication of the quality of the models. Average absolute percentage error was used also as another indicator for the amount of error resulting from the model compared to the recorded rheological parameters. The process was like building four different models or dealing with four different problems. Those four models were successfully developed for predicting the plastic viscosity, apparent viscosity, yield point, and flow behavior index.

3. RESULTS

For all of the four parameters investigated in this study, the number of neurons in the hidden layer that produced the most accurate models was found to be 32, which is the same for all. The transfer function was changing as well in the trials to choose between the log-sigmoid function and the tan sigmoid function and also for all of the four parameters. The tan sigmoid function is found to be the best transfer function. This made the architecture of the artificial neural networks for all of the four developed models the same. The weights and biases were then extracted from the code for all of the models. The neural networks have internal normalization for the input and output values between (1) maximum and (−1) minimum. For any simple program or automation process, eqs 3 and 4 for normalization of the inputs must be used, where the normalized parameters would have a subscript (n) added to their symbols.

\[
\rho_{\text{norm}} = 0.045\left(\rho_m - 76\right) - 1 \tag{3}
\]

\[
\mu_{\text{norm}} = 0.026\left(\mu_i - 44\right) - 1 \tag{4}
\]

The equations derived from the neural networks used in the optimization process would be used for the normalized inputs, and a table of weights and biases was used for each output. Eqs 5–8 were used to denormalize the output to get the predicted value.

\[
\mu_p = \frac{\mu_{\text{norm}} + 1}{0.033} + 12 \tag{5}
\]

\[
\gamma = \frac{\gamma_n + 1}{0.08} + 14 \tag{6}
\]

\[
\eta = \frac{\eta_n + 1}{6.452} + 0.51 \tag{7}
\]

\[
\mu_s = \frac{\mu_{\text{norm}} + 1}{0.029} + 20 \tag{8}
\]

Table 2. Weights and Biases for Plastic Viscosity Model

| i  | w1,i | w1,2 | b1 | w2  |
|----|------|------|----|-----|
| 1  | 1.33 | -9.42| -6.60 | -7.39 |
| 2  | -2.17| 9.12 | 6.80 | 7.71 |
| 3  | 0.58 | 4.08 | 0.87 | 21.32 |
| 4  | -1.30| 3.97 | 0.26 | -25.99 |
| 5  | -1.59| 7.00 | 0.73 | 12.50 |
| 6  | 21.75| -25.02| -16.43 | 24.50 |
| 7  | -51.37| -22.45 | 24.45 | -0.28 |
| 8  | -13.74| 27.31 | 7.78 | 20.04 |
| 9  | -0.98 | 3.89 | -0.17 | 20.48 |
| 10 | -25.38| -12.95| 27.79 | 0.45 |
| 11 | -1.74 | -4.21 | 1.15 | 2.19 |
| 12 | 2.88 | 8.99 | 1.53 | 7.89 |
| 13 | -12.97| 7.67 | 10.95| 0.92 |
| 14 | 83.37 | 62.30| -39.01| -0.15 |
| 15 | -1.61 | 21.59| -3.63| -0.22 |
| 16 | 5.81 | -14.21| 3.51 | 0.50 |
| 17 | -10.99| -3.34| -0.84| 0.56 |
| 18 | 0.05 | 4.16 | 4.07 | 2.32 |
| 19 | -4.81 | -16.99| 3.72 | -0.32 |
| 20 | 53.55 | 24.65| 22.20 | -0.41 |
| 21 | 3.58 | 1.57 | 0.82 | 5.55 |
| 22 | -4.53 | -12.69 | -2.20 | 3.38 |
| 23 | -69.70| 49.28| -35.31| 0.16 |
| 24 | -17.97| -9.71| -4.14 | 8.91 |
| 25 | -7.77 | -24.01| -6.48 | -12.37 |
| 26 | 21.10 | 11.73| 4.85 | 7.32 |
| 27 | -10.03| 3.69 | -9.53 | 12.05 |
| 28 | -9.05 | -28.79| -7.42 | 7.26 |
| 29 | 10.03 | -1.85 | 9.24 | 12.42 |
| 30 | -5.09 | -12.83 | -4.44 | 6.40 |
| 31 | 3.87 | 5.39 | 9.08 | 0.10 |
| 32 | -1.69 | -6.64 | -8.99 | 1.83 |

Figure 3. Plastic viscosity ANN-based model results vs actual measurements: (a) training data set and (b) testing data set.
The normalized outputs had their equations related to the inputs according to the transfer function used with all of the four networks for the four parameters (tansig). The training set had 223 points, which constitute 58% of the total data set that is cleaned purified and checked for quality.

