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Comparative study of the effect of additives in water-based drilling mud on filtrate volume, along with presentation of an artificial neural network estimator model

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ABSTRACT

Fluid loss during drilling operations is one of the primary causes of formation damage and reduced well productivity. Therefore, minimizing drilling mud filtrate volume is essential for improving drilling efficiency and maintaining wellbore integrity. In this study, the effects of three additives, namely rice husk, natural gum (apricot gum), and xanthan gum, on the filtrate volume of water-based drilling mud were experimentally investigated. Static filtration tests were conducted using additive concentrations of 0.5, 1, 2, and 3 gr and filtration times ranging from 0.25 to 7.5 min. The results indicated that increasing the additive concentration consistently reduced filtrate volume for all tested additives. For all additives, adding 0.5 g caused the largest incremental decrease in filtrate volume, while further increases in concentration produced diminishing reductions. Xanthan gum exhibited the highest filtration-control efficiency, followed by apricot gum and rice husk. At the maximum additive concentration, filtrate volume was reduced by 60.0%, 84.0%, and 88.4% for rice husk, apricot gum, and xanthan gum, respectively, compared with the base mud. To estimate filtrate volume under arbitrary additive concentrations and filtration times, a two-layer feedforward artificial neural network (ANN) with 10 neurons in the hidden layer was developed. The ANN demonstrated great predictive capability, achieving overall correlation coefficients (R) of 0.99979, 0.99988, and 0.99991 for rice husk, apricot gum, and xanthan gum datasets, respectively. The corresponding minimum mean squared errors (MSEs) were 1.52×10^{-5}, 1.08×10^{-5}, and 8.56×10^{-6}, while the average prediction errors were 0.59%, 1.27%, and 1.86%, respectively. These results confirm the effectiveness of the investigated additives for fluid-loss control and demonstrate the reliability of the proposed ANN model for rapid filtrate-volume prediction.

KEYWORDS

Rice husk, natural/apricot gum, xanthan gum, drilling mud filtration, feedforward artificial neural network

I. INTRODUCTION

Drilling mud has many roles, among which control of the wellbore wall situation is of paramount importance. In this regard, one of its primary functions is to create an impermeable mud cake. However, a significant challenge arises from drilling mud loss, which may occur for various reasons, since substantial fluid loss volumes from the mud into the formation can have serious adverse effects. This loss not only prolongs inefficient drilling time but also results in substantial costs. Drilling fluid filtration is a critical factor contributing to drilling mud loss. It leads to the formation of a mud cake with low permeability on the wellbore wall (Sherwood and Meeten, 1997). For different reasons, such as preventing formation damage and avoiding wellbore diameter reduction, mud filtrate volume entering into neighboring rocks of the wellbore during overbalanced drilling should be decreased as much as possible (Ladva et al., 2000). Drilling variables, like weight and chemical composition of mud, mud circulation pressure, and filtration process time, may affect the ultimate depth of mud filtrate invasion into the formation. Furthermore, in-situ formation properties such as porosity, absolute permeability, relative permeability, pore pressure, shale chemistry, capillary pressure, and fluid saturation play a critical role in the control of mud cake formation and the evolution of the filtration process (Outmans, 1963). Hence, the use of drilling mud additives, which do not damage the formation and are cheap, is a necessity.

Okon et al. (2014) evaluated the effectiveness of rice husk as a possible filtration loss control additive in water-based drilling mud and compared the results with the commonly used polymers. They described properties of rice husk and its potential application in

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the oil and gas industry. The results indicated about a 65% reduction in fluid loss at a rice husk content of 20 g per 350 mL mud. Finally, they concluded that rice husk can be utilized as a fluid loss control additive in water-based drilling mud as it shows good filtration loss control potential. Agwu and Akpabio (2018) presented a review paper regarding the use of cellulosic agro-waste materials as filter loss control agents in drilling muds. They highlighted the potential benefits of using these materials, including reducing environmental pollution and lowering drilling fluid costs. Various agro-waste materials were discussed, and their cost-effectiveness was compared to that of conventional fluid loss control materials. The gaps in the literature in terms of microscopic analysis and filter cake properties of muds using agro-waste materials were also discussed. Agwu et al. (2019) discussed the use of rice husk and sawdust as a filter loss control agent for water-based muds and highlighted why preventing mud filter loss is critical to assessing the performance of drilling mud. They provided experimental evidence that using rice husk in water-based muds is more effective than sawdust in terms of preventing fluid loss. Raza et al. (2023) discussed rice husk ash as a sustainable alternative to chemical additives in drilling fluids. They found that increasing concentrations of rice husk ash considerably improved the rheology at higher concentrations. The study suggested that rice husk ash can serve as a sustainable and cost-effective alternative to conventional chemical additives. Nzerem et al. (2023) discussed the use of organic-based drilling mud additives sourced locally in Nigeria, particularly those made from organic waste materials such as rice husk, cassava, and corn cobs. Various studies and experiments conducted on the use of local polymers and natural materials as substitutes for imported additives in water-based drilling mud were reviewed in their paper, and finally, their effectiveness in improving mud qualities and reducing fluid loss was analyzed. Other relevant papers regarding the application of rice husk in filtration loss control can be found in Biltayib et al. (2018), Raipuria et al. (2018), Zarei and Nasiri (2021), and Akinyemi and Abdulhadi (2022).

Howard et al. (2017) discussed the use of pseudoplastic fluids viscosified with xanthan gum to control fluid loss, as well as the design of a radial fluid loss tester to measure fluid loss for formate brine with various concentrations of xanthan gum. They concluded that when solubilized in high-density formate brines, xanthan gum generates pseudoplastic fluids with non-zero yield stress that can control fluid loss through the development of a high apparent viscosity that increases exponentially with the radial distance from the borehole. Ali et al. (2022) discussed the utilization of biopolymers, including xanthan gum, in water-based drilling muds as a means for reducing filtrate loss. They focused on the use of biopolymers and starches for increasing viscosity and reducing fluid loss. They provided details about the biopolymers that can be added to the drilling mud and the factors that influence their effectiveness in terms of filtrate volume and filter cake thickness. Peter and Olamilekan (2022) presented a comparative study of rice husk and xanthan gum as viscosifiers in water-based drilling fluids. The study investigated the possibilities of replacing xanthan gum with rice husk as a viscosifier. It concluded that rice husk could be recommended for use as a viscosifier in the production of water-based drilling fluids. Akinyemi et al. (2023) elaborated on the impacts of different additives on the rheological properties of rice husk and xanthan gum-modified drilling fluid. Four samples containing bentonite clay, rice husk, and xanthan gum in different proportions were made, and then different chemicals were added to them. The results demonstrated that the chemical additives positively affected the rheological properties of the drilling fluid samples. One sample that included 20 g of rice husk and 1 g of xanthan gum could be improved by adding any of the chemical additives tested in an appropriate quantity for effective performance in drilling operations. Akinyemi and Abdulhadi (2023) considered developing water-based drilling fluids using bentonite clay and rice husk, with the addition of xanthan gum. The rheological properties of different blends were investigated, and it was found that drilling mud modified with rice husk did not have a negative impact on its properties at higher temperatures. Li et al. (2024) presented a review paper on polymer-based additives, including xanthan gum and rice husk, which are utilized as filtrate reducers in water-based drilling fluids. These additives help us minimize fluid loss, maintain wellbore stability, and avoid formation damage in high-pressure, high-temperature (HPHT) conditions encountered during deep drilling operations. The design, preparation, and application of polymeric filtrate reducers for fluid loss control were put forward, and the structure-property-performance relationships of these additives and their prospects for designing high-performance drilling fluids with optimal rheological and filtration properties were discussed by these scholars. Kumar et al. (2024) published a research paper regarding the formation and evolution of particle migration/filtration zones in porous media, specifically related to drilling fluid compositions. They reported that the concentration of barite and xanthan gum predominantly controls the filtration process by enhancing particle plugging and retention time, respectively.

Zhange et al. (2015) reported on the modification of a plant gum (SP gum) using epichlorohydrin to optimize its performance as a drilling fluid additive. The researchers optimized the modification conditions, such as pH, temperature, and the mass ratio of the crosslinking agent. They found that Modified SP (MSP) gum showed better performance in water-based drilling fluids than SP-treated drilling fluids. Almahdawi et al. (2017) aimed at finding local alternatives to foreign drilling fluid materials, which can reduce the cost of drilling oil wells. Plum Tree Gum was successfully tested as a drilling fluid material under API Specification 13A. The study also compared Plum Tree Gum to similar foreign materials for the same sample to assess its physical and rheological properties. It was discovered that Plum Tree Gum could be used as a filtration control material for water-based drilling fluid and as a partial alternative for bentonite to increase viscosity.

