

Artificial Intelligent for Real-Time Prediction of Rheological Drilling Mud Properties

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Abstract

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Rheological characteristics are very important for drilling fluid functions since it is directly influenced the cutting transportability, hole cleaning ability, lubricity, and filtration loss behaviour while drilling. The Plastic Viscosity (PV), Yield Point (YP), Apparent Viscosity (μ_a), and gel strength are mud's rheological attributes that can contribute to achieve the drilling fluid functions, but they are only measured once or twice a day, leading to insufficient performance of the drilling fluid functions. In contrast, mud density, marsh funnel, and solid percent are frequently and continuously measurable. There are few attempts to link between the most frequent mud measurements to the less frequent mud measurements which also have a high error rate in their predictions. The Artificial Neural Networks (ANN) and multiple regression analysis (MRA) were conducted using real field measurements to develop new models to determine the rheological mud properties. The ANN was optimized using training and validation datasets of 70% and 30%, respectively. The coefficient of determination (R^2) and the root mean square error (RMSE) are found for each model. Upon creating a plot of the predicted PV versus the actual PV, the obtained R^2 and RMSE of the ANN model are 0.955 and 0.694 for training datasets, and 0.954 and 0.634 for validation datasets, respectively. In contrast, the results of the MRA are R^2 of 0.91 and RMSE of 0.914. The results of other models for determining YP, μ_a , and gel strength are also successfully checked. These results showed that ANN is able to predict the rheological mud properties with high accuracy, which outperformed the obtained results of MRA. The presented models will help to track in real-time the rheological mud properties that allows better control for the drilling operation problems.

Keywords: Drilling mud; Multiple regression analysis; Artificial neural networks

1. Introduction

A convenient selection of drilling mud rheological properties can achieve its essential functions during drilling operations. Mud density (MW), Yield Point (YP), Apparent Viscosity (μ_a), Plastic Viscosity (PV), and gel strength are important properties by which the drilling mud can control

subsurface formation pressure, transport cuttings from the wellbore, prevent wellbore from collapsing, and lubricate the drill string and the drill bit. However, more uncertainties in selecting these properties meant that operators were exposed more drilling challenges with inexpressible variations between the applied and the required mud characteristics, resulting in many drilling problems including wellbore collapse and fracturing, reservoir damage, and deficient hydraulic mud system (Almahdawi et al., 2020; Hadi et al., 2022).

Drilling fluid is a complex system that is primarily composed of different materials including base fluid, rheological modifier, weighting agents, lost circulation materials, and alkalinity for fluid stability and polymer hydration. Continuous measurements of the mud rheological properties are expensive, time wasting, and required a special technique for cleaning (Elkatatny et al., 2018). Another issue is that some drilling mud properties including PV, YP, μ_a , and gel strength are less frequently measured for cost and time-saving purposes. In contrast, mud weight (MW), Marsh Funnel (MF), and solid content (S%) are more frequently measured (Al-Azani et al., 2018; Al-Sabaa et al., 2020; Hadi et al., 2022). Gowida et al. (2019) stated that it is important for checking the mud rheology periodically during the drilling operations. However, the mud measurements as PV, YP, and μ_a , are typically conducted in the field twice a day. It is practically taken a long time around 2-3 hr to do measurements and clean the instrument. In contrast, marsh funnel and mud weight are periodically measured every 15 to 20 minutes.

The oil industry has recently gained interest in machine learning and artificial intelligence as potential solutions to overcome challenges (Naji et al., 2022b). Many researchers have attempted to develop models that predict rheological mud properties using the artificial intelligence. Al-Azani et al. (2018) developed five ANN-based models that could be accurately forecast the rheological characteristics of oil-based drilling fluid. Al-Khdheawi and Mahdi (2019) presented two models to predict μ_a of drilling muds based on its mud density and MF using empirical correlations and artificial neural networks. Elkatatny et al. (2018) presented a modified self-adaptive technique to forecast the rheological properties of water-based drilling fluid, the results of the ANN model were more than 90% of determination coefficient (R^2) and less than 8.6% of average absolute error (APE). Gowida et al. (2019) also developed new models with a high degree of accuracy to predict the rheological characteristics of calcium chloride brine-based mud based on 515 data points. Alsaba et al. (2022) also presented a study to use machine learning to ascertain the rheological characteristics of synthetic oil-based systems with flat rheology. Based on that, there is a need for developing simple models to predict the less frequent measured rheological properties based on the more frequent measured properties. The greatest difference between this study and literature is that there is a need for simple mathematical models that can be used to determine the rheological properties of KCl/ Polymer mud based on frequent mud measurements using ANN and MRA techniques.

This study presents ANN technique to create novel models aimed to predict the rheological mud attributes. To achieve that, the following steps are undertaken: Collect and filtrate datasets from daily drilling reports (DDR) of two wells of WQ-2 oilfield, analyze the collected datasets to ensure that the relationships between the independent and dependent variables are reasonable and logical, apply ANN to develop new models and compare their results with MRA. The determination coefficient (R^2) and the root mean square error (RMSE) are found for each model.

2. Geology of Field Study

The data utilized in this research were obtained from the daily drilling reports of two wells drilled in West Qurna-2 oilfield (WQ-2), located in the south-eastern part of Iraq, approximately 50 km north-westwards from basra and 30 km from Zubair oilfield. WQ-2 oilfield is situated at the lower part of the largest Asian Tigris-Euphrates river system, along the Shatt Al-Arab waterway formed by confluence of the Tigris and the Euphrates (Al-Haleem et al., 2016; Jubair and Hadi, 2021; Bashara and Hadi, 2023).

The relief of the area is described as a plateau of low-lying coastal sand plain having an elevation 2 to 50 m. The main objective of this field is the Upper cretaceous shallower Mishrif reefal limestone. The Mishrif reservoir is mainly composed of greyish white tight algal and detritus porous limestones that have undergone some degree of Dolomitization. Mishrif Formation is characterized by quite complex framework. In the uppermost portion of succession, there is a layer of tight shale limestone known as Cap Rock. The Mishrif thickness varies from 154m up to 252m on the western flank.

The aim of this study is to develop new models that can be used to determine the rheological mud properties using ANNs. A comparison has been also performed in this study between the obtained results of ANN and MRA based on two metrics criteria which are R2 and RMSE.

