Development of New Rheological Models for Class G Cement with Nanoclay as an Additive Using Machine Learning Techniques

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ABSTRACT: The rheology of the oil well cement plays a pivotal role in the cement placement. Accurate prediction of cement rheological parameters helps to monitor the durability and pumpability of the cement slurry. In this study, an artificial neural network is used to develop different models for the prediction of various rheological parameters such as shear stress, apparent viscosity, plastic viscosity, and yield point of a class G cement slurry with nanoclay as an additive. An extensive experimental study was conducted to generate enough data set for the training of artificial intelligence models. The class G oil well cement slurries were prepared by fixing the water–cement ratio to 0.44 and adding organically modified nanoclays as a strength enhancer. The rheological properties of the oil well cement slurries were investigated at a wide range of temperatures (37 ≤ T ≤ 90 °C) and shear rates (5 ≤ γ ≤ 500 s⁻¹). Experimental data generated were used for the training of feed-forward neural networks. The predicted values of the rheological properties from the trained model showed a good agreement when compared with the experimental values. The average absolute percentage error was less than 5% in both training and validation phases of modeling. A trend analysis was carried out to ensure that the proposed models can define the underlying physics. From the validation and the trend analysis, it was found that the new models can be used to predict cement rheological properties within the range of data set on which the models were trained. The proposed models are independent of laboratory-dependent variables and can give quick and real-time values of the rheological parameters.

1. INTRODUCTION

The primary objective of oil well cementing is to prevent the interzonal migration of fluid inside the geological formations surrounding the wellbore.¹⁻¹² A cement slurry is pumped in the annulus between the casing and the geological formation. Cement provides a good bond for the support of a casing in the well. When drilling to the deeper depths, the cement sheath also provides protection to the casing from corrosion and shock loads.¹⁴ The success of cementing job depends on the quality of cement, its additives, mixing, and pumpability. At the rig side, cement is prepared by adding a cementitious material in water with various additives such as accelerators, retarders, friction loss controllers, polymers, etc. Cement additives are used to improve the rheology, strength, and curing time.⁶⁻⁹ Cement slurries depend on the homogeneous behavior of the additive concentration, quality, and quantity.

For enhanced durability and toughness of the cement slurry, the criteria of designing depend on the slurry formulation, density, plastic viscosity (PV), shear stress (τ), yield point (YP), and gel strength.¹⁰ To design, execute, and evaluate the cementing process, a thorough understanding of the rheology of the cement slurry is indeed necessary.¹¹ Rheological characteristics of cement slurry are required to evaluate the slurry mixability, pumpability, mud displacement for optimum removal, and pressure ratings. Ensuring a good cement rheology is a key for any successful cementing operation.¹² Rheology is also an important factor in achieving plug or turbulent flow required for efficient mud cleanup, which is important to ensure good cement bond and prevent zonal communication. Despite of extensive research done during the past many years, a complete characterization of the rheology has yet to be achieved. The due reason is the complexity of a slurry rheological behavior that is subjected to many different factors including the type of additives, downhole conditions, water-to-cement ratio, mixing and testing procedures, etc.¹³

Nanomaterials of particle size 1–100 nm are commercially used in many areas of drilling engineering such as fluid loss additives,¹⁴ improved rheology of drilling fluids,¹⁵⁻²⁰ and oil well cementing.¹¹⁻²⁰ Large surface areas of reactive nanomaterials have tremendous benefits as an additive in cement slurry such as early high strength, fluid loss control, acceleration, reduction in permeability and porosity, and improved rheology.²¹⁻²⁶ Several types of nanomaterials such as nanosilica, nanoclay, nanoiron oxides, and nanotitanium oxide are investigated in oil well cementing applications.²⁷,²⁸

There are various rheological models including Bingham plastic model, power law model, and Herschel–Bulkley model.
that are used in determining the rheological properties of oil well cement slurries. Such models are composed of empirical relations derived from limited experimental data or based on simple assumptions. The Bingham plastic model was introduced to distinguish the non-Newtonian fluid characteristics. The Bingham plastic model is given by eq 1

$$\tau = \tau_0 + \mu_p \times \gamma$$  \hspace{1cm} (1)$$

where \(\tau\) is the shear stress, \(\tau_0\) is the yield stress, \(\mu_p\) is the plastic viscosity, and \(\gamma\) is the shear rate.

To determine the PV and YP in an experiment, the software automatically collects data at a rate of one sample per second for each desired schedule step. The average of this data is calculated for each schedule step and applied to the following formula to get PV and YP, eqs 2 and eq 1

$$PV = \frac{\left(\sum \gamma_{avg} \times \sum \tau_{avg}\right) - \left(N \times \sum \gamma_{avg} \tau_{avg}\right)}{\left(\sum \gamma_{avg}\right)^2 - \left(N \times \sum \gamma_{avg}^2\right)}$$ \hspace{1cm} (2)$$

$$YP = \frac{\left(\sum \gamma_{avg} \tau_{avg} \times \sum \tau_{avg}\right) - \left(N \times \sum \gamma_{avg} \tau_{avg}\right)}{\left(\sum \gamma_{avg} \tau_{avg}\right)^2 - \left(N \times \sum \gamma_{avg}^2 \tau_{avg}\right)}$$ \hspace{1cm} (3)$$

where \(\tau_{avg}\) is the average shear stress, \(\gamma_{avg}\) is the average shear rate, and \(N\) is the number of schedule steps.