Although previous studies have investigated the use of rice husk, xanthan gum, or natural plant-based polymers individually as drilling-fluid additives, a comprehensive comparative evaluation of rice husk, apricot gum, and xanthan gum under identical experimental conditions has not been reported. Furthermore, previous studies have primarily focused on experimentally measuring filtration characteristics and rheological properties, while limited attention has been devoted to developing predictive models capable of estimating filtrate volume as a function of additive concentration and filtration time. The present study addresses these gaps by combining laboratory filtration experiments with ML-based prediction and by providing a direct performance comparison among all three additives. Therefore, the performance mechanism of the aforementioned drilling fluid additives for the reduction and prevention of fluid loss during the drilling operation and their impact on effective parameters of drilling fluid filtration are investigated in depth in this study. The main objective of the present study is to measure the filtrate volume of water-based drilling mud after adding different masses (0.5 gr, 1 gr, 2 gr, and 3 gr) of additives (namely rice husk, natural gum/apricot gum, and xanthan gum) to the mud at different filtration times (from 0.25 min to 7.5 min with 0.25-min intervals), and then to compare the obtained results for the muds containing different types and masses of additives. To estimate the filtrate volume of drilling fluids for the aforementioned additives under arbitrary masses of the additive and arbitrary filtration time, a two-layer feedforward artificial neural network is designed and trained through experimental data. The designed smart model is novel and possesses high accuracy in estimating the filtrate volume of drilling mud, and has a good contribution to the area of petroleum drilling engineering.

II. Methodology

All drilling mud samples were prepared in the drilling mud laboratory according to the American Petroleum Institute (API). The water-based drilling mud sample used in this research is a mixture of 350 cc water and 15 gr bentonite. Different masses (0.5 gr, 1 gr, 2 gr, and 3 gr) of additives (rice husk, natural gum/apricot gum, and xanthan gum) are added to the base mud, and mixing and stirring in a mixer continue until a stable mud is achieved. Static filtration tests are conducted on drilling fluid using an API FILTER PRESS apparatus. The device consists of a mud cell pressurized with a CO_2 cartridge using a pressure gauge and regulator. The mud cell has three parts: a cylindrical body, a base with a filtrate discharge tube, and a top with a pressurization system. The mud cell is placed on a frame, and the filtrate is collected in a graduated glass measuring cylinder. The experiments were conducted at ambient temperature (25 °C) and a constant pressure of 100 psi. The test starts with a 100 Psi flow pressure, and the fluid volume gathered in the container is recorded as a function of time (from 0.25 min to 7.5 min with 0.25-min intervals) at 25 °C. The filtration test duration was selected as 7.5 min to capture the transient stage of filtrate invasion and filter-cake development, where the greatest changes in filtrate volume occur. Filtrate volume was recorded every 0.25 min, which provided 30 time points for each experiment and allowed the transient filtration behavior to be captured before the filtration rate approached a quasi-steady trend. This time interval provided sufficient temporal resolution for evaluating filtration kinetics and generating an adequate dataset for ANN training and validation while maintaining experimental repeatability.

III. Experimental Results and Discussion

Comparative curves of filtrate volume changes of drilling fluid vs. filtration time for different masses of the additives are shown in Figs. 1-3 for rice husk, apricot gum, and xanthan gum, respectively. As observed, when the mass of the additive in the base mud increases, the filtered fluid volume in the apparatus decreases at all times during the filtration process. This demonstrates the appropriate performance and influence of the additives introduced to drilling mud for reducing drilling fluid loss during drilling operations. The reason for this phenomenon can be described as follows: as the concentration of additives in the drilling fluid increases, solid components (rice husk) or semi-solid components (apricot gum and xanthan gum) mixed in the mud become more resistant to passing through the filter screens of the apparatus. By creating an impermeable layer and further blocking the pores of the screens, it prevents a higher volume of filtrate from passing through and accumulating in the corresponding container. As a 0.5 gr additive is introduced into the base mud, a substantial reduction occurs in the filtrate volume. However, the reduction rate of filtrate volume is significantly reduced as higher masses of the additive are mixed with the base mud. These changes are noticeable in Figs. 1-3. Note that the plastic viscosity of the base mud before filtration equals 4 cP, and its measured shear stress vs. shear rate data are presented in Table 1.

Table 1. Shear stress vs. shear rate measured experimentally for the base mud

Shear rate (RPM)	3	6	100	200	300	600
Shear stress (lb/100ft^2)	3	3	3.5	4	6	8

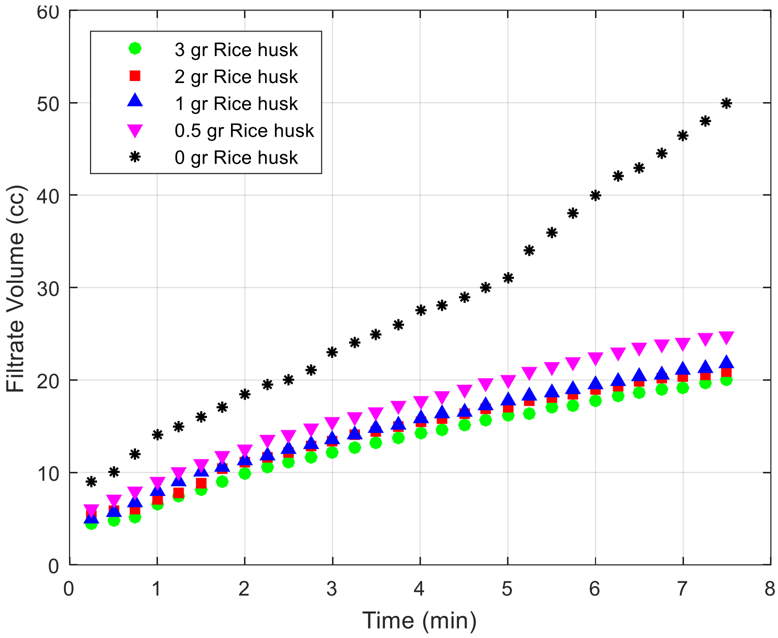

Fig. 1. Filtrate volume changes of mud sample containing different masses of rice husk vs. filtration time

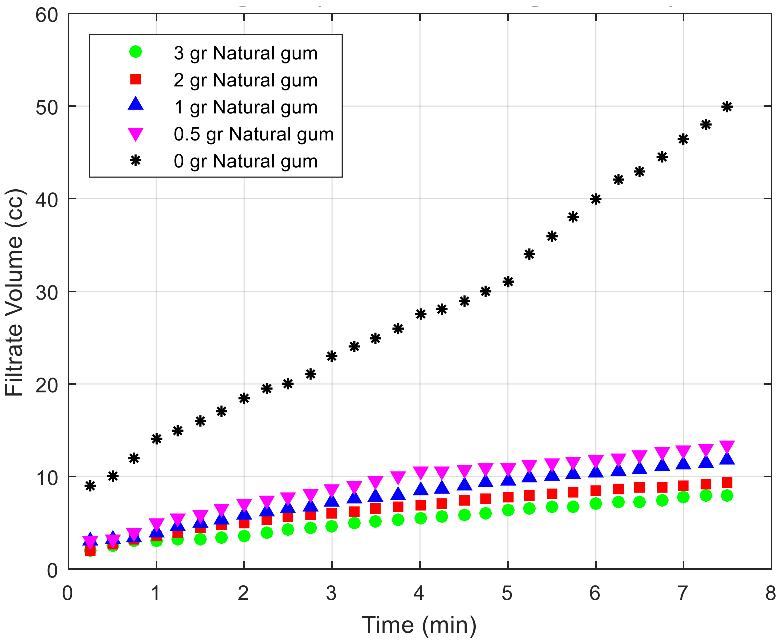

Fig. 2. Filtrate volume changes of mud sample containing different masses of natural gum (apricot gum) vs. filtration time