3. Data Analysis and Drilling Mud Data

Data analysis is a process of checking, cleaning, and modeling data so that the discovery of information is useful. It is applied to ensure the reasonably of the correlation between the input and out parameters. The raw datasets that have been used in this study are mud density, marsh funnel, $\theta 600$, $\theta 300$, $\theta 200$, $\theta 100$, $\theta 6$, $\theta 3$, solid %, and 10 min gel in lbf/100 ft². Mud density, marsh funnel, and solid% were considered as the input factors for developing the ANN models, while the drilling mud characteristics (PV, YP, μ_a , and 10-min gel strength) were considered the output parameters of the ANN model.

Fig. 1 shows the well design summary sheet of two wells drilled in WQ-2 oil field in which the formation name, formation depth, pore pressure, fracture gradient, drilling mud type, bit type, casing depth, and hole size are presented.

Formation	Form. Top (TVDRIT\MDRT, m)	Incl. (°)	Azi. (°)	Pore Press. (sg)	Frac. Press. (sg)	BHST (24.6+TVDRIT*2.6/100, °C)	Mud Type & Density (sg)	Bit Type & Size (in.)	BHA	Csg. Depth (TVDRIT\ MDRT, m)	Hole Size (in.)	Casing Design
Hammar	28\28	0	127			26	Pre-Hydrated Bentonite, MW: 1.05 – 1.08	Primary: TCI GTX - CG1	Rotary	113\113	24	18 5/8" J-55 87.5 ppf BTC
Upper Fars	73\73	0	127			32						
Dibdiba	274\274	0	127	1.00	1.75	37	Pre-Hydrated Bentonite/ Salt-Water Polymer, MW: 1.10 – 1.14	Primary: TCI VGA-T310M	Directional, Motor	987\1,003	16	13 3/8" K-55 68 ppf BTC
Lower Fars	469\469	3	127	1.00	1.82	48						
Ghar	909\920	20	127	1.05	1.85	50						
Dammam	982\998	20	127	1.10	1.86	57						
Rus	1,253\1,300	35	127	1.10	1.87	58						9 5/8" L-80 47 ppf BTC
Um Er-Raduma	1,276\1,329	36	127	1.10	1.87	69	KCL / Polymer, MW: 1.10 – 1.14 (Can be increased to 1.16 if experience any Sulfurous water flow from Tayarat formation)	Primary: Steerable PDC QD506FX	Directional, Motor	TOL @ 1892 \2159 DV @ 1929 \2209 2,122\2,470	12 1/4	TOL overlaps stage collar by 50 m MD 9 5/8" stage collar 20 m TVD above top of Hartha
Tayarat	1,707\1,907	42	127	1.14	1.90	72						
Shiranish	1,808\2,046	42	127	1.14	1.90	75						
Hartha	1,949\2,236	42	127	1.15	1.93	79						
Saadi	2,097\2,437	42	127	1.23	1.94	82						
Tanuma	2,219\2,602	42	127	1.25	1.99	84	KCL NaCl/ Glycol, MW: 1.26 – 1.28 (Increase the mud weight up to 1.28 sg if necessary)	Primary: Steerable PDC QD506	Directional, Motor	TBD while drilling 2,493\2,973	8 1/2	7 " Liner L-80 29 ppf VAM TOP
Khasib	2,265\2,665	42	127	1.20	1.96	85						
Mishrif	2,316\2,733	42	127	1.14	1.98	88						
Target	2,443\2,906	42	127	1.14	1.98	88						

Fig. 1. Well design summary sheet of one well drilled in WQ-2 oilfield.

Fig. 2 presents the histograms of the datasets that have been collected from the whole section of two wells drilled in this field which strating from the Hammar formation to the Mishrif reservoir. The

datasets of KCL/ Polymer and Spud muds will be used for models development. The whole datasets of the presented well revealed that the formation lithology and the burial depth play a key role in selecting the drilling mud reological properties. A clear increase of the required mud density, plastic viscosity, and solid % is observed with increasing the formations depths.

There is also a clear difference in the values of Marsh Funnel, Plastic viscosity, and Apparent viscosity against Mishrif Formation rather than no difference in mud weight and 10-min gel strength. This can attributed to the carbonate heterogeneity because of its unique depositional environment and complex diagenetic process. In contrast, the values of the 10-min gel strength property are higher at shallow formations rather than the deeper formations. This shows the importance of this suspension property at shallow unconsolidated depths which depends on the chemical treatment type used in the drilling mud, the concentration of solids, timing and the temperature.

The presented data in Fig. 2 was subjected to two statistical techniques for model development and comparison. The techniques employed are the artificial neural networks (ANNs) and multiple regression analysis (MRA). Both techniques are used to develop new models.