The power law model is applied on pseudoplastic fluids in which the fluid flows immediately when a shear rate is applied. Power law fluids are described by eq 4

$$\tau = K \times \gamma^n$$ \hspace{1cm} (4)$$

where \(\tau\) is the shear stress, \(K\) is the consistency, \(n\) is the power law exponent, and \(\gamma\) is the shear rate. The exponent \(n\) is an important parameter in describing the shear-thinning and shear-thickening behaviors. Cement slurries are considered as shear-thinning when \(n < 1\) and shear-thickening when \(n > 1\), whereas in the case when \(n = 1\), the fluid is considered as a Newtonian fluid. The cement slurries behave as a shear-thinning fluid in which viscosity decreases with an increase in the shear rate.

In the Herschel–Bulkley model, the power law and Bingham plastic models are combined and rheological parameters are calculated using the following formula

$$\tau = \tau_0 \times YP + \mu_p \times \gamma$$ \hspace{1cm} (5)$$

where \(\tau\) is the shear stress, \(\tau_0\) is the yield stress, \(YP\) is the yield point, \(\mu_p\) is the plastic viscosity, and \(\gamma\) is the shear rate. The model assumes that the slurry behaves as a rigid solid below the yield stress, like the Bingham plastic model. Moreover, after the yield stress, the shear stress–shear rate curve behaves as a power law model.

1.1. Artificial Intelligence (AI) and Cement Rheology Prediction. Artificial intelligence (AI) is a captivating field that integrates computational power with human intelligence to produce smart and reliable solutions of extremely nonlinear and highly complicated problems. In drilling and geomechanics, AI brought new opportunities by giving results with higher accuracy. The focus of our work is centered around the utilization of artificial neural networks (ANNs) to predict rheological parameters of class G cement with nanoclay as an additive. The current predictive models for oil well cementing rheological parameters fulfill the basic needs for the drilling engineers, but there is always a need for reliable and improved results. An ANN is an intelligent technique that mimics the biological nervous system to process information. It consists of several neurons organized in different layers such as input layer, output layer, and one or more hidden layers. The input layer processes input data for the network, and the output layer delivers the results. The hidden layer(s) are mainly responsible for learning the characteristics of the input data and the relationship between inputs and outputs. The neurons are composed of weights, biases, and transfer functions. The network learns the desired feature from the given training data set and uses the knowledge later to process the unknown inputs. The application of ANN can be found in various fields such as pattern recognition, classification, image processing, and function approximations.

The application of ANN in the field of petroleum engineering has increased over the last two decades due to its capability of mapping input and corresponding output. Prediction of cement rheology can save a lot of time, cost, and resources. By developing such a model, the tedious task of measuring the rheological properties on site at different temperatures and concentrations of nanoclay can be performed in a short span. Previously developed models have a limited domain with limited predictive capability. In addition to that, previously developed models for prediction of cement rheological parameters do not consider the effect of the concentration of nanoclay on rheology since the concentration and arrangement of solid elements have an important impact on the rheological behavior of the slurry. In this study, rheological properties of oil well cement slurries are predicted by training an ANN model. The ANN models are built on slurry composition (dosage of nanoclay) and test conditions such as shear rate and temperature. The output parameters are the rheological properties of oil well cement. The proposed models can help cementing engineers at the well site to find rheological parameters of oil well cement slurry at different depths, and temperature conditions vary along the length of the wellbore.

2. DEVELOPMENT OF NEW MODELS FOR PREDICTION OF RHEOLOGICAL PARAMETERS

The complete workflow to develop new models for the prediction of the rheological parameters of the class G cement slurry with nanoclay as an additive is given in Figure 1. After carrying out the extensive laboratory experimental study, the data set was collected and then analyzed before feeding into AI models. First, the data set obtained from the experiments was cleaned from the misleading values such as negative or extreme values. These unreasonable measurements were raised due to the instrumental or mishandling of the equipment.