### 3.1. Plastic Viscosity Model

The artificial neural network architecture of a single hidden layer extracted the inputs as mud weight and Marsh funnel viscosity while the output was defined as plastic viscosity only. Several automatic trials through a loop were running the learning algorithm with changing the number of neurons starting from 5 neurons up to 50. Regarding the trials, they included loops for different randomization of the data with training data set percent at minimum 50–80%. The trials included changing the training function from the following: trainlm, trainbr, trainscg, trainrp, trainbfg, traincgb, traincgf, traincgp, trainoss, traindx, traindm, and trainfda, and also the transfer function was chosen from several trials for the following different transfer functions: tansig, logsig, elliotsig, purelin, satlin, satlins, and poslin. The optimization process included the testing stage with 160 points. The values of correlation coefficient and average absolute percentage error for training and testing with each number of neurons tried were recorded, and the whole process was evaluated according to that. The optimum number of neurons on the hidden layer was 32 neurons that achieved an R of 0.96 and an AAPE of 4.59% for the training phase between the model results and the actual values (Figure 3a). The correlation coefficient of the testing set for the plastic viscosity model was lower but still accurate enough to have a robust model as it was 0.93 along with a low AAPE of only 5.31% (Figure 3b). Eq 9 was extracted from the resulted artificial neural networks model.

A table containing the weights and biases was extracted from the network with the number of neurons (N) and neuron index (i). The weights ($w_1$ and $w_2$) are presented in Table 2 along with the values of the biases ($b_1$). For the bias ($b_2$), it was found to be (-1.40).

$$
\mu_{\text{pl}} = \sum_{i=1}^{N} w_1 \left( \frac{2}{1 + \exp(-2(w_{1,i}p\text{max} + w_{1,i}p\text{min} + b_1))} - 1 \right) + b_2
$$

(9)

### 3.2. Yield Point Model

By following the same approach, the results of the yield point model showed that R was 0.91 for both training and testing data sets as shown in Figure 4. AAPE

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**Table 3. Weights and Biases for Yield Point Model**

| i  | $w_{1,i}$ | $w_{2,i}$ | $b_1$ | $w_2$ |
|----|-----------|-----------|-------|-------|
| 1  | -8.96     | -8.25     | 13.10 | -7.59 |
| 2  | 11.67     | -5.97     | -11.34| -5.84 |
| 3  | 11.16     | 18.61     | -18.65| -2.01 |
| 4  | -11.72    | -0.21     | 9.01  | -4.04 |
| 5  | 15.47     | -13.44    | -9.78 | -0.75 |
| 6  | 1.59      | -6.08     | 2.36  | 0.40  |
| 7  | -26.20    | -22.20    | 18.88 | -0.09 |
| 8  | -11.97    | 1.36      | 8.69  | 4.34  |
| 9  | 39.19     | 15.14     | -6.63 | 0.15  |
| 10 | -2.09     | 8.52      | 2.02  | -4.54 |
| 11 | -14.66    | 4.78      | 4.11  | -1.40 |
| 12 | 0.86      | 2.81      | -0.81 | 2.81  |
| 13 | -0.66     | 1.55      | 1.08  | -20.42|
| 14 | 3.37      | -64.51    | 12.18 | 0.03  |
| 15 | -5.67     | 2.52      | 1.50  | 3.25  |
| 16 | 15.06     | -7.76     | 2.23  | -0.06 |
| 17 | 28.67     | 10.46     | -2.17 | 0.14  |
| 18 | -8.58     | -3.87     | 1.29  | 0.86  |
| 19 | -5.66     | -3.90     | -0.90 | -4.15 |
| 20 | -1.61     | -3.36     | -0.59 | -2.77 |
| 21 | 5.15      | 3.12      | 0.90  | -6.51 |
| 22 | 5.03      | 0.34      | 4.54  | -12.18|
| 23 | -36.30    | 43.15     | -46.10| -8.20 |
| 24 | -30.67    | -2.51     | -11.63| 0.21  |
| 25 | 14.83     | -0.52     | 12.53 | 1.18  |
| 26 | 5.42      | 0.73      | 2.98  | -8.41 |
| 27 | -4.57     | -0.22     | -2.56 | -9.21 |
| 28 | -6.77     | -4.78     | -5.97 | -1.77 |
| 29 | -0.82     | 6.75      | 2.18  | 13.43 |
| 30 | -1.15     | 4.40      | -10.74| -7.58 |
| 31 | 4.14      | -0.89     | 4.06  | 7.92  |
| 32 | 60.64     | -75.65    | 77.30 | -25.77|

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**Figure 4. Yield point ANN-based model results vs actual measurements: (a) training data set and (b) testing data set.**
weights and biases are listed in Table 3. The model equation derived for normalized yield point is eq 10 with the bias ($b_2$) of 15.90, and the remaining weights and biases are listed in Table 3.

was 4.85 and 4.98% for training and testing processes, respectively. The model equation derived for normalized yield point is eq 10 with the bias ($b_2$) of 15.90, and the remaining weights and biases are listed in Table 3.