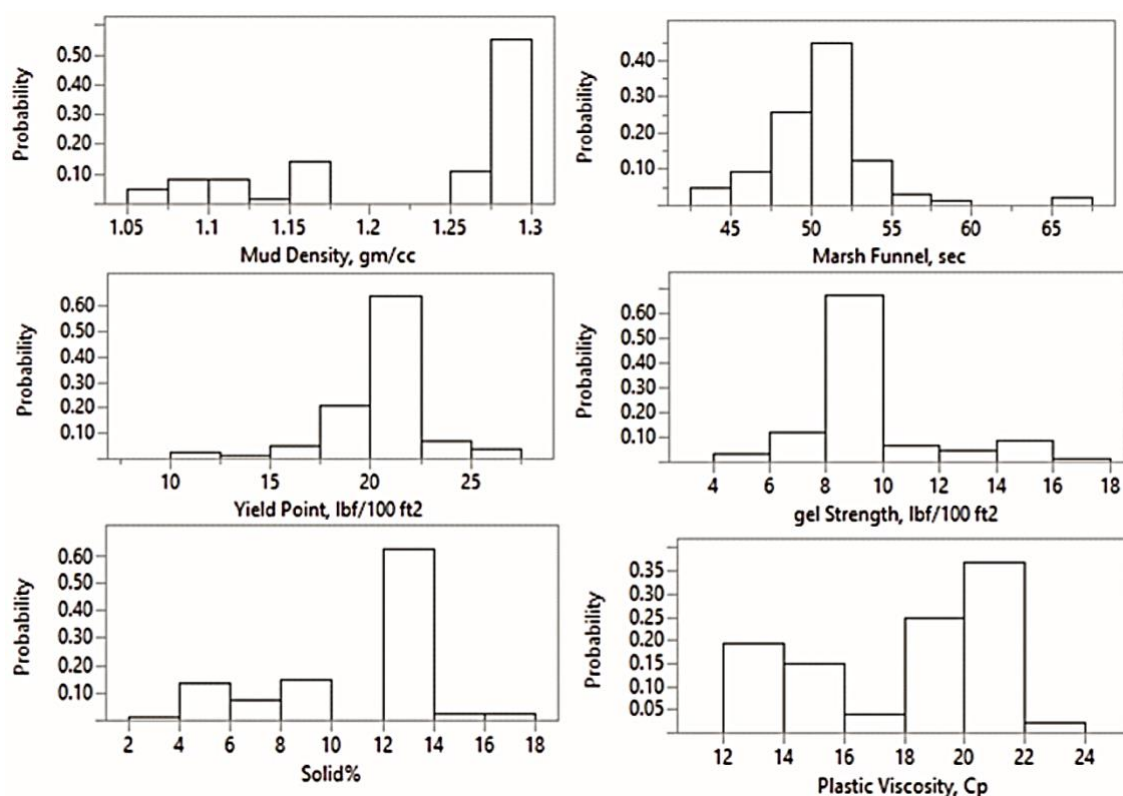


Fig. 2. Histograms of data used for models development

4. Mechanics of ANNs

As an application of machine learning, artificial neural networks (ANNs) have proved their potential in solving complex problems in petroleum industry, especially when the input data are limited or not available. It can learn and extrapolate the behavior of unknown parameters by utilizing configurations of connection weights, biases, and activation functions (Hadi and Nygaard, 2018, Al-zubaidy et al., 2022, Al-Saady and Rezouki, 2023).

ANN is a powerful tool for solving nonlinear engineering challenges especially when there is no simple analytical solution, non-linear data, multidimensional data, incomplete data, or even no numerical solutions for solving a problem. Backpropagation Neural Networks (BPNN) is a simple

technique and it is applicable for various applications related to oil and gas industry (Alkinani et al., 2019, Naji et al. 2022a). The data in BPNN flows in two directions. Firstly, training the ANN model, and secondly go back to readjust the network's weights and biases to minimize the overall error of the ANN, ideally zero. The BPNN is typically consisted of three layers, input layer, hidden layer, and output layer. Within the hidden layer, the number of neurons is normally determined by trial and error. Through training the network, the weights of the neurons or input parameters are adjusted to produce outputs with less difference from the target values (less errors between the predicted and actual values, ideally zero).

In backpropagation algorithm, as mentioned previously, the predicted output is compared with the target or actual measurement, then send backward to the connected links between the neuron to readjust the connection weights and biases so that minimizing the difference between the predicted and actual outputs. This performance can help in modifying the weights of links to minimize the errors in the results.

5. Results and Discussion

In order to create ANN models that may be utilized to ascertain the rheological mud qualities using other measurably observable properties, the study's results are presented in this part. Two basic steps can be used to summarize the findings: (1) Creation of ANN-models for each rheological property, and (2) Comparing the results of ANN with the results of multiple regression analysis. For each model that is developed, the determination coefficient (R^2) and the root mean square error (RMSE) are found to be two performance metrics.

5.1. Development of New Models Using Artificial Neural Networks

In this section, the results of the neural networks for developing new models are presented. Fig. 3 shows the schematic diagram of the neural networks in which the input parameters are shown in the input layer: MW, MF, and solid %. With respect to the output layer, it refers to the output rheological properties: PV, YP, μ_a , and 10-min gel.

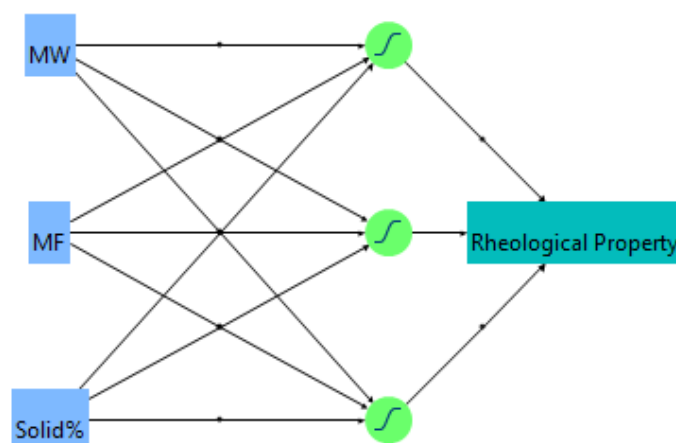


Fig.3. Schematic diagram showing the layers of the neural networks.

This means that the rheological mud characteristics (PV, YP, μ_a , and 10-min gel) can be determined based on the frequent measurable properties (MW, MF, and solid %) by using the weights and bias of the neural network. The neural networks are trained using BPNN technique, which can make the learning faster and it's possible to detect important predictive models between parameters (Hadi and

Nygaard, 2021). In this section, two datasets of Fig. 2 were subjected to the artificial neural network technique.

5.1.1. Plastic viscosity model

Fig. 4 presents the actual and predicted plastic viscosity values based on the artificial neural networks. A well matching between the predicted and actual values of plastic viscosity can be seen from this figure. For training datasets, the obtained results revealed that the R2 and the RMSE are 0.954 and 0.694, while for validation datasets, they are 0.954 and 0.634, respectively.