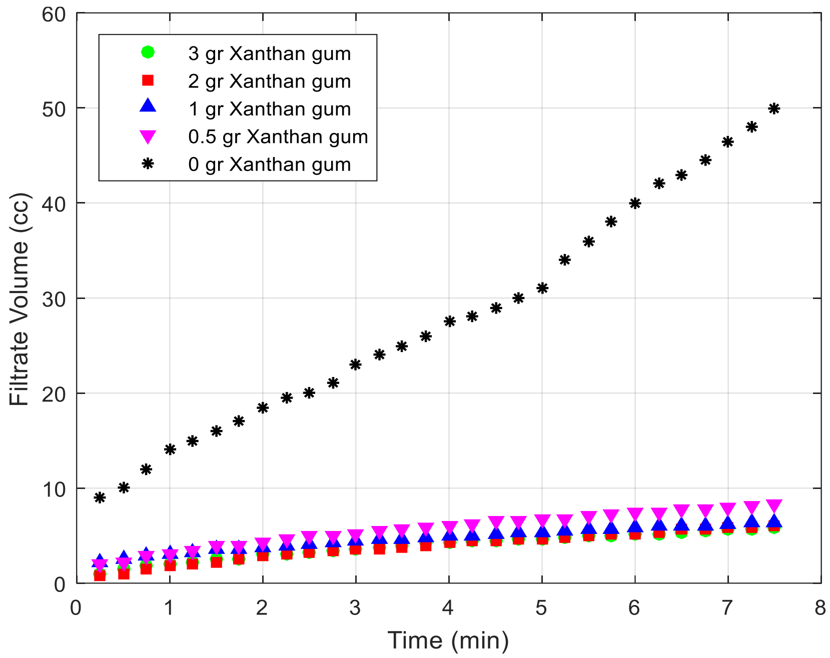

Fig. 3. Filtrate volume changes of mud sample containing different masses of xanthan gum vs. filtration time

Figures 4-7 display the comparative curves of mud filtrate volume changes vs. filtration time for mud samples mixed with 0.5 gr, 1 gr, 2 gr, and 3 gr of rice husk, apricot gum, and xanthan gum, respectively. It is evident that for all mass values of added additives and for all filtration times, the greatest reduction in filtrate volume belongs to xanthan gum, followed by apricot gum and rice husk. This shows that from the viewpoint of drilling mud filtration, xanthan gum has the largest effect and rice husk has the smallest effect on the improvement of mud loss during drilling operation. The stronger impact of adding apricot gum and xanthan gum on reducing the volume of drilling mud filtrate, compared to rice husk, can be attributed to their semi-solid nature and high adhesiveness. These two additives can create an impermeable coating on the filter screens of the device, preventing the filtrate from passing through the screens and allowing it to accumulate in the corresponding container. However, the reduction in filtrate volume cannot be attributed solely to the adhesive characteristics of the additives. Instead, it stems from several coupled mechanisms. First, additive molecules increase the viscosity and yield stress of the aqueous phase, reducing fluid mobility through the filter medium. Second, rice husk particles and polymer aggregates contribute to physical pore plugging and the formation of a denser filter cake. Third, xanthan gum and apricot gum possess hydrophilic functional groups capable of absorbing water and forming a three-dimensional network, thereby decreasing the permeability of the filter cake. As filtration proceeds, the accumulated solids and hydrated polymer chains create a compact, low-permeability barrier that restricts additional filtrate invasion. According to classical drilling-fluid filtration theory, filtration initially proceeds rapidly. However, as solids accumulate on the filter surface, a mud cake develops whose permeability progressively decreases, thereby reducing subsequent filtrate flow. The superior performance of xanthan gum is attributed to its high molecular weight, strong hydration capacity, and ability to generate highly viscous pseudoplastic structures, which enhance filter-cake quality and reduce fluid loss.

Table 2 presents the maximum percentage reduction in filtrate volume for drilling fluids containing varying mass fractions of rice husk, natural gum, and xanthan gum additives.

Table 2. Maximum percentage reduction in filtrate volume for drilling fluids containing varying mass fractions of rice husk, apricot gum, and xanthan gum additives

Additive type	Additive mass in drilling mud (350 cc water + 15 gr bentonite)			
	0.5 gr	1 gr	2 gr	3 gr
Rice husk	50.4	56.4	58.2	60.0
Natural gum	73.2	76.4	81.2	84.0
Xanthan gum	83.4	87.2	88.0	88.4

IV. Modeling, Results, and Discussion Based on ANN

Recently, machine-learning (ML) techniques have attracted considerable attention in petroleum engineering because they can capture highly nonlinear relationships between operational parameters and engineering responses. Artificial neural networks (ANNs), support vector machines (SVMs), random forests (RFs), and other data-driven approaches have been successfully applied to predict drilling-fluid rheological properties, wellbore stability, rate of penetration, reservoir properties, and production performance. In drilling fluids, most predictive studies have focused on viscosity, gel strength, yield point, density, and other rheological parameters (Rooki and Rahimi, 2025). However, a few investigations have addressed the prediction of filtration behavior and filtrate volume using ML methods, despite the critical role of fluid loss control in maintaining drilling efficiency and minimizing formation damage. Consequently, developing reliable predictive models for drilling-fluid filtration remains an area requiring further research.

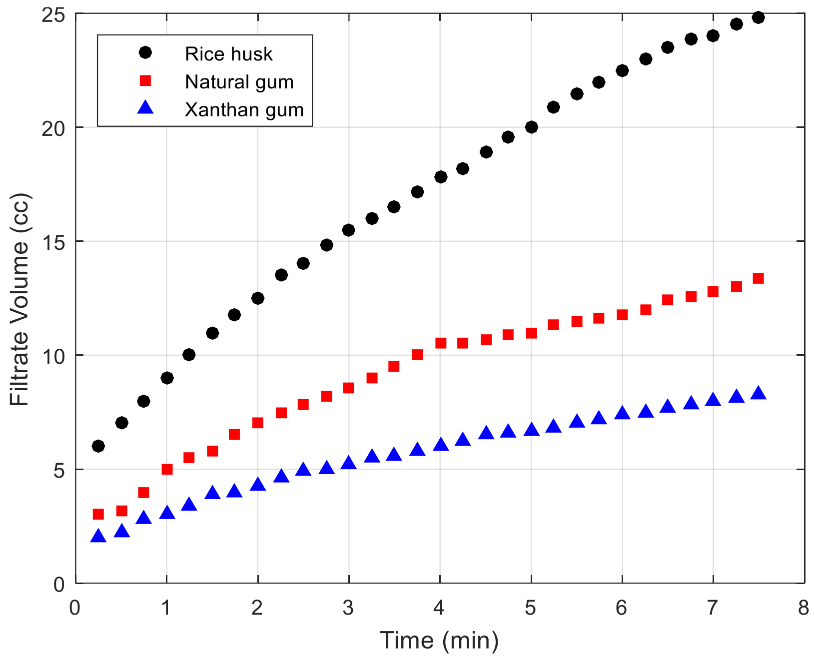

Fig. 4. Comparative curves of filtrate volume changes for mud containing 0.5 gr rice husk, natural gum (apricot gum), and xanthan gum vs. filtration time

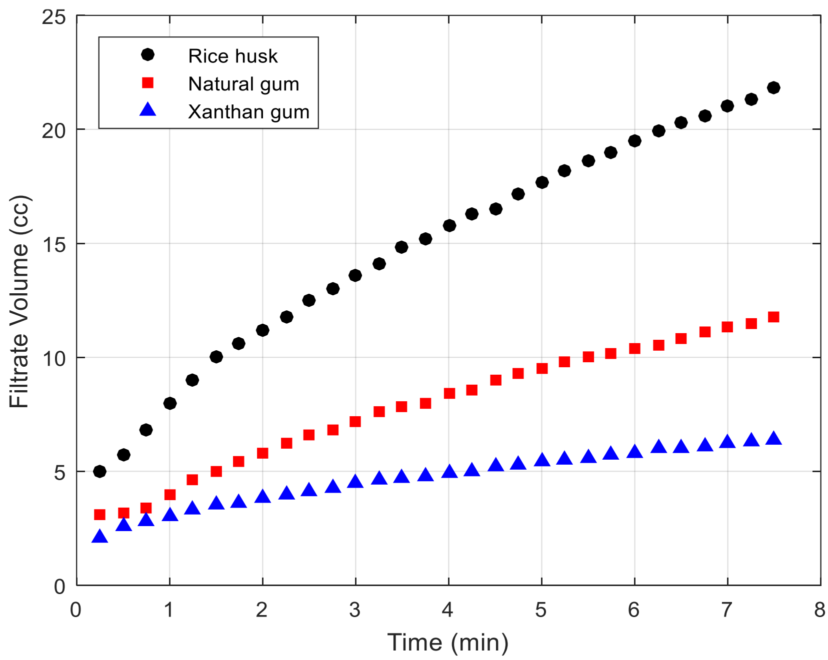

Fig. 5. Comparative curves of filtrate volume changes for mud containing 1 gr rice husk, natural gum (apricot gum), and xanthan gum vs. filtration time