The statistical parameters such as minimum values, maximum values, mean, median, mode, range, skewness, and kurtosis of the data set obtained from the experiments was given in Table 1. The complete data set is given in Appendix A. The ranges of the varied parameters are
Table 1. Description of the Data Used for AI Modeling

| statistical parameters | nanoclay fraction | temperature, °C | shear rate, s⁻¹ | shear stress, lb/100 ft² | AV, cP | PV, cP | YP, lb/100 ft² |
|------------------------|------------------|-----------------|-----------------|-------------------------|-------|-------|--------------|
| mean                   | 0.009            | 61.500          | 169.76          | 53.703                  | 377.503 | 79.465 | 27.544       |
| median                 | 0.010            | 60.000          | 102.00          | 58.200                  | 331.150 | 82.944 | 27.016       |
| mode                   | 0.000            | 37.000          | 5.100           | 66.000                  | 467.300 | 94.902 | 28.610       |
| standard deviation     | 0.008            | 18.719          | 176.57          | 33.631                  | 271.494 | 17.327 | 3.413        |
| sample variance        | 0.000            | 350.397         | 31177.08        | 1131.073                | 73708.989 | 300.219 | 11.650       |
| Kurtosis               | −1.433           | −1.342          | −0.59           | −1.201                  | 2.823  | −1.183 | 0.766        |
| skewness               | 0.131            | 0.186           | 0.90            | −0.075                  | 1.399  | −0.406 | 1.164        |
| range                  | 0.020            | 53.000          | 5.100           | 5.300                   | 59.900 | 48.406 | 22.905       |
| maximum                | 0.020            | 90.000          | 51.000          | 114.090                 | 1546.926 | 102.427 | 35.816       |

Table 2. Correlation Coefficient Study

| statistical parameters | nanoclay fraction | temperature | shear rate | shear stress | AV | PV | YP |
|------------------------|------------------|-------------|------------|--------------|----|----|----|
| mean                   | 1.00 × 10        | 1.00 × 10   | 1.00 × 10  |              |    |    |    |
| median                 | −1.37 × 10⁻¹     | 0.00 × 10   | 1.00 × 10  |              |    |    |    |
| mode                   | −4.39 × 10⁻¹     | 0.00 × 10   |              |              |    |    |    |
| standard deviation     | 6.83 × 10⁻¹      | −8.68 × 10⁻¹|              |              |    |    |    |
| sample variance        | −4.21 × 10⁻²     | −1.27 × 10⁻²| −7.48 × 10⁻¹|              |    |    |    |
| Kurtosis               | 3.85 × 10⁻¹      | −3.35 × 10⁻¹| 1.29 × 10⁻¹  |              |    |    |    |
| skewness               | −2.12 × 10⁻²     | 4.41 × 10⁻¹  | 1.16 × 10⁻¹  |              |    |    |    |

Table 3. Topography of Proposed ANN Models

| parameters            | values |
|-----------------------|--------|
| number of input layers| 3      |
| hidden layer          | 1      |
| number of neurons in a hidden layer | 10       |
| learning algorithm    | LM     |
| rate of learning, α   | 0.15   |
| transfer function of a hidden layer | tangential sigmoidal |
| transfer function of an outer layer | linear |

The proposed equation to predict the shear stress (τ) for a class G cement with nanoclay as an additive using ANN is as follows, eq 9

τ = 108.669 × τ₀ + 114

where

τ₀ = \left[\sum_{i=1}^{N} w_{i} \sigma_{i}(w_{i} NC_{n} + w_{i} T_{n} + \gamma_{n} + b_{1}) + b_{2}\right]

(10)

where \sigma_{i}(x) = (2/1 + e^{-2x}) − 1; \sigma_{i}(x) = x; and w_{i}, w_{i} T_{n}, \gamma_{n} and b_{1}, b_{2} are the weights and biases of the shear stress model, given in Table 4. NC_{n} is the normalized value of a fraction of nanoclay additive in a class G cement, T_{n} is a normalized value of curing temperature, and \gamma_{n} is a normalized value of a shear rate. The equations to find NC_{n}, T_{n} and \gamma_{n} are as follows, eqs 11–eq 4.

NC_{n} = 2 \times \left(\frac{NC}{0.02}\right) - 1

(11)

T_{n} = 2 \times \left(\frac{T - 37}{90 - 37}\right) - 1

(12)
γ

Table 4. Weights and Biases for the New Proposed Equation of ANN for Shear Stress

| hidden layer neurons (N_h) | weights between input and hidden layers (w_i) | weights between hidden and output layers (w_o) | hidden layer bias (b_h) | output layer bias (b_o) |
|----------------------------|-----------------------------------------------|-----------------------------------------------|------------------------|------------------------|
| 1 0.4196                   | -0.5227                                       | -0.0993                                       | 1.7437                 | -5.3282                |
| 2 1.6359                   | -1.1636                                       | -3.8581                                       | 0.1022                 | 4.0618                 |
| 3 -0.0656                  | 0.2222                                        | 2.8646                                        | -0.0689                | -1.1512                |
| 4 3.6203                   | -0.6291                                       | -2.4376                                       | -1.1092                | 3.6595                 |
| 5 1.5731                   | -0.6124                                       | 2.3141                                        | 0.0160                 | -3.7395                |
| 6 -0.4780                  | 3.8888                                        | -4.0219                                       | 3.4222                 | -9.2319                |
| 7 -1.9074                  | 0.5457                                        | 5.4270                                        | 0.0332                 | -2.0614                |
| 8 3.9985                   | 0.1912                                        | -0.9993                                       | 0.0814                 | -0.9188                |
| 9 -5.3218                  | 3.6255                                        | -2.7057                                       | -0.0459                | -1.1781                |

\[
\gamma_n = 2 \left( \frac{9.1 - 5.1}{510 - 5.1} \right) - 1
\] (13)