3.3. Flow Behavior Index Model. Figure 5 shows that the results of the flow behavior index model were 0.91 and 0.94 for $R$, while AAPEs were 1.68 and 1.66% for the training and testing data sets, respectively. Weights and biases to normalize the flow behavior index equation (eq 11) are listed in Table 4, and the bias ($b_2$) was −11.80.

$$
\gamma_n = \left[ \sum_{i=1}^{N} \frac{w_{2i}}{1 + \exp[-2(w_{1i}\gamma_{mn} + w_{1i}\gamma_{fn} + b_1)]} \right] - 1
+ b_2
$$

3.4. Apparent Viscosity Model. The apparent viscosity model performed well for training and testing phases, and the results showed $R$ values of 0.97 and 0.93 and AAPEs of 3.51 and 4.67% for the training and testing data sets, respectively (Figure 6). Table 5 presents the weights and biases for the apparent viscosity equation (eq 12) while bias ($b_2$) was 9.96.

$$
\eta_n = \left[ \sum_{i=1}^{N} \frac{w_{2i}}{1 + \exp[-2(w_{1i}\eta_{mn} + w_{1i}\eta_{fn} + b_1)]} \right] - 1
+ b_2
$$

3.5. Cross-Validation of the Four Models. The training data set used for developing the four models went through rigorous checking using the cross-validation technique. The training data were distributed over five portions. Each partition is used to test the developed model with the results recorded and compare to each other as in Table 6, which lists the correlation coefficients ($R$) for the testing fold of the four rheological parameters and in Table 7, which lists the AAPEs. It was found that the accuracy of the models was assured according to the evaluation that needed several runs for each rheological parameter.

Figure 5. Flow behavior index ANN-based model results vs actual measurements: (a) training data set and (b) testing data set.
4. DISCUSSION

In this study, we successfully employed artificial intelligence as an approach for better prediction of the mud rheology in real time from only two inputs. In addition, the study enhanced the automation process for tracking the mud rheological properties.

Table 5. Weights and Biases for Apparent Viscosity Model

| i   | $w_{1,1}$ | $w_{1,2}$ | $b_1$ | $w_2$ |
|-----|-----------|-----------|-------|-------|
| 1   | -30.20    | -31.64    | 35.35 | 8.63  |
| 2   | 2.93      | -0.85     | -8.30 | -8.11 |
| 3   | -0.38     | 17.62     | -13.69| -0.08 |
| 4   | -32.52    | -33.64    | 37.85 | -7.90 |
| 5   | 10.90     | -6.99     | -7.60 | 13.86 |
| 6   | 7.95      | -7.72     | 7.41  | -1.09 |
| 7   | -29.97    | -17.05    | 15.10 | 0.39  |
| 8   | -12.75    | 8.86      | 8.89  | 11.49 |
| 9   | 3.33      | 17.20     | -6.35 | 0.26  |
| 10  | -9.54     | 10.62     | 4.54  | 25.60 |
| 11  | -10.99    | 3.08      | 4.16  | -2.46 |
| 12  | 33.41     | 68.75     | -23.10| -0.20 |
| 13  | -8.81     | 10.66     | 3.93  | -24.29|
| 14  | -38.69    | -156.60   | 8.64  | 0.07  |
| 15  | -8.95     | 8.48      | 2.54  | 3.10  |
| 16  | 27.95     | -4.76     | 0.45  | -0.17 |
| 17  | 5.90      | -0.43     | 1.34  | 19.38 |
| 18  | -6.39     | 0.52      | -1.43 | 18.22 |
| 19  | -16.54    | -18.43    | -3.52 | 5.95  |
| 20  | -23.38    | 2.93      | -9.92 | -8.94 |
| 21  | 21.81     | -2.68     | 9.22  | -9.70 |
| 22  | 37.14     | 10.01     | 25.67 | -2.65 |
| 23  | -67.91    | 27.82     | -26.97| -0.11 |
| 24  | -16.20    | -17.94    | -3.45 | -6.08 |
| 25  | 16.30     | 9.66      | 11.10 | 9.80  |
| 26  | 15.36     | 16.58     | 10.25 | -24.79|
| 27  | -27.36    | 30.42     | -33.45| -15.53|
| 28  | -15.74    | -18.78    | -10.45| -17.88|
| 29  | 15.80     | -14.48    | 14.89 | 0.57  |
| 30  | -25.31    | 81.48     | -38.20| -0.14 |
| 31  | 6.54      | -4.40     | 5.83  | -1.08 |
| 32  | 31.46     | -30.37    | 37.95 | -33.55|