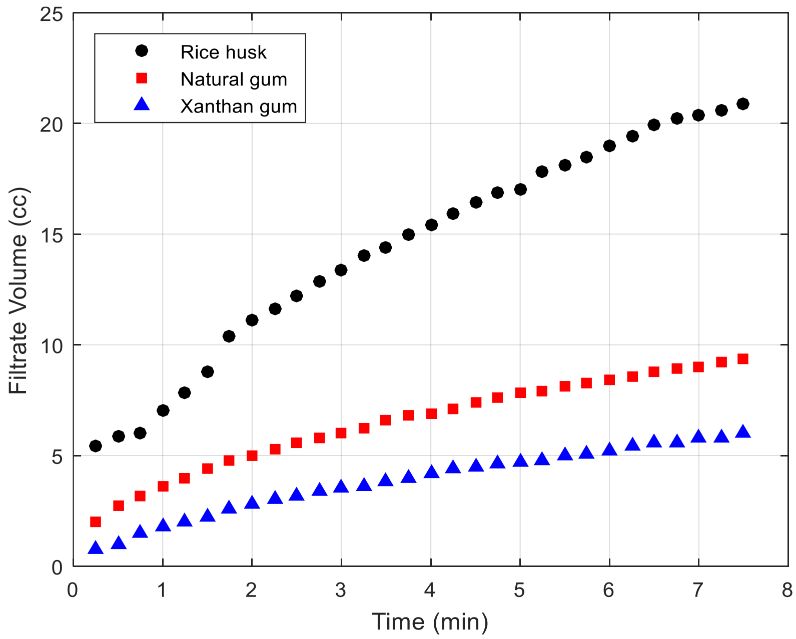

Fig. 6. Comparative curves of filtrate volume changes for mud containing 2 gr rice husk, natural gum (apricot gum), and xanthan gum vs. filtration time

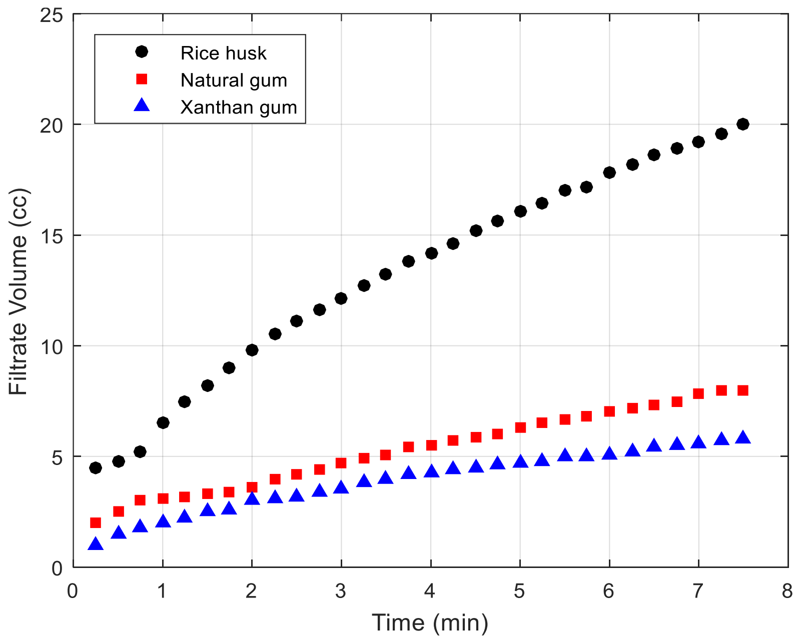

Fig. 7. Comparative curves of filtrate volume changes for mud containing 3 gr rice husk, natural gum (apricot gum), and xanthan gum vs. filtration time

Given the nonlinear relationship between additive concentration, filtration time, and filtrate volume, an ML approach was adopted to develop a predictive model. Among available ML techniques, ANNs have demonstrated excellent performance in modeling complex engineering systems when sufficient experimental data are available. The ANN's ability to learn from experience and its generalizability in solving novel problems have resulted in the superiority of this technique over other approaches in the oil and gas industry (Rashidi et al., 2011). Therefore, a feedforward ANN is selected to establish a quantitative relationship between filtration time, additive concentration, and filtrate volume.

To represent an accurate estimation model for the filtrate volume of drilling mud samples containing one of the additives of rice husk, apricot gum, and xanthan gum, a two-layer feedforward artificial neural network model with 10 neurons in the hidden layer is configured, trained, and prepared for feeding using MATLAB software. The role of this network, whose schematic is shown in Fig. 8, is to find a relationship between input properties (namely, additive mass in the mud sample and filtration time) and target output quantity (namely, filtrate volume of the drilling mud sample).

For each of the additives added to the mud sample, 150 data points were obtained in the laboratory. 70% of these data are assigned for training, 15% for validation, and 15% remaining for network testing. Also, the Levenberg-Marquardt optimization algorithm and the mean squared error (MSE) function between actual output and target values are used for network training and as the performance indicator, respectively. All input values (additive mass and filtration time) and output values (filtrate volume) gathered from the experiments are normalized in the zero-to-one range. Tangent Sigmoid and Linear transformation functions are considered in the hidden and output layers, respectively. Training stops when the number of validation performance failures reaches 10.

One of the most important indicators reflecting the training trend of an artificial neural network (ANN) is the network performance curve, which shows MSE changes during network training steps. Figs. 9-11 exhibit this curve for estimation networks of filtrate volume for mud samples containing rice husk, apricot gum, and xanthan gum. The decreasing trend of the MSE performance indicator value for each group of data relevant to training, validation, and testing is clear in these figures. Moreover, the best value obtained for the performance indicator of the validation data during training steps is marked by a green circle. The best validation performance obtained for the ANN estimator of filtrate volume prediction in samples containing rice husk, apricot gum, and xanthan gum is 2.5696e-5 in epoch 71, 8.8871e-6 in epoch 140, and 1.217e-5 in epoch 131. The minimum MSE across all data for the ANN corresponding to rice husk is equal to 1.5155e-5, and that corresponding to apricot gum and xanthan gum is equal to 1.0845e-5 and 8.5598e-6, respectively.

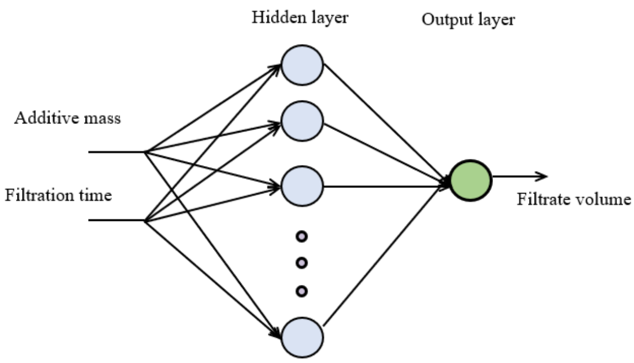

Fig. 8. Schematic of a two-layer backpropagation neural network for filtrate volume prediction

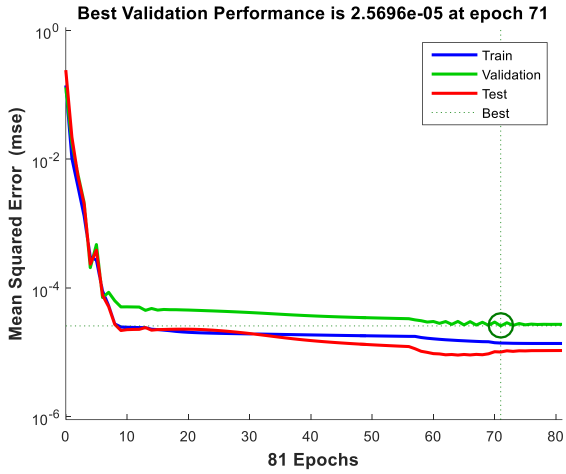

Fig. 9. ANN performance change curves during optimization steps of the MSE indicator for mud sample containing rice husk

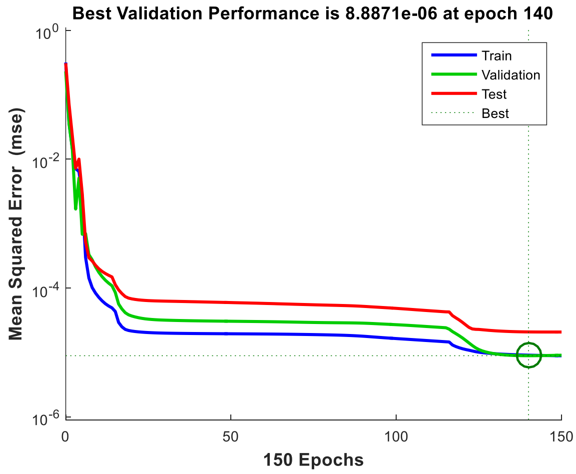

Fig. 10. ANN performance change curves during optimization steps of the MSE indicator for mud sample containing natural gum (apricot gum)