An ANN model to predict AV is also developed. The proposed equation to predict AV for a class G cement with nanoclay as an additive is as follows, eq 14

\[ AV = 743.513 \times AV_n + 803.413 \] (14)

where

\[
AV_n = c_0 \left[ \sum_{i=1}^{N_h} w_1 \sigma_L(w_i)NC_n + w_2 T_n + w_3 \gamma_n + b_1 \right] + b_2
\] (15)

where \(c_0(x) = (2/1 + e^{-2x}) - 1\), \(\sigma_L(x) = x\), and \(w_1, w_2, b_1, b_2\) are the weights and biases of the AV model, given in Table 5.

\[ \text{NC}_n \] is the normalized value of a fraction of nanoclay additive in a class G cement, \(T_n\) is a normalized value of a curing temperature, and \(\gamma_n\) is a normalized value of a shear rate. The equations to find \(\text{NC}_n, T_n, \) and \(\gamma_n\) are as follows, eqs 11–eq 6.

The proposed equation to predict PV for a class G cement with nanoclay as an additive using ANN is as follows, eq 16

\[ PV = 27.0105 \times PV_n + 75.416 \] (16)

where

\[
PV_n = c_0 \left[ \sum_{i=1}^{N_h} w_1 \sigma_L(w_i)NC_n + w_2 T_n + w_3 \gamma_n + b_1 \right] + b_2
\] (17)

where \(\sigma_L(x) = (2/1 + e^{-2x}) - 1\), \(\sigma_B(x) = x\), and weights and biases for the PV model are given in Table 6.
First, the shear stress was predicted with the ANN technique. On a set of 70% of the data for training, the ANN model predicted the shear stress with R² of 0.98 and with AAPE of 4.23%, while for testing, the ANN model predicted the shear stress with R² of 0.95 and AAPE of 4.9%. The cross-plots for the training and testing are shown in Figure 2. Figures 3 and 4 show the plots of predicted apparent viscosity during the training and testing phases of modeling with the ANN tool. A standard error was calculated, which is shown in the form of error bar in these figures. The standard error quantifies the precision of the data and tells how variable the mean is. The standard error is the ratio of standard deviation (SD) and the total number of data points in a sample and is calculated using eq 21.

\[
\text{standard error} = \frac{SD}{\sqrt{n}}
\]  

(21)

where SD is the standard deviation and n is the total number of data points. SD was determined using eq 22.

\[
SD = \sqrt{\frac{\sum (X - \overline{X})^2}{n - 1}}
\]  

(22)

where X is the sample value and \( \overline{X} \) is the average mean of the whole data set.

For the AV prediction, on a set of 70% of the total data set for training, an ANN model predicted the AV with R² of 0.97 and

Table 7. Weights and Biases for the New Proposed Equation of ANN for YP

| hidden layer neurons (N_h) | NC | T | Y | weights between input and hidden layers (w_ih) | weights between hidden and output layers (w_ho) | hidden layer bias (b_h) | output layer bias (b_o) |
|---------------------------|----|---|---|-----------------------------------------------|-----------------------------------------------|------------------------|------------------------|
| 1                         | 0.8764 | 1.1192 | -2.7026 | 0.0451 | 3.9604 | 2.2342 |
| 2                         | -1.4097 | -3.3831 | -1.4133 | 0.0506 | 3.7862 |
| 3                         | -5.3278 | -6.6985 | -0.4138 | -0.3092 | -0.7042 |
| 4                         | -0.8936 | 3.7800 | 4.2812 | 0.0521 | -0.5224 |
| 5                         | 0.7938 | 3.0686 | -0.1670 | -0.5223 | 2.4700 |
| 6                         | -5.0167 | -3.5743 | -3.1835 | 0.0692 | 0.3917 |
| 7                         | -0.4690 | 0.4368 | -1.4109 | 0.4289 | -3.2528 |
| 8                         | 4.6657 | -1.5607 | 0.0303 | 0.1204 | 0.5727 |
| 9                         | -0.4253 | 1.3505 | 3.1971 | -0.0198 | 0.4710 |
| 10                        | -0.1111 | 3.2478 | 0.0420 | 2.0818 | -3.6885 |

The proposed equation to predict YP for a class G cement with nanoclay as an additive using ANN is as follows, eq 18

\[
YP = 6.455 \times YP_n + 29.36
\]  

(18)

where

\[
YP_n = \sigma_1 \left[ \sum_{i=1}^{N_h} (w_{i1} \sigma_1 (w_{1i} NC + w_{1i} T + w_{1i} Y + b_1) + b_2) \right]
\]  

(19)

where \( \sigma_1 (x) = (2/1 + e^{-2x}) - 1 \), \( \sigma_1 (x) = x \), and weights and biases for the YP model are given in Table 7.