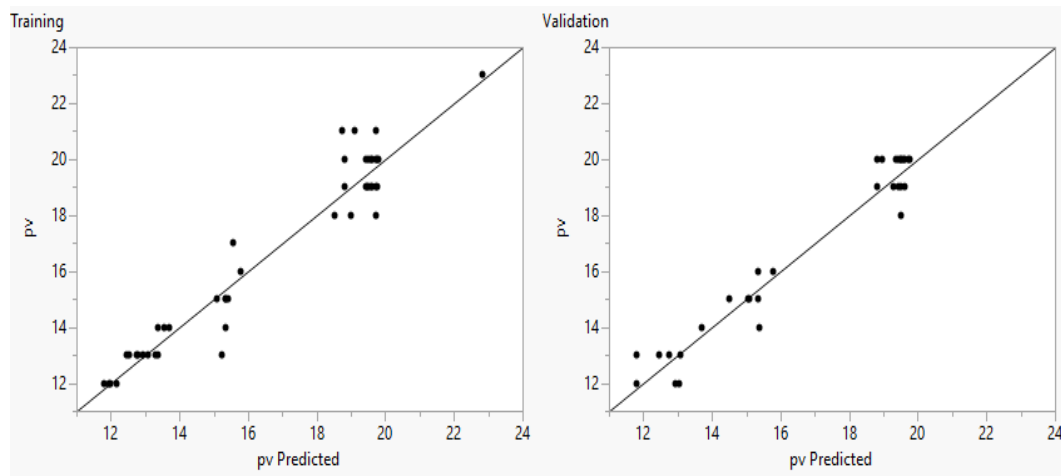


Fig.4. Plastic viscosity modeling Using ANN techniques

Equation (1) represents the mathematical expression of the developed model for determining PV using ANN. This means that Eq. 1 can be used to determine this property using the neural network's weights and biases as presented in Table 1.

$$PV_n = \left[\sum_{i=1}^N w_{2i} * \left(\frac{2}{1 + e^{-2(w_{1i,1} * MW_n + w_{1i,2} * MF_n + w_{1i,3} * S\%_n + b_{1i})}} - 1 \right) \right] + b_2 \quad (1)$$

Where:

Table 1. The weights and biases of ANN model for determining plastic viscosity

Number of Neurons(i)	Input-Hidden Weight (w_{1i})			Hidden-Output Weight	Bias	
	MW	MF	$Solid\%$	w_{2i}	b_{1i}	b_2
1	-12.517	-0.161	-0.0255	-9.932	23.18	17.23
2	-1.974	-0.177	-0.1164	-3.015	13.42	
3	2.53	-0.285	-0.327	6.519	14.618	

5.1.2. Yield point model

The datasets of two wells that presented in Fig. 2 were also subjected to the ANN techniques for determining the yield point of KCL/Polymer mud. Fig. 5 presents the cross plots showing the real YP and the estimated YP using ANNs for both the learning and validation datasets. The obtained R^2 and RMSE of the ANN model (Eq. 2) are 0.91 and 0.879 for training datasets. In contrast, the datasets that used to validate the accuracy of Eq.2 for determining the yield point have 0.90 and 0.891, respectively. These results revealed the reasonable prediction of yield point of drilling mud using ANN. Hence,

Equation (2) in conjunction with the neural network's weights and biases in Table 2 is well workable for determining YP with high achievement prediction.

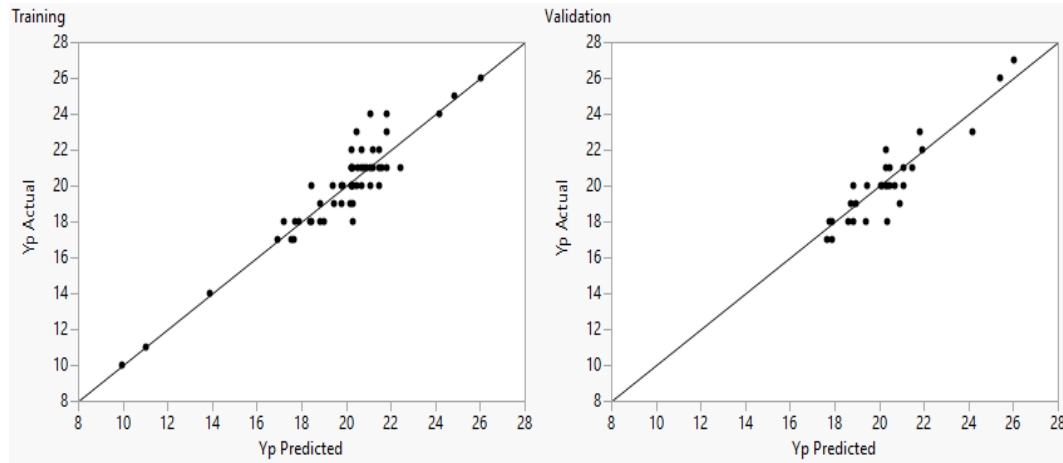


Fig. 5. Yield point modelling Using ANN techniques

$$YP_n = \left[\sum_{i=1}^N w_{2i} * \left(\frac{2}{1 + e^{-2(w_{1i,1} * MW_n + w_{1i,2} * MF_n + w_{1i,3} * S\%_n + b_{1i})}} - 1 \right) \right] + b_2 \quad (2)$$

Where:

Table 2. The weights and biases of ANN model for determining yield point

Number of Neurons(i)	Input-Hidden Weight (w_{1i})			Hidden-Output Weight	Bias	
	<i>MW</i>	<i>MF</i>	<i>Solid</i> %	w_{2i}	b_{1i}	b_2
1	-1.248	0.0117	0.0127	-2320	0.9101	521.03
2	1.5378	0.0117	-0.0633	-1463	-1.9651	
3	-0.1098	0.0083	-0.0118	5446	-0.3414	

5.1.3. Apparent viscosity model

Apparent viscosity (μ_a) is one of the essential rheological mud properties during the drilling operations by which various drilling problems can be controlled as well as enhancement the lifting capacity of the drilled cuttings and thus improving the hole cleaning. Fig. 6 along with Table 3 present the results of modeling of the μ_a drilling fluid utilizing ANNs. As shown in this figure, there is a good matching between the predicted and actual values of μ_a of drilling mud. The obtained R2 and RMSE for the learning datasets of the neural network model (Eq. 3) are 0.952 and 0.741. For the validation process, in contrast, R2 and RMSE are 0.948 and 0.866, respectively.