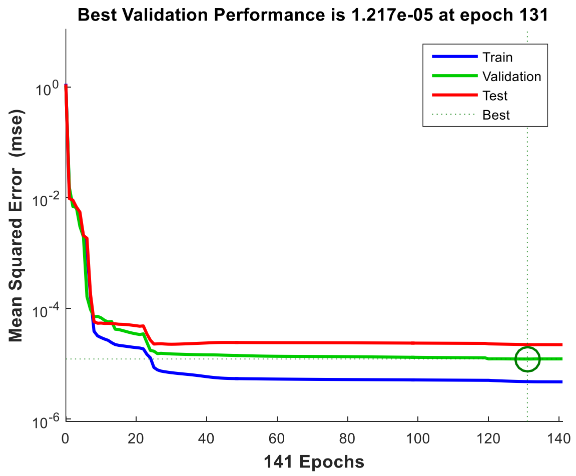

Fig. 11. ANN performance change curves during optimization steps of the MSE indicator for mud sample containing xanthan gum

Another indicator for determining the ANN training situation is the regression chart and correlation coefficient between actual output data and target values, shown in Figs. 12-14, respectively, for rice husk, apricot gum, and xanthan gum. Each of these figures. indicates the final values obtained from the network for training, validation, and testing data (vertical axis) vs. actual values of corresponding filtrate volume (horizontal axis). In a trained network, an ideal case occurs when actual output and network values become identical for all data, suggesting a zero value for the MSE performance indicator. Therefore, for an ideal network, the correlation coefficient value (R) and the fitting line slope are equal to one, and the intercept (bias) of the fitting line (B) is equal to zero. Based on the indicator values in Figs. 12-14, it can be found that ANN output values for each group of data have high predictive accuracy and are close enough to the target values. The value of correlation coefficient R for each group of training data, validation data, testing data, and all data for ANN corresponding to rice husk (Fig. 12) is equal to 0.99978, 0.99967, 0.9999, and 0.99979, respectively, and that for ANN corresponding to apricot gum (Fig. 13) is equal to 0.9999, 0.9998, 0.99983, and 0.99988, respectively, and that for ANN corresponding to xanthan gum (Fig. 14) is equal to 0.99995, 0.99985, 0.99985, 0.99991, respectively. All these R values are very close to the ideal value of 1. This indicates that the designed artificial neural network models can estimate the filtrate volume of mud samples containing different mass values of the studied additives with very high accuracy under various filtration times.

Figures 15-17 display fitting charts and the error between actual and output values of the trained network for testing data for mud samples containing rice husk, apricot gum, and xanthan gum. The great match between actual and output values of the ANN, and therefore negligible corresponding error values, indicate that the network has a great performance in predicting the filtrate volume of the mud sample containing arbitrary mass values of the additive, under any arbitrary filtration time.

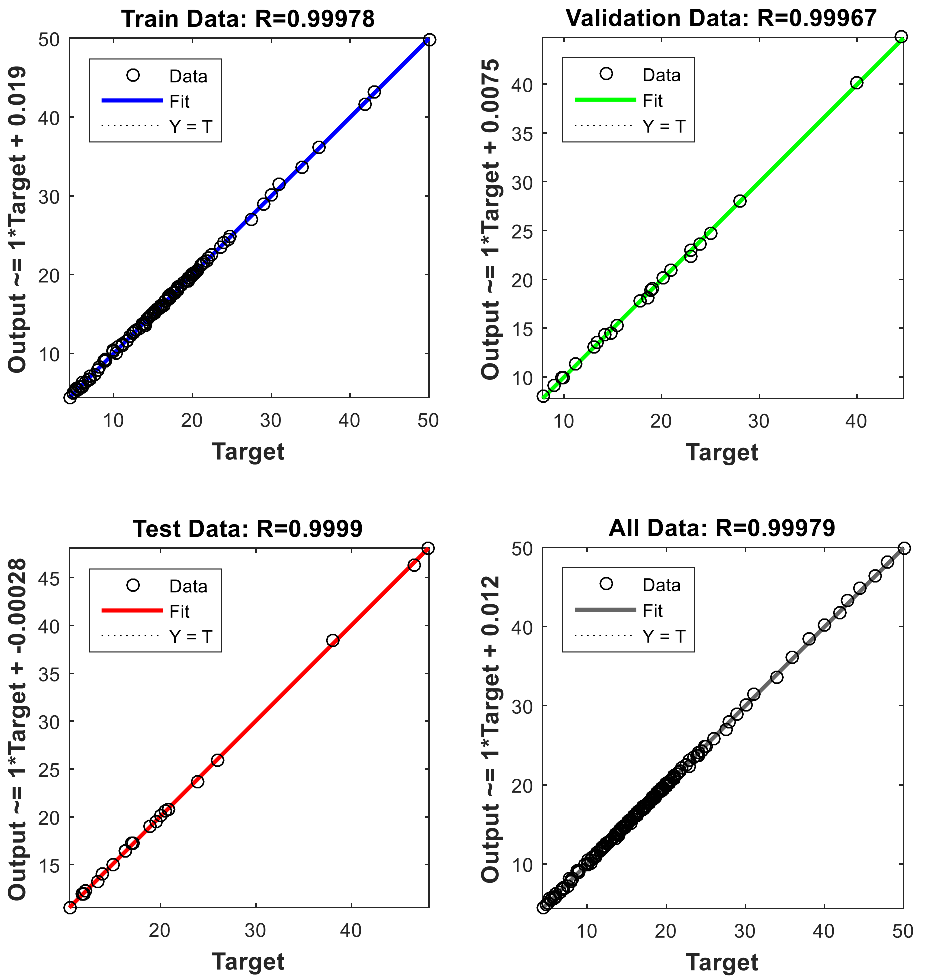

Fig. 12. ANN regression chart corresponding to each group of data for the mud sample containing rice husk

The maximum error percentage (the ratio of the difference between the actual value and output of ANN to the actual value) for network testing data corresponding to estimator ANNs of filtrate volume of mud samples containing rice husk, apricot gum, and xanthan gum equals 2.55, 6.77, and 10.11, respectively. The average error percentage of data equals 0.59, 1.27, and 1.86. This reflects the high predictive accuracy of the designed and trained networks in estimating the filtrate volume of mud samples containing any arbitrary mass values of the additive under any arbitrary filtration times.

V. K-fold Cross-Validation

To evaluate the relative accuracy and robustness of the ANN models in predicting drilling fluid filtrate volume, the coefficient of variation of errors (CV) was employed. In this study, CV is defined as the ratio of the standard deviation of the prediction errors for the test dataset to the mean of the corresponding target values. Consequently, this metric quantifies the dispersion of the model's errors relative to the actual scale of the output variable; a lower CV value signifies greater consistency, higher accuracy, and superior predictive stability. The results obtained for each fold are presented as bar charts in Figs. 18-20, corresponding to the ANN models for drilling fluids containing rice husk, apricot gum, and xanthan gum, respectively.

The cross-validation results demonstrate that the mean CV values for the three aforementioned models are 2.96%, 3.60%, and 3.50%, respectively, while their corresponding maximum CV values are 5.82%, 5.53%, and 5.08%. Overall, the consistently low mean and maximum CV values across all three models indicate that the developed ANNs exhibit satisfactory performance in terms of error dispersion, prediction stability, and generalizability. Consequently, these models can be reliably employed to predict the filtrate volume of drilling fluids containing the investigated additives.