3. RESULTS AND DISCUSSION

A total of 90 experiments were performed to measure rheological properties of the class G cement. From these experiments, 90 data points were obtained. Of the 90 data points, 70% were used to train the model and remaining 30% were used to test the model. To avoid the model to stuck on a local minimum, a total of 10 000 realizations were made to arrive at the most optimum AI model. ANN is a stochastic algorithm that generates different results in each run. To fix this issue, the seeds were generated randomly. All of the results were unique for each seed. To get the most accurate and generalized robust model, a multiobjective function was designed. In this study, a total of 10 000 realizations were made and in every realization the seed numbers were changed and the multiobjective function was evaluated. The seed number corresponding to the maximum value of objective function was taken as the best model. The definition of the designed multiobjective function is expressed by eq 20

\[
\text{objective function} = \max(0.5 \times (0.25 \times R^2_{\text{training}} + 0.25 \times R^2_{\text{testing}}) + 0.5 \times (0.25 \times \text{AAPE}_{\text{training}}^{-1} + 0.25 \times \text{AAPE}_{\text{testing}}^{-1}))
\]  

(20)
with AAPE of 7.1%, while on testing of the ANN model to predict the shear stress, the $R^2$ obtained was 0.98 and AAPE was 5.16%. The cross-plots for training and testing are shown in Figure 5. Figures 6 and 7 show the plots of predicted shear stress during training and testing, with a standard error bar.

Similarly, for the prediction of PV, during training with 70% of the total data set, an ANN model makes the prediction with $R^2$ of 0.988 and with AAPE of 1.43%, while on testing, the ANN model predicted PV with $R^2$ of 0.971 and AAPE of 3.06%. The cross-plots for training and testing are shown in Figure 8. Figures 9 and 10 show the plots of predicted plastic viscosity during training and testing, with a standard error bar.

Similarly, for the prediction of YP, the ANN model predicted YP during training on 70% of the data set with $R^2$ of 0.99 and AAPE of 0.347%, while on testing, the ANN model predicted YP with $R^2$ of 0.98 and AAPE of 0.80%. The cross-plots for training and testing are shown in Figure 11. Figures 12 and 13 show the plots of the predicted yield point during training and testing, with a standard error bar. A complete summary of the performances of the models is given in Table 8.

A trend analysis was carried using the developed models. The purpose of carrying out the trend analysis was to make sure that the proposed models are capturing the underlying physics behind them. A trend analysis was carried out by varying only one parameter while keeping the other parameters constant at their average values. Figure 14 shows the trend analysis of shear stress with different shear rates at different temperatures. Figure 14a shows the constitutive plot of shear rate versus shear stress. The shear-thinning behavior of a class G oil well cement slurry without

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**Figure 4.** Predicted values of apparent viscosity during testing, with a standard error bar.

**Figure 5.** Training and testing cross-plots between the experimental shear stress and the predicted shear stress with a standard error bar.

**Figure 6.** Predicted values of shear stress during training, with a standard error bar.

**Figure 7.** Predicted values of shear stress during testing, with a standard error bar.

**Figure 8.** Training and testing cross-plots between experimental PV and predicted PV with a standard error bar.

**Figure 9.** Predicted values of plastic viscosity during training, with a standard error bar.

**Figure 10.** Predicted values of plastic viscosity during testing, with a standard error bar.
addition of nanoclay was predicted by plotting the shear stress with the changing shear rate ($5 \leq \gamma \leq 500 \text{ s}^{-1}$) at different temperatures ($30 \leq T \leq 60 \, ^\circ \text{C}$). The graph shows that the shear stress with the corresponding shear rate decreases with the increase in temperature. In general, Figure 14b shows the plot of shear stress with shear rate for a class G cement with 1% BWOC nanoclay, and Figure 14c shows the plot of shear stress with shear rate for a class G cement with 2% BWOC nanoclay. The trend analysis was carried out on the full range of shear rate on which the model was trained. In all three plots, the trend predicted by the ANN model matched with the experimental data reported in Figures 10–12.

Figure 15 shows the trend analysis of AV with different shear rates ($5 \leq \gamma \leq 500 \text{ s}^{-1}$) at different temperatures ($30 \leq T \leq 80 \, ^\circ \text{C}$). Figure 15a shows the plot of AV with shear rate for a class G cement without addition of nanoclay additive. Figure 15b shows the plot of AV with shear rate for a class G cement with 1% BWOC nanoclay, and Figure 15c shows the plot of AV with shear rate for a class G cement with 2% BWOC nanoclay. The trend analysis showed that initially AVs at different concentrations of NC were decreased drastically with increasing shear rate. With a further increase in shear rate, the curves became almost flattened. The effect of temperature is clearly visible on all AV plots, that is, with the increase of temperature, the AV's decreased. From trend analysis, it can be observed that the ANN model to predict AV can capture the effect of temperature and shear rate very well.