Table 6. Correlation Coefficient ($R$) for the Testing Fold for the Four Rheological Parameters

|          | $\mu_p$ | $\gamma$ | $\eta$ | $\mu_a$ |
|----------|---------|----------|--------|---------|
| $R_1$    | 0.97    | 0.91     | 0.97   | 0.96    |
| $R_2$    | 0.97    | 0.81     | 0.92   | 0.97    |
| $R_3$    | 0.96    | 0.91     | 0.92   | 0.98    |
| $R_4$    | 0.98    | 0.81     | 0.92   | 0.97    |
| $R_5$    | 0.96    | 0.88     | 0.94   | 0.97    |

Table 7. AAPE for the Testing Fold for the Four Rheological Parameters

|          | $\mu_p$ | $\gamma$ | $\eta$ | $\mu_a$ |
|----------|---------|----------|--------|---------|
| AAPE$_{1}\%$ | 4.7    | 6.5      | 1.4    | 4.1     |
| AAPE$_{2}\%$ | 3.9    | 7.0      | 1.9    | 3.2     |
| AAPE$_{3}\%$ | 4.7    | 4.9      | 1.7    | 3.0     |
| AAPE$_{4}\%$ | 4.3    | 7.6      | 1.6    | 3.7     |
| AAPE$_{5}\%$ | 4.6    | 5.4      | 1.7    | 3.6     |

Figure 6. Apparent viscosity ANN-based model results vs actual measurements: (a) training data set and (b) testing data set.

Figure 7. Actual values of apparent viscosity versus predicted values from the equation developed by this study, Pitt’s equation, and Almahdawi’s equation.
for better performance in drilling operations. The developed models for the mud rheological properties were compared with other conventional models to check the prediction accuracy. Pitt had developed an equation that can be used to calculate the apparent viscosity depending on mud weight and Marsh funnel viscosity. This correlation was updated by Almahdawi. The correlations developed by Pitt and Almahdawi were developed depending on samples not representing all types of mud which makes it unreliable when exposed to different types of mud.

Studying the relation between Marsh funnel viscosity and rheology considering the type of mud is a more successful approach. Elkatatny et al. succeeded in having highly accurate models not only for apparent viscosity but also for plastic viscosity, yield point, flow behavior index, and flow consistency index. However, the study included the solid content measured in percentage as a parameter on the developed models that involve an issue for measurement error. The rheology of mud predicted from mud weight, Marsh funnel viscosity in some studies, and solid percent in some other studies, it was possible to omit the solid percent from inputs, which was revisited by researchers many times manipulating data for different types of mud.

Elkatatny dealt with invert emulsion mud using artificial neural networks, but including the solid percent on the inputs besides mud weight and Marsh funnel viscosity. This type of mud was revisited by Alsabaa et al. using an adaptive network-based fuzzy inference system (ANFIS) into having highly accurate models predicting rheological properties but, this time without solid percent, which is an advantage that allows for high resolution of rheology tracking with no time consumed in determining the solid percent on mud sample.

Elkatatny et al. have used a simple nonlinear regression technique for developing models to predict the rheology of invert emulsion mud using mud weight and Marsh funnel viscosity as inputs, and the developed equations were included in that research. The equations developed by Elkatatny et al. for invert emulsion mud indicate the logarithmic relationships between Marsh funnel viscosity ($\mu_m$) in seconds and plastic viscosity ($\mu_p$) (eq 13) measured in (cP), yield point ($\gamma$) (eq 14) measured in (lb/100ft$^2$), flow behavior index ($\eta$) (eq 15), and apparent viscosity ($\mu_a$) (eq 16) measured in (cP). The mud weight is used as the input in eqs 13−16 and was measured in (g/cm$^3$), which needed conversion for values of data used in this study as mud weight was in (pcf).