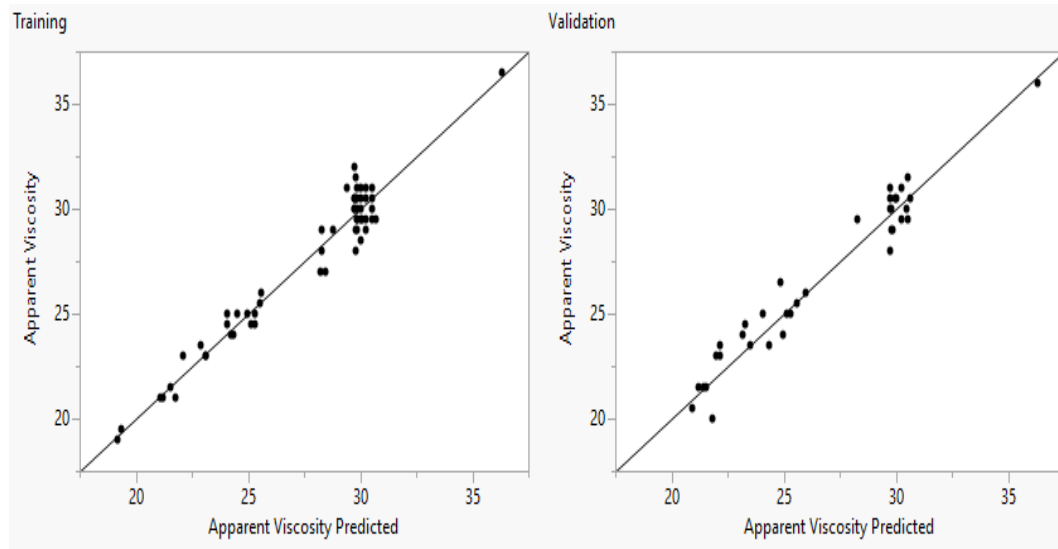


Fig. 6. Apparent Viscosity Modelling Using ANN Techniques

$$Apparent\ Viscosity_n = \left[\sum_{i=1}^N w_{2i} * \left(\frac{2}{1 + e^{-2(w_{1i,1} * MW_n + w_{1i,2} * MF_n + w_{1i,3} * S\%_n + b_{1i})}} - 1 \right) \right] + b_2 \quad (3)$$

Where:

Table 3. The weights and biases of ANN model for determining apparent viscosity

Number of Neurons(i)	Input-Hidden Weight (w_{1i})			Hidden-Output Weight	Bias	
	MW	MF	$Solid\%$	w_{2i}	b_{1i}	b_2
1	-39.717	-0.1609	-0.411	7.1303	61.799	32.742
2	-19.742	0.1652	0.4504	8.389	9.094	
3	52.904	-0.017	-0.5084	11.975	-58.05	

5.1.4. Gel strength model

Gel strength is a measurement of the drilling fluid's gelation and its an indicator of the inter-particle tensions in the fluid when the drilling operation or drilling mud circulation is initially stopped or stalled after 10 minutes. Cross plots of the drilling fluid's actual and anticipated 10-min gel strength are shown in Fig. 7. The findings obtained from this figure demonstrate the superiority of ANN approaches in determining the gel strength of the drilling fluid. For the training datasets, the resulting R2 and RMSE are 0.92 and 0.61, respectively. For the validation datasets, in contrast, they are 0.81 and 1.237, respectively. Consequently, using the neural network's weights and biases in Table 4, Equation (4) is well workable for determining the 10 min-gel strength of the drilling fluid.

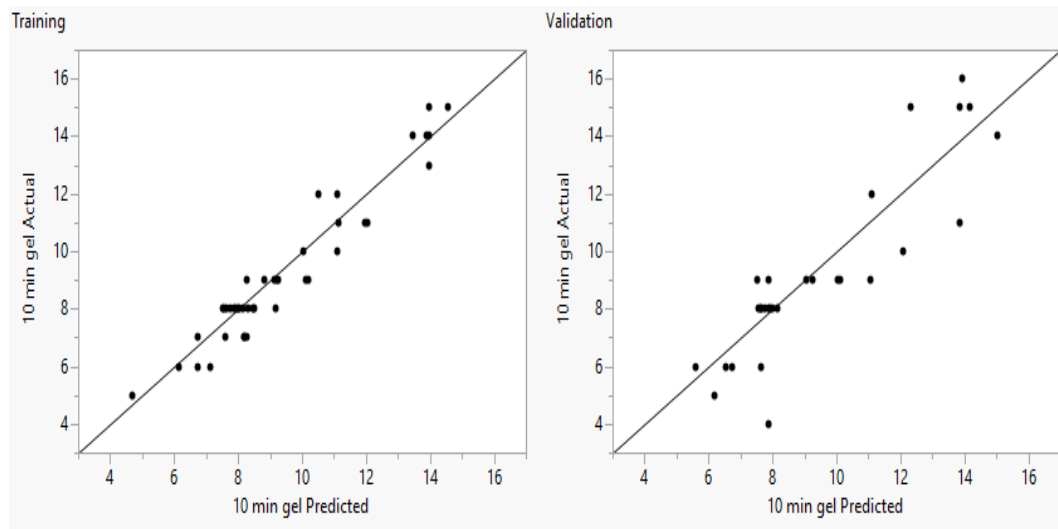


Fig.7. 10-Min Gel Strength Modelling using ANN techniques

$$10 - \text{Min Gel}_n = \left[\sum_{i=1}^N w_{2i} * \left(\frac{2}{1 + e^{-2(w_{1i,1} * MW_n + w_{1i,2} * MF_n + w_{1i,3} * S\%_n + b_{1i})}} - 1 \right) \right] + b_2 \quad (4)$$

Where:

Table 4. The weights and biases of ANN model for determining 10-min gel strength

Number of Neurons(i)	Input-Hidden Weight (w_{1i})			Hidden-Output Weight	Bias	
	MW	MF	Solid%	w_{2i}	b_{1i}	b_2
1	-13.066	0.265	0.367	-7.439	-2.372	6.466
2	-60.877	0.549	1.033	5.066	34.524	
3	43.746	0.225	-0.938	3.285	-53.734	

5.2. Development of New Models Using MRA

The multiple regression analysis (MRA) is a significant statistical approach used for detecting the output model using independent parameters. This approach has been used in this study to figure out if there is any improvement in determining the rheological mud properties using ANN techniques. In other words, the presented models in this section can be used for determining the rheological mud characteristics (PV, YP, AV, and 10-min gel strength) based on frequent measurable properties which are Mud Density, Marsh Funnel, and solid%.

The results of the multiple regression analysis for forecasting the rheological mud properties are presented in Table 5. Equations (5, 6, 7, and 8) represent the mathematical expressions with the performance capacity of the developed models for determining PV, YP, μ_a , and 10 min gel strength, respectively.