4. CONCLUSIONS

In this research work, an experimental study was carried out to measure the rheology of class G cement with nanoclay as an additive. The experiments were performed at different concentrations of nanoclay at various cement slurry curing temperatures.

Table 8. Summary of the Performances of the ANN Models to Predict AV, Shear Stress, PV, and YP

| model            | training |       |       |
|------------------|----------|-------|-------|
|                 | AAPE     | $R^2$ | AAPE  | $R^2$ |
| apparent viscosity | 7.074    | 0.882 | 7.429 | 0.924 |
| shear stress     | 7.135    | 0.972 | 5.16  | 0.989 |
| plastic viscosity | 1.431    | 0.988 | 3.065 | 0.971 |
| yield point      | 0.347    | 0.998 | 0.806 | 0.988 |
After the experimental investigation, enough data was generated to develop AI models to predict the rheological parameters. Based on the experimental and machine learning approaches, the following conclusions can be drawn:

1. The experimental study showed that the addition of nanoclay in a class G cement improves the rheological properties such as shear stress, YP, PV, and AV. Addition of nanoclay in a class G cement provides a controlled rheology compared to a simple class G cement slurry when moving from lower temperatures to higher temperatures.

2. The ANN models proposed in this study are used to predict rheological parameters of a class G cement with nanoclay as an additive.

3. The developed equations using the ANN technique to predict shear stress, AV, PV, and YP do not require any AI software for execution.

4. The models were tested within a range of values on which the models were trained. The range of the tested values is quite reasonable in oil and gas fields.

5. The trend analysis results showed that the proposed models can give similar trends to those observed in the experimental analysis.

All AI models are data-driven; they can be used within the range of the input parameters on which they are trained. Using them beyond their range will result in unreliable results. Users of the proposed correlations are recommended to apply these models within the range of data set given in Table 1. The developed correlations are not recommended to use beyond the range of input parameters on which they are developed.

5. MATERIALS AND METHODS

5.1. Experimental Program. In this study, rheological tests were carried out on four cement slurries with nanoclay for application in oil well cementing under various temperatures such as 37, 50, 60, 80, and 90 °C. The class G cement has temperature limitations in an oil well. Usually, it is not recommended to pump class G cement slurry alone without property controller additives in the wellbore where the bottom hole temperature exceeds more than 70 °C. At high temperature, 90 °C, the class G cement started behaving as gel with limited pumpability because at and above this temperature, it sets early within short time. The cement slurries were prepared according to API RP 10B-2.36 A 15.8 lbm/gal slurry density with a recommended water-to-cement ratio of 0.44 was used for hydrating the cement. Tap water was used in all of the mixes. The effect of nanoclay on various cement properties was examined at varying dosages of 0 to 2%. The rheological properties measured were shear stress, AV, PV, and YP.

5.2. Cement Type. In this study, all test specimens were prepared using class G cement produced by Saudi Cement Company complying with American Petroleum Institute (API) specifications.37 The class G cement has a density of 3.15 g/cc. The composition of class G cement is characterized by the X-ray diffraction (XRD) technique and is displayed in Figure 16. The phase composition of class G cement is listed in Table 9.

5.3. Organically Modified Nanoclay Additive. The nanoclay material used in this study is organically modified, prepared by modifying natural montmorillonite with a quaternary ammonium salt. Montmorillonite is a layered magnesium aluminum silicate, which was organically modified by the cation exchange reaction using a quaternary ammonium salt to transform it into hydrophobic nanoclay. The montmorillonite-based nanoclay was modified with methyl, Tallow (65% C18, 30% C16, and 5% C14), and bis 2-hydroxyethyl quaternary ammonium chloride. Table 10 provides the characteristics of the nanoclay used in this study.
Nanoclay consisted of an octahedral sheet of magnesia or alumina sandwiched between two tetrahedral sheets of silica.\textsuperscript{38} High concentrations of oxides of silica and alumina existed in the tested nanoclay as shown in Figure 17.

### 5.4. Sample Preparation.

The cement slurries were prepared using an adjustable speed, high shear mixer unit as per API specifications. Nanoclay was blended in a cement slurry before mixing with water. The wet mixing procedure was used for additives in which all of the additives were mixed in water. For tests performed on field formulation at 90 °C temperature, nanoclay was blended with cement. First, liquid and dry additives were admixed in tap water at a low speed of 4000 RPM. The dry-blended mixture of cement and nanoclay were added to the water/additive mixture within 15 s. Then, the high-speed mixer was run at a speed of 12000 RPM for 35 s to get a homogeneous and uniform cement slurry. The cement slurry was then conditioned in an atmospheric consistometer at 90 °C temperature.

### 5.5. Rheological Test.

In a rheological study, apparent flow properties like shear stress, AV, PV, and YP of a cement slurry were measured using a rotational viscometer, OFITE 900, at various temperature conditions. The conditioned slurry was poured into a preheated cup of viscometer. The viscometer was run at various shear rates. The PV and YP results were calculated using built-in software in the equipment by applying the correlation given in eqs 2 and eqs 7.