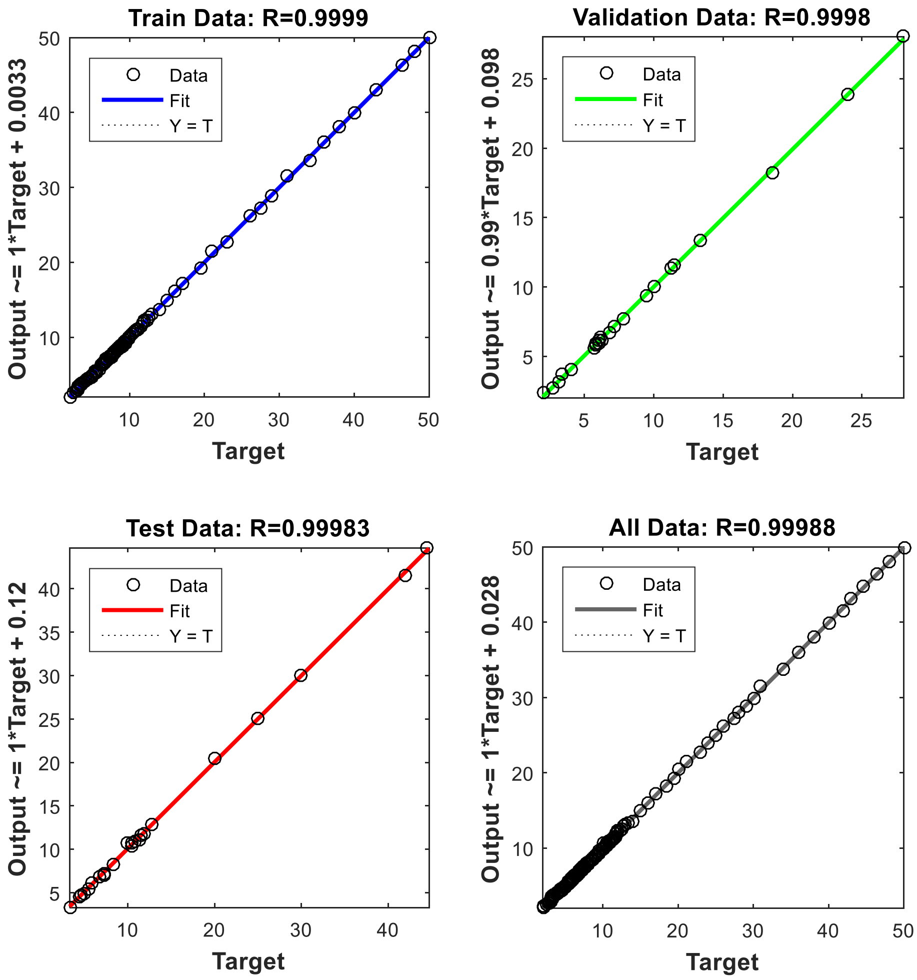

Fig. 13. ANN regression chart corresponding to each group of data for the mud sample containing natural gum (apricot gum)

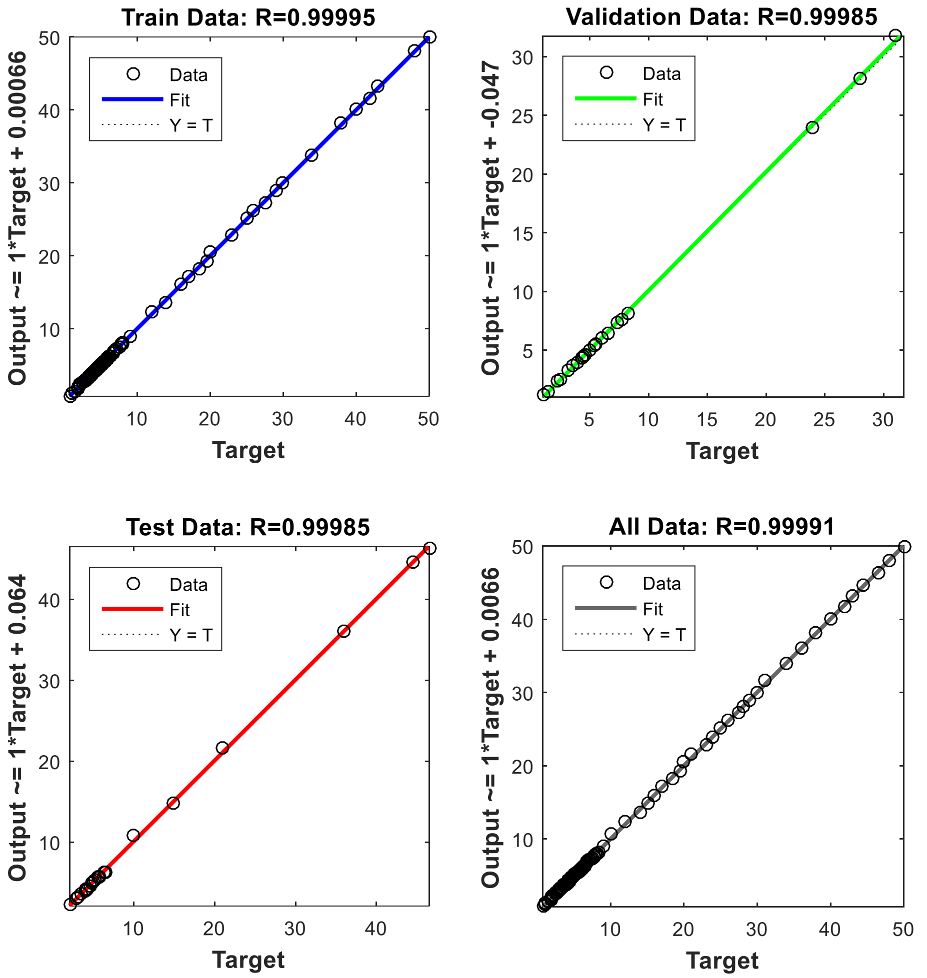

Fig. 14. ANN regression chart corresponding to each group of data for the mud sample containing xanthan gum

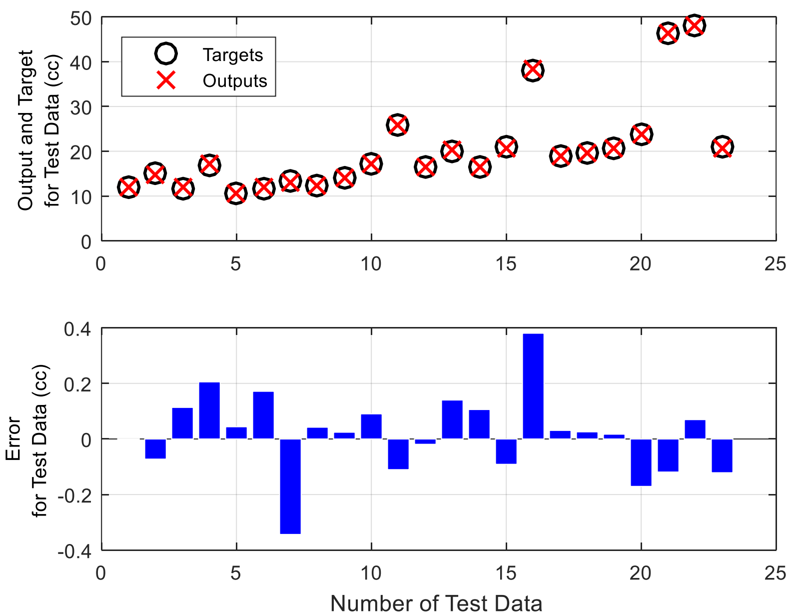

Fig. 15. Fitting chart and the error between actual and output values of ANN for testing data for mud sample containing rice husk

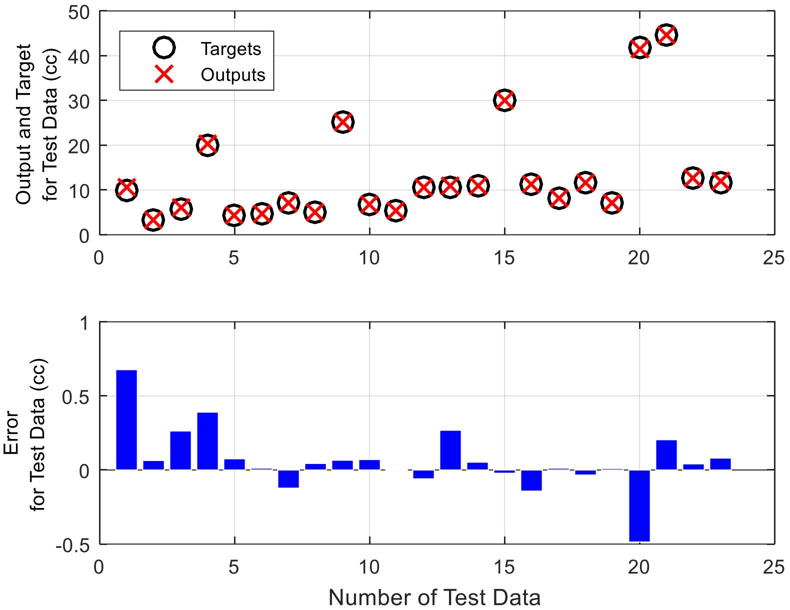

Fig. 16. Fitting chart and the error between actual and output values of ANN for testing data for mud sample containing natural gum (apricot gum)