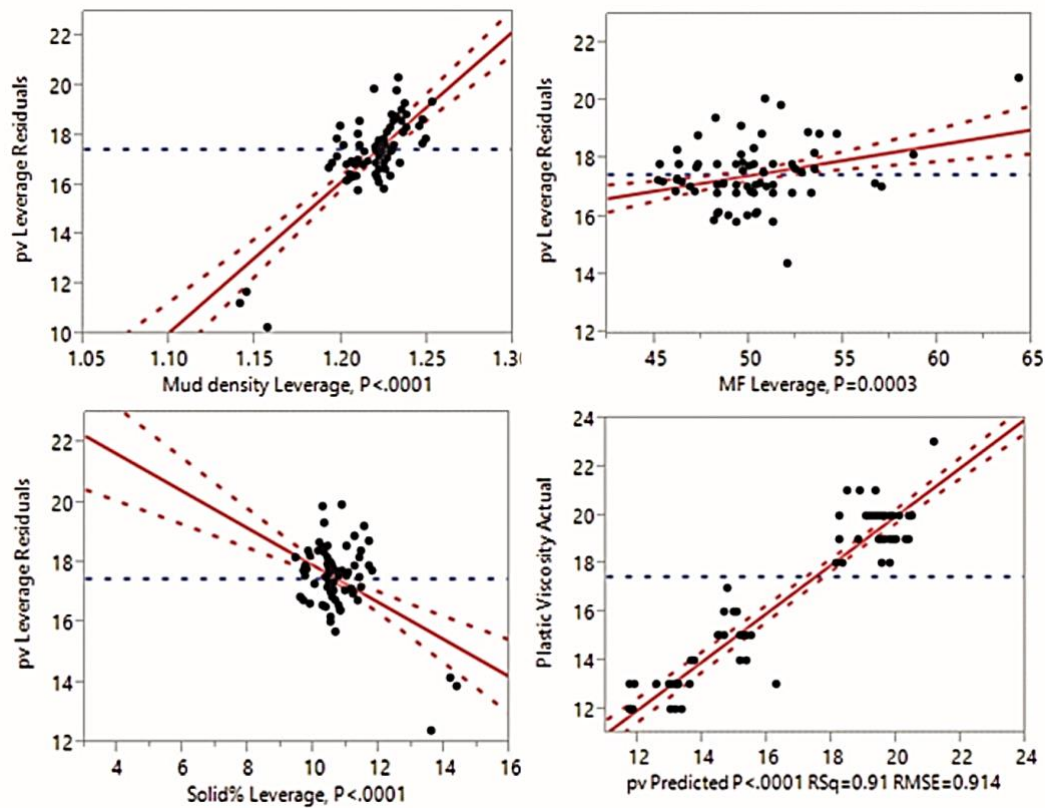
As the values of R^2 and RMSE in this table demonstrated that the multiple regression analysis performs well in forecasting the PV and μ_a of the drilling mud. It is also conservative in determining other drilling fluid rheological properties (YP and 10-min Gel Strength).

Figs. 8, 9, 10 and 11 showed the partial regression leverage plots for predicting four rheological properties (plastic viscosity, yield point, apparent viscosity, and gel strength), respectively. The obtained P-values can be used to identify how each rheological property affects other rheological properties.

Table 5. Results of Multiple Regression Analysis for determining the rheological mud properties

Rheological Property	Artificial Neural networks				Multiple Regression Analysis	
	Training		Validation			
	R ²	RMSE	R ²	RMSE	R ²	RMSE
Plastic Viscosity	0.955	0.694	0.954	0.634	0.91	0.914
Yield Point	0.910	0.879	0.90	0.891	0.78	1.108
Apparent Viscosity	0.952	0.741	0.948	0.866	0.90	1.145
Gel strength	0.920	0.610	0.810	1.237	0.67	1.333

The red dashed line denotes a 5% confidence interval, while the blue dashed line represents the mean output property (i.e., rheological parameter such as plastic viscosity). For instance, if the mean plastic viscosity exceeds the confidence interval at a sharp angle, the mud density, marsh funnel, or solid percentage all have a significant role in determining the drilling fluid's plastic viscosity (Hadi and Nygaard 2021). As a result, mud density seems to be more conservative than other metrics in predicting other rheological mud features, followed by decreasing order of marsh funnel and solid%.