$$\mu_p = 17.735\mu_m \log(30.9) - 7.979$$ (13)

$$\gamma = 1.5492\mu_m \log(30.9) + 18.84$$ (14)

$$\eta = 0.1193\mu_m \log(11.249) + 0.3459$$ (15)

$$\mu_a = 18.833\mu_m \log(30.9) + 0.9186$$ (16)

4.1. Comparison with Published Studies. One of the earliest studies on the relationship between Marsh funnel viscosity and mud rheology was done by Pitt. The formula that Pitt developed for predicting the apparent viscosity depending on mud weight and Marsh funnel viscosity can be used with the 383 data points to evaluate the value of the work done here compared to previous studies. It was found that the correlation coefficient for the apparent viscosity obtained from Pitt’s equation (eq 1) was 0.74, which is fairly good, but the model developed from this study is much more accurate as it had a correlation coefficient of 0.96 and the values resulted from this model had higher quality when checked for average absolute percentage error that was extremely low, i.e., 3.99%, which is far less than the average absolute percentage error from Pitt’s equation (eq 1) that was 78.44%. Even the modified version of Pitt’s equation, that is, Almahdawi’s equation (eq 2), is still outperformed by the model developed by this study for predicting apparent viscosity when tested against the 383 points used with a correlation coefficient of 0.96 and high error in terms of average absolute percentage error that was 73.87% (Figure 7). The results from this comparison confirmed the success and high accuracy of the developed ANN models.
The whole data set used for training and testing for the Max-bridge oil-based mud models was used for comparison with other models. Generally, the developed models for the Max-bridge oil-based mud outperformed all of the models developed by Elkatatny et al. in terms of $R$ (Figure 8a) and AAPE (Figure 8b).

5. CONCLUSIONS
This work facilitates the monitoring of rheological parameters in real time with an automated approach using the ANN. High-frequency measured data like mud weight and Marsh funnel viscosity are used directly to predict the rheological parameters of Max-bridge oil-based mud. The following conclusion can be drawn:

- Four ANN models were developed for predicting the rheological properties such as plastic viscosity ($\mu_p$), yield point ($\gamma$), flow behavior index ($\eta$), and apparent viscosity ($\mu_a$) in real time with a high accuracy.
- Each model has its optimized parameters; however, 32 neurons in the hidden layer and tan sigmoid (tansig) function transfer function were the best parameters for all models.
- The models’ training and testing phases showed a high performance with $R$ greater than 0.91 and AAPE less than 5.31%.
- The models outperformed other published studies in terms of $R$ and AAPE between the actual and predicted values.
- This study provided empirical equations for estimating the mud rheological parameters to be employed for estimation in real time with a high accuracy.

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Author Contributions
The manuscript was written through the contributions of both authors. Both of them have approved the final version of the manuscript.

Funding
This research received no external funding.

Notes
The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS
The authors acknowledge King Fahd University of Petroleum & Minerals for permitting the publication of this work.

■ NOMENCLATURES

| Term          | Definition                                      |
|---------------|-------------------------------------------------|
| ANN           | artificial neural network                       |
| $\rho$        | mud density                                     |
| $\mu$         | marsh funnel viscosity                          |
| $\gamma$      | yield point                                     |
| $\mu_p$       | plastic viscosity                               |
| $\mu_a$       | apparent viscosity                              |
| $\eta$        | flow behavior index                             |
| $C_p$         | centipoise                                      |
| OBM           | oil-based mud                                   |
| $R$           | correlation coefficient                         |
| AAPE          | average absolute percentage error               |
| trainlm       | Levenberg–Marquardt backpropagation             |
| trainbr       | bayesian regularization                         |
| trainscg      | scaled conjugate gradient backpropagation       |
| trainrp       | resilient backpropagation ($R$prop)             |
| trainbfg      | BFGS quasi-Newton backpropagation               |
| traincgf      | Powell–Beale conjugate gradient backpropagation |
| traincgp      | Polak–Ribière conjugate gradient backpropagation|
| trainoss      | one-step secant backpropagation                 |
| traindx       | gradient descent with momentum and adaptive     |
| traindm       | gradient descent with momentum backpropagation  |
| trainda       | gradient descent with adaptive learning rule    |
| tansig        | hyperbolic tangent sigmoid transfer function    |
| logsig        | log-sigmoid transfer function                   |
| elliotsg      | elliot symmetric sigmoid transfer function      |
| purelin       | linear transfer function                        |
| satlin        | saturating linear transfer function             |
| satlins       | symmetric saturating linear transfer function   |
| poslin        | positive linear transfer function               |

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