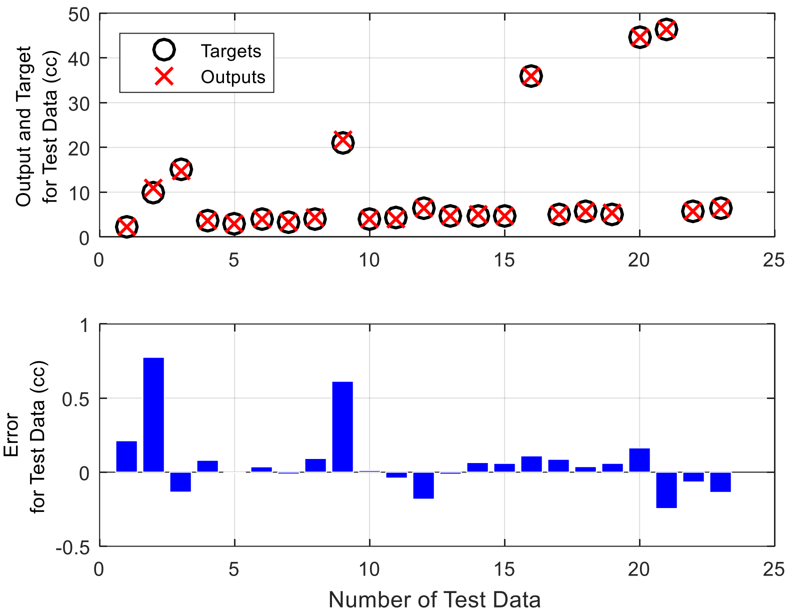

Fig. 17. Fitting chart and the error between actual and output values of ANN for testing data for mud sample containing xanthan gum

VI. Monte Carlo Uncertainty Analysis

The Monte Carlo simulation method was employed to perform uncertainty analysis and to propagate error distributions in the predictions of trained models (BIPM/JCGM 101, 2008; Taylor, 2022). In this approach, assuming a normal distribution for the measurement errors of the additive mass and filtration time, the standard deviation of each parameter was defined as a fraction of the measured value (coefficient of 0.005 for mass and coefficient of 0.005 for time). After generating 1000 random samples for each data point, the trained ANN models were applied to these samples. Finally, the standard deviation of the output distribution was calculated as the "standard uncertainty" for each point, and its ratio to the predicted value was defined as the "relative uncertainty" (expressed as a percentage).

The results of the Monte Carlo uncertainty propagation analysis showed that the relative uncertainty in filtrate volume was strongly dependent on both filtration time and additive concentration. Fig. 21 presents the variation in the relative uncertainty of filtrate volume as a function of filtration time for different rice husk masses. As evident from the trend, the highest uncertainty occurs during the initial stages of filtration, particularly at the mass of 3 gr. Subsequently, as filtration proceeds, the uncertainty decreases noticeably and reaches lower levels during the intermediate stages. At some lower masses, a slight fluctuation or increase is observed toward the end of the test, which may be attributed to the model's sensitivity near the boundaries of the available data and the reduced rate of change in the output variable. Overall, the figure indicates that the system remains reasonably stable in the presence of rice husk, with the overall uncertainty maintained at a relatively low level.

Figure 22 presents the relative uncertainty in filtrate volume over time for different masses of apricot natural gum. The overall behavior of the curves indicates that the uncertainty is higher at the initial stages, particularly at higher masses; however, it decreases rapidly as filtration proceeds and subsequently stabilizes within a relatively narrow range with limited fluctuations. Minor and localized variations are observed during the intermediate stages, but their magnitude is limited and does not substantially affect the overall trend. Therefore, it can be concluded that the predictive model exhibits acceptable robustness for systems containing apricot natural gum. However, it is more sensitive to variations in the input parameters during the initial stages of the process.

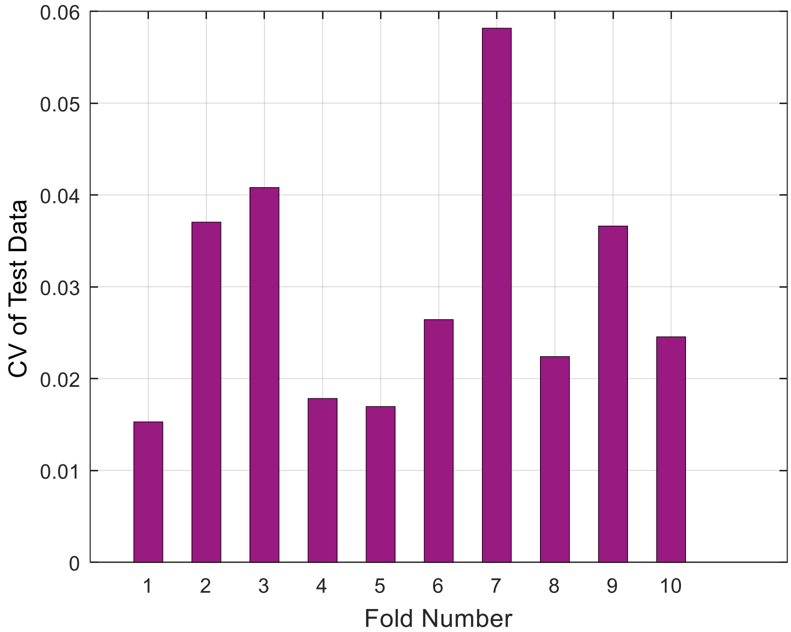

Fig. 18. Test data CV of filtrate volume of drilling mud containing rice husk corresponding to 10 partitions created by the K-fold Cross Validation approach

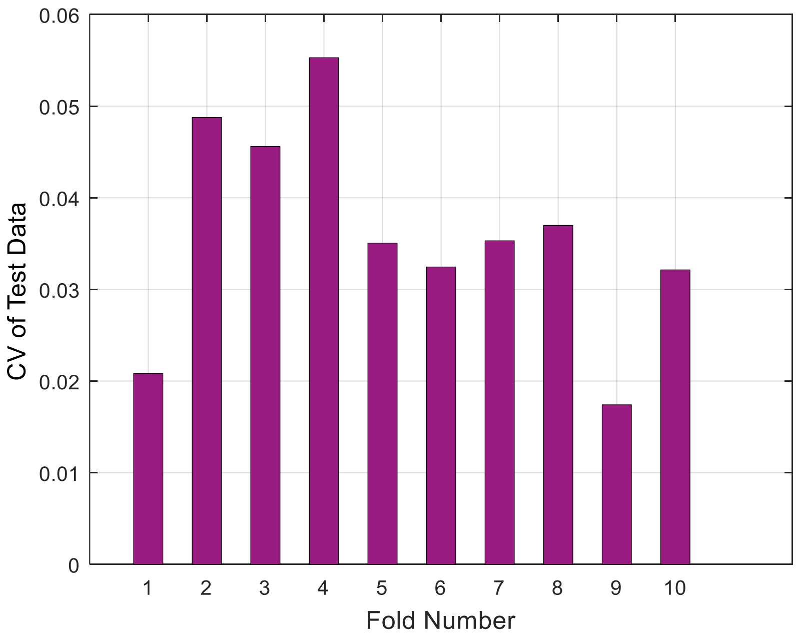

Fig. 19. Test data CV of filtrate volume of drilling mud containing natural gum corresponding to 10 partitions created by the K-fold Cross Validation approach

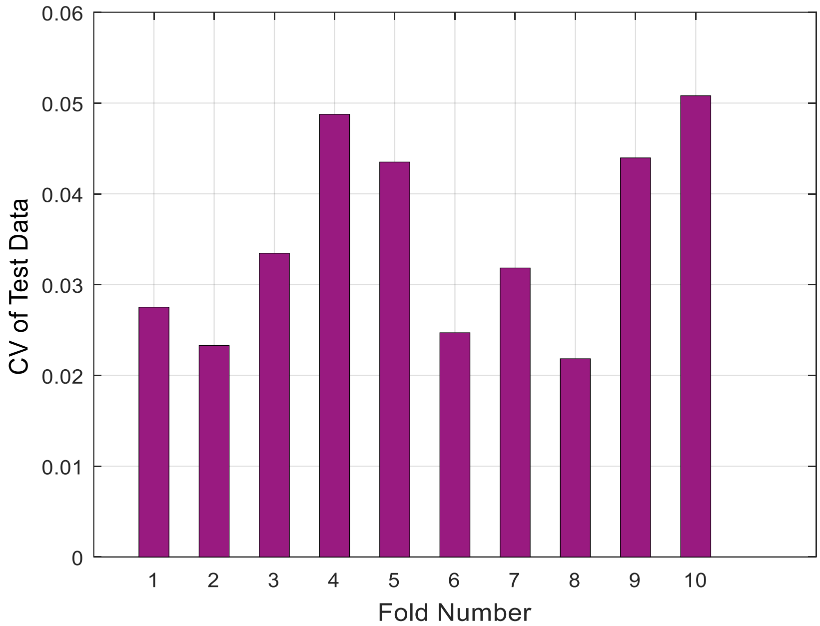

Fig. 20. Test data CV of filtrate volume of drilling mud containing xanthan gum corresponding to 10 partitions created by the K-fold Cross Validation approach

Figure 23 illustrates the variation in the relative uncertainty of filtrate volume in the presence of xanthan gum at different masses. Compared with the other two additives, the level of uncertainty is higher in this system, with the highest values observed during the initial stages and at masses of 2 gr and 3 gr. As filtration proceeds, the uncertainty decreases, and the curves converge toward lower values. At certain intermediate points, particularly around 5–6 min, brief localized fluctuations can be observed; however, these fluctuations do not have a significant effect on the overall trend. From an analytical perspective, this behavior may be attributed to the rheological characteristics of xanthan gum and the greater sensitivity of the system to this additive. Therefore, although the model exhibits acceptable performance in this case as well, it demonstrates greater sensitivity than that observed for the other two additives.