Different formulations were tested at various temperatures under various loadings of nanoclay as discussed in Section 2.1. The shear stress changed with the increase in temperature. When class G cement slurry rheology was measured at 37 °C temperature range 37 ≤ T ≤ 90 °C and at shear rates 5 ≤ γ ≤ 500 s\(^{-1}\) with a standard error bar.
Figure 21. Variation of PV with change in temperature at different concentrations of nanoclay with a standard error bar.

Figure 22. Variation of YP with change in temperature at different concentrations of nanoclay with a standard error bar.

Table A1. Experimental Data Obtained for a Simple Class G Cement

| nanoclay fraction | temperature, °C | shear rate, s⁻¹ | shear stress, lb/100 ft² | AV, cP | PV, cP | YP, lb/100 ft² |
|-------------------|-----------------|-----------------|--------------------------|--------|--------|----------------|
| 0                 | 37              | 5.1             | 8.7                      | 866.3  | 95     | 28.61          |
| 0                 | 37              | 10.2            | 11.8                     | 392    |
| 0                 | 37              | 51              | 48.2                     | 482.8  |
| 0                 | 37              | 102             | 66                       | 330.3  |
| 0                 | 37              | 170             | 79.7                     | 239.2  |
| 0                 | 37              | 340             | 98.1                     | 147.3  |
| 0                 | 37              | 510             | 108.6                    | 108.7  |
| 0                 | 50              | 5.1             | 9                        | 904.3  | 64     | 25.00          |
| 0                 | 50              | 10.2            | 13.1                     | 653.4  |
| 0                 | 50              | 51              | 41.4                     | 414.6  |
| 0                 | 50              | 102             | 51.6                     | 258.4  |
| 0                 | 50              | 170             | 58.2                     | 174.9  |
| 0                 | 50              | 340             | 70.8                     | 106.3  |
| 0                 | 50              | 510             | 79.9                     | 79.9   |
| 0                 | 60              | 5.1             | 6                        | 596.7  | 60.63  | 22.91          |
| 0                 | 60              | 10.2            | 9.3                      | 467.3  |
| 0                 | 60              | 51              | 37.6                     | 376.6  |
| 0                 | 60              | 102             | 51.3                     | 256.8  |
| 0                 | 60              | 170             | 58                       | 174    |
| 0                 | 60              | 340             | 66.5                     | 99.9   |
| 0                 | 60              | 510             | 72.7                     | 72.8   |
| 0                 | 80              | 5.1             | 5.4                      | 541.3  | 48.41  | 24.84          |
| 0                 | 80              | 10.2            | 7.1                      | 353.4  |

Table A1. continued

| nanoclay fraction | temperature, °C | shear rate, s⁻¹ | shear stress, lb/100 ft² | AV, cP | PV, cP | YP, lb/100 ft² |
|-------------------|-----------------|-----------------|--------------------------|--------|--------|----------------|
| 0                 | 90              | 5.1             | 14.3835                  | 1546.926 | 93     | 36             |
| 0                 | 90              | 10.2            | 7.1                      | 763.673 |
| 0                 | 90              | 51              | 47.945                   | 530.655 |
| 0                 | 90              | 102             | 72.407                   | 384.774 |
| 0                 | 90              | 170             | 87.2795                  | 280.209 |
| 0                 | 90              | 340             | 102.74                   | 160.959 |
| 0                 | 90              | 510             | 110.959                  | 111.026 |