**Fig.8.** Plastic Viscosity Modeling Using MRA Technique

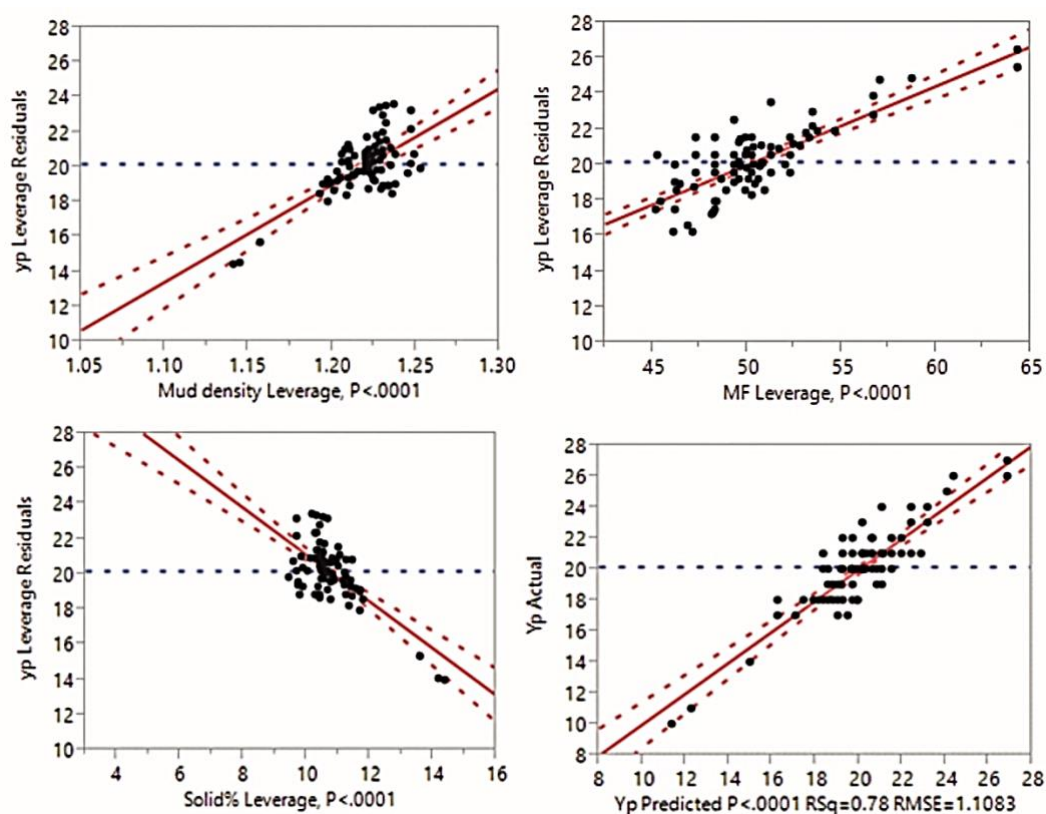


Fig.9. Yield point modeling Using MRA technique

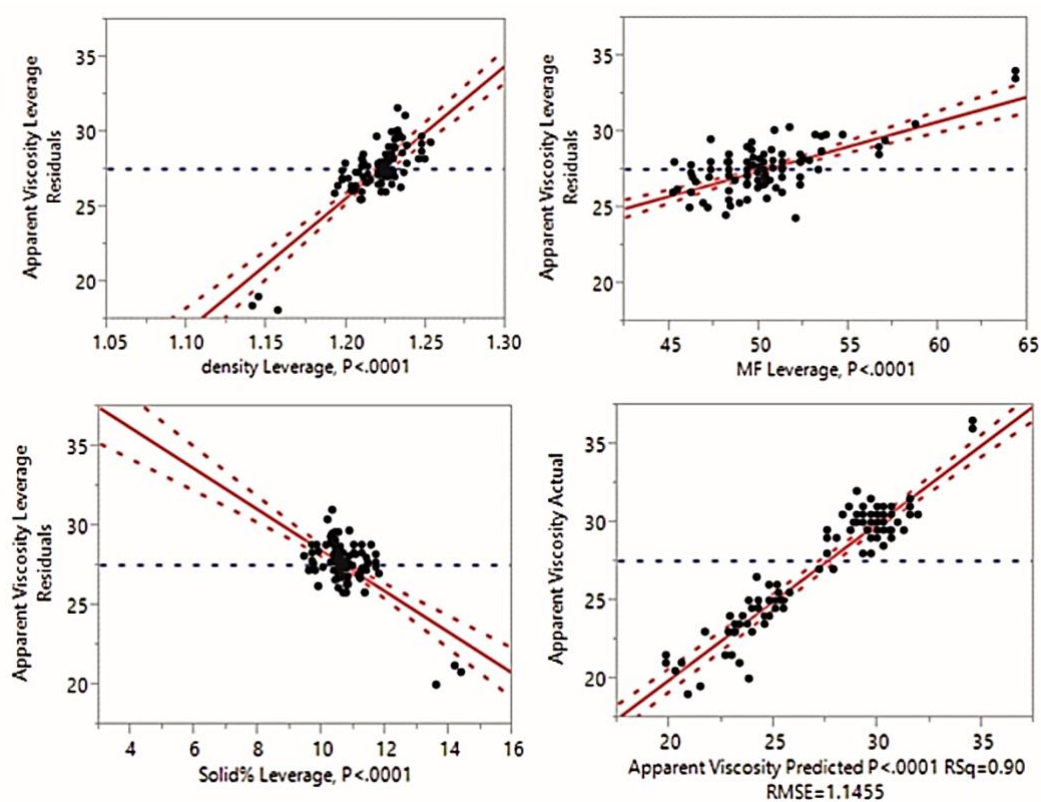


Fig.10. Apparent viscosity modeling using MRA technique

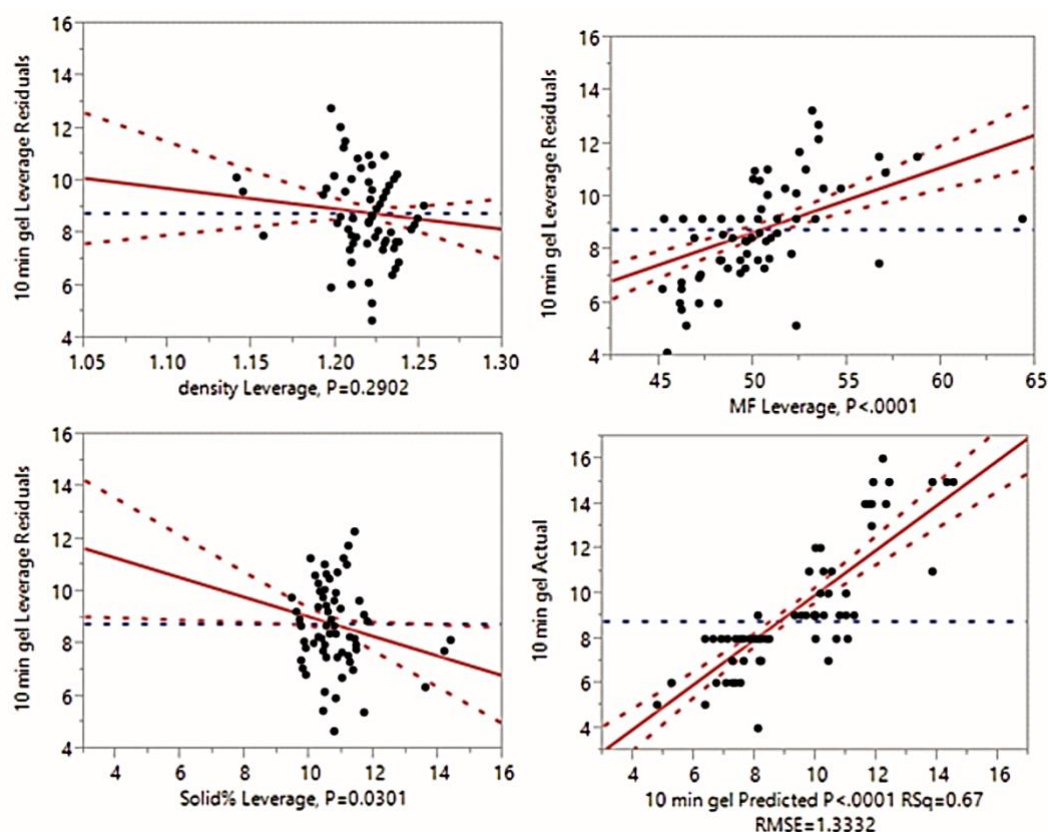


Fig.11. Gel strength modeling using MRA technique

5.3. Comparison Between ANN and MRA

This section summarizes the results of ANN and MRA in predicting the rheological mud properties. Table (6) along with Figs. (12 and 13) compare the results of ANN and MRA based on two error-based metrics, R^2 and RMSE. It is evident that artificial neural networks are more accurate than multiple regression analysis in determining the rheological mud qualities. This means that higher R^2 and lower RMSE has been obtained using ANN rather than using MRA. For instance, the results of YP modeling using the ANN approach are 0.91 of R^2 and 0.879 of RMSE. On the other hand, the obtained results of YP modelling using MRA are 0.78 and 1.108, respectively.