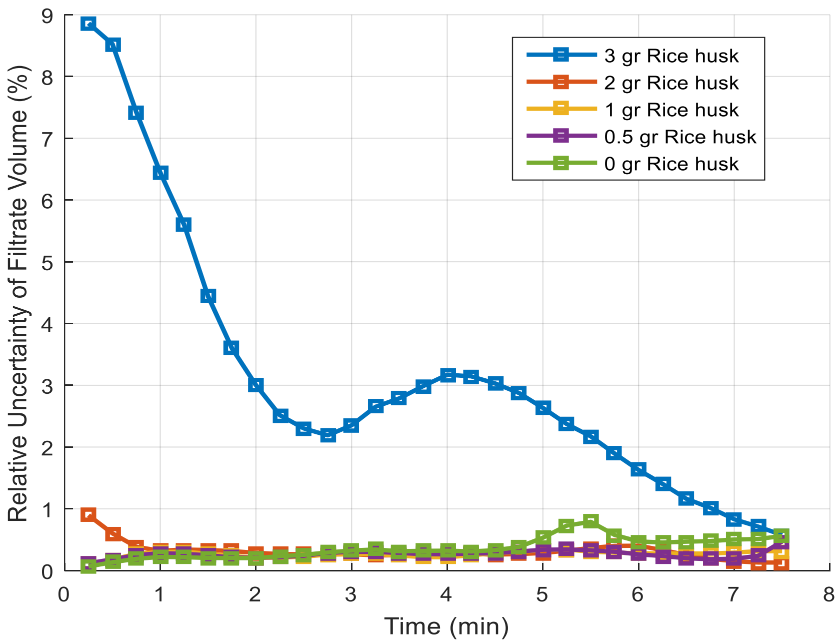

Fig. 21. Relative uncertainty curves of filtrate volume as a function of filtration time for different rice husk mass values in drilling fluid samples containing 350 cc of water and 15 g of bentonite

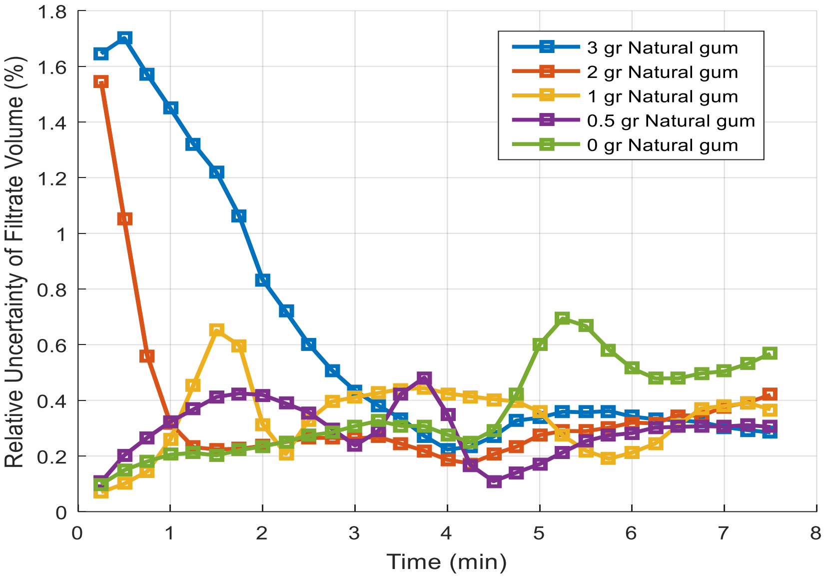

Fig. 22. Relative uncertainty curves of filtrate volume as a function of filtration time for different natural gum (apricot gum) mass values in drilling fluid samples containing 350 cc of water and 15 g of bentonite

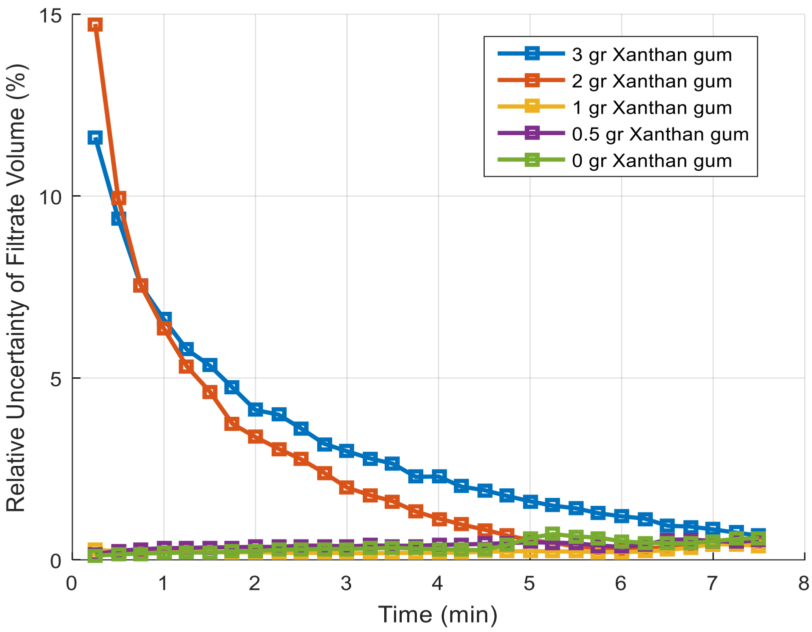

Fig. 23. Relative uncertainty curves of filtrate volume as a function of filtration time for different xanthan gum mass values in drilling fluid samples containing 350 cc of water and 15 g of bentonite

VII. CONCLUSION

This study comparatively evaluated the effectiveness of rice husk, natural gum (apricot gum), and xanthan gum as fluid-loss control additives in water-based bentonite drilling mud. Experimental filtration tests demonstrated that increasing the concentration of each additive reduced filtrate volume throughout the filtration period. Among the investigated additives, xanthan gum exhibited the highest fluid-loss reduction capability, followed by apricot gum and rice husk. In addition, the developed two-layer feedforward ANN successfully predicted filtrate volume with high accuracy over the investigated range of additive concentrations and filtration times. The study demonstrated the feasibility of using ANN-based models for accurate prediction of drilling-fluid filtrate volume, thereby reducing the need for extensive laboratory measurements during drilling-fluid design.

Beyond the experimental observations, the results have important implications for drilling-fluid design and wellbore stability. Reduced filtrate invasion can minimize permeability impairment near the wellbore and enhance drilling efficiency. The superior performance of xanthan gum suggests that it is particularly suitable for drilling operations where strict fluid-loss control is required. Apricot gum also demonstrated good performance and may represent a cost-effective and environmentally friendly alternative to conventional synthetic additives, while rice husk offers potential as a sustainable agricultural by-product for applications where moderate fluid-loss control is acceptable.

The findings are expected to be especially relevant for formations that are highly susceptible to filtrate invasion, such as high-permeability sandstones and naturally fractured carbonate formations where excessive fluid penetration may lead to formation damage, wellbore instability, or reduced productivity. In such geological settings, the use of effective fluid-loss control additives can contribute to maintaining formation integrity and reducing non-productive time during drilling operations.

Nevertheless, several limitations of the present study should be acknowledged. The experiments were conducted under laboratory-scale static filtration conditions at a single temperature and pressure, which do not fully represent the dynamic downhole environment encountered during field drilling operations. The ANN models were trained using data obtained from a specific mud formulation and additive concentration range; therefore, their predictive capability outside these conditions should be validated before field application. Future research should investigate the performance of these additives under HPHT conditions and validate the ANN models using larger datasets and field-scale measurements. Such studies will facilitate the development of more robust and environmentally sustainable drilling-fluid systems for a wide range of geological environments. Another limitation of the present study is that repeatability analyses were not systematically performed through multiple repetitions of each experimental test. Further investigations should include replicated experiments to quantify measurement variability further and enhance confidence in the reported results.

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