Table A2. Experimental Data Obtained for a Class G Cement with 1% Nanoclay BWOC

| nanoclay fraction | temperature, °C | shear rate, s⁻¹ | shear stress, lb/100 ft² | AV, cP | PV, cP | YP, lb/100 ft² |
|-------------------|-----------------|-----------------|--------------------------|--------|--------|----------------|
| 0.01              | 37              | 5.1             | 9                        | 1144.2 | 95.90  | 29.00          |
| 0.01              | 37              | 10.2            | 10.2                     | 789.4  |
| 0.01              | 37              | 51              | 38.7                     | 610    |
| 0.01              | 37              | 102             | 70.8                     | 403.2  |
| 0.01              | 37              | 170             | 87.0                     | 278.4  |
| 0.01              | 37              | 340             | 98.2                     | 167.5  |
| 0.01              | 37              | 510             | 109.0                    | 126.5  |
| 0.01              | 50              | 5.1             | 6.4                      | 925.6  | 74.02  | 24.52          |
| 0.01              | 50              | 10.2            | 9.8                      | 708.7  |
| 0.01              | 50              | 51              | 40.4                     | 626.9  |
| 0.01              | 50              | 102             | 57.2                     | 411.5  |
| 0.01              | 50              | 170             | 65.7                     | 287.7  |
| 0.01              | 50              | 340             | 78.7                     | 170.4  |
| 0.01              | 50              | 510             | 85.8                     | 128.7  |
| 0.01              | 60              | 5.1             | 6.3                      | 627.1  | 70.28  | 25.14          |
| 0.01              | 60              | 10.2            | 9.7                      | 484.5  |
| 0.01              | 60              | 51              | 40.2                     | 400.4  |
| 0.01              | 60              | 102             | 58.2                     | 291.1  |
| 0.01              | 60              | 170             | 66.6                     | 200    |
| 0.01              | 60              | 340             | 76.8                     | 115.3  |
| 0.01              | 60              | 510             | 82.1                     | 82.1   |
| 0.01              | 80              | 5.1             | 8.9                      | 895.1  | 52.65  | 27.23          |
| 0.01              | 80              | 10.2            | 9.5                      | 476.2  |
| 0.01              | 80              | 51              | 39.7                     | 397.7  |
| 0.01              | 80              | 102             | 59.1                     | 295.7  |
| 0.01              | 80              | 170             | 63                       | 189.1  |
| 0.01              | 80              | 340             | 66                       | 99     |
| 0.01              | 80              | 510             | 66.9                     | 66.9   |
| 0.01              | 90              | 5.1             | 6.0665                   | 979.067 | 102.43 | 33.73          |
| 0.01              | 90              | 10.2            | 9.8865                   | 724.51 |
| 0.01              | 90              | 51              | 47.0645                  | 411.208 |
| 0.01              | 90              | 102             | 81.2135                  | 367.15 |
| 0.01              | 90              | 170             | 95.2055                  | 252.599 |
| 0.01              | 90              | 340             | 107.1425                 | 148.916 |
| 0.01              | 90              | 510             | 114.09                   | 114.159 |
Table A3. Experimental Data Obtained for a Class G Cement with 2% Nanoclay BWOC

| Nanoclay fraction | Temperature, °C | Shear rate, s⁻¹ | Shear stress, lb/100 ft² | AV, cP | YP, cP | YP, lb/100 ft² |
|------------------|----------------|----------------|-------------------------|-------|-------|---------------|
| 0.02             | 37             | 5.1            | 7.1                     | 713.9 | 99    | 26.74         |
| 0.02             | 37             | 10.2           | 10                      | 499.2 |       |                |
| 0.02             | 37             | 51             | 43.8                    | 437.8 |       |                |
| 0.02             | 37             | 102            | 67.7                    | 338.7 |       |                |
| 0.02             | 37             | 170            | 80.1                    | 240.5 |       |                |
| 0.02             | 37             | 340            | 97.9                    | 146.9 |       |                |
| 0.02             | 37             | 510            | 110.8                   | 110.9 |       |                |
| 0.02             | 50             | 5.1            | 6.6                     | 662.5 | 91    | 27.63         |
| 0.02             | 50             | 10.2           | 9.6                     | 479.8 |       |                |
| 0.02             | 50             | 51             | 46.7                    | 467.3 |       |                |
| 0.02             | 50             | 102            | 66.7                    | 333.8 |       |                |
| 0.02             | 50             | 170            | 78.7                    | 236.2 |       |                |
| 0.02             | 50             | 340            | 93.8                    | 140.7 |       |                |
| 0.02             | 50             | 510            | 103.9                   | 103.9 |       |                |
| 0.02             | 60             | 5.1            | 7.2                     | 725.1 | 82    | 26.81         |
| 0.02             | 60             | 10.2           | 9.7                     | 484.3 |       |                |
| 0.02             | 60             | 51             | 42.5                    | 425.2 |       |                |
| 0.02             | 60             | 102            | 63                      | 315.2 |       |                |
| 0.02             | 60             | 170            | 75                      | 225.3 |       |                |
| 0.02             | 60             | 340            | 87.5                    | 131.3 |       |                |
| 0.02             | 60             | 510            | 93.6                    | 93.7  |       |                |
| 0.02             | 80             | 5.1            | 5.3                     | 534.1 | 84    | 27.65         |
| 0.02             | 80             | 10.2           | 8.8                     | 450.6 |       |                |
| 0.02             | 80             | 51             | 45                      | 438.8 |       |                |
| 0.02             | 80             | 102            | 66.4                    | 332   |       |                |
| 0.02             | 80             | 170            | 78.6                    | 236   |       |                |
| 0.02             | 80             | 340            | 89.8                    | 134.7 |       |                |
| 0.02             | 80             | 510            | 95                      | 95.1  |       |                |

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NOMENCLATURE

AAPE averaged absolute percentage error.
AI artificial intelligence.
ANN artificial neural network.
API American Petroleum Institute.
ASTM American Society for Testing and Materials.
BWOC by weight of cement.
HPHT high-temperature high-pressure.
CC correlation coefficient.
FFNN feed-forward neural network.
LM Levenberg–Marquardt learning algorithm.
Logsig logistic sigmoid activation/transfer function.
RMSE root-mean-square error.
Std standard deviation.
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