Table 6. Summary of the results of ANN and MRA

Rheological Property	Artificial Neural networks				Multiple Regression Analysis	
	Training		Validation		R^2	RMSE
	R^2	RMSE	R^2	RMSE		
Plastic Viscosity	0.955	0.694	0.954	0.634	0.91	0.914
Yield Point	0.910	0.879	0.90	0.891	0.78	1.108
Apparent Viscosity	0.952	0.741	0.948	0.866	0.90	1.145
Gel strength	0.920	0.610	0.810	1.237	0.67	1.333

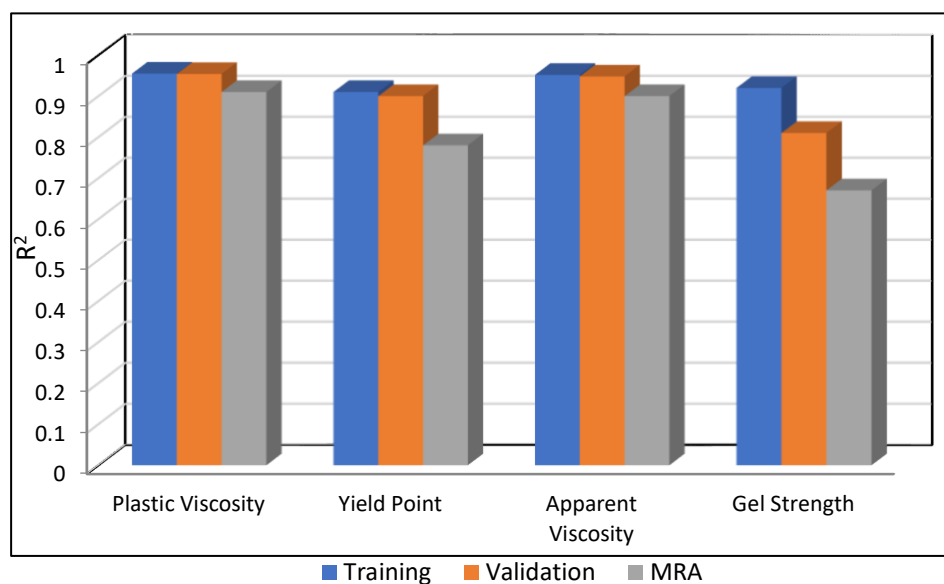


Fig.12. Comparison between ANN and MRA based on R^2

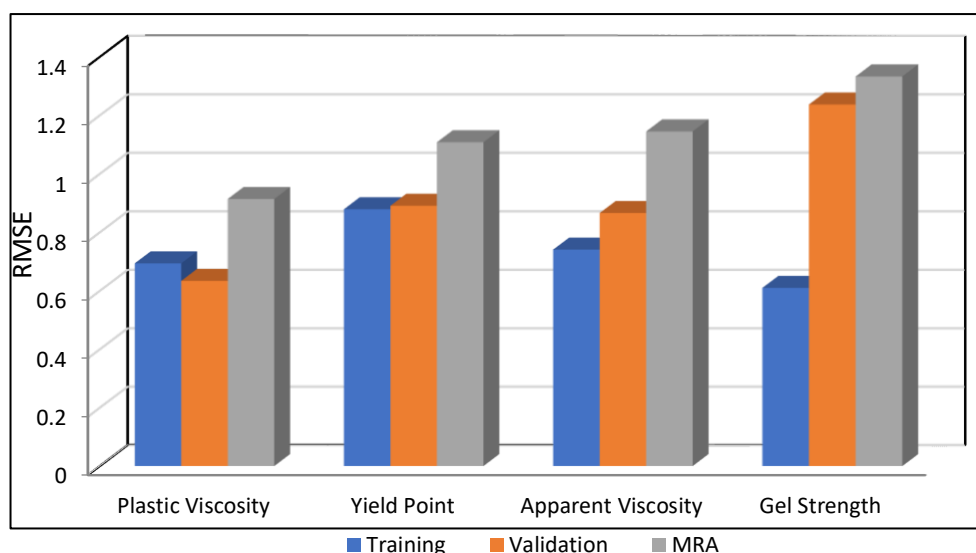


Fig.13. Comparison between ANN and MRA based on RMSE

6. Conclusions

It is of great importance to frequently control the drilling fluid rheological properties through drilling operations since these properties are the key parameters for optimizing the drilling operations, evaluating hole cleaning, optimizing the drilling hydraulics, and thus increasing the penetration rates, otherwise, many drilling challenges may be exposed during the drilling operations. Such these drilling problems are lost circulation, tight holes, wellbore collapse, well kick, and pipe stick problems.

This study presents an effective approach for determining the rheological properties of KCL/Polymer mud using artificial neural networks. Indeed, the most significant point between this study and literature is that few ANN-mathematical expressions for determining the rheological characteristics of KCL/Polymer mud. The obtained results from this study can be summarized in the following:

- Both the MRA and ANN techniques are powerful tools in determining the rheological mud properties, but the obtained results of ANN are more conservative than MRA.

- Artificial neural networks have proven to be reliable tools in identifying the relationships between the independent parameters and the dependent parameter or the output rheological property.
- Mud density is a great contributor of drilling mud rheological properties, followed in decreasing order by solid content and marsh funnel.
- Without the requirement for laboratory measurements, the newly developed models can be analyzed to measure the rheological mud properties.
- The performance of the drilling fluid can be improved in real time to obtain the optimum rate of penetration, thus boosting the economic benefits of the drilled well.

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