

Evolving a SVM-Based Grey Wolf Concept Model to Predict Yield Point and Plastic Viscosity of Water-Based Drilling Fluids

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Article Info	ABSTRACT
Article type: Research Article	Application of soft computing (SC) proves instrumental in optimizing drilling costs through pre-estimations of incidents. This study presents a novel approach to develop a robust model for estimating the yield point and plastic viscosity of water-based drilling fluids. Leveraging the grey wolf optimization (GWO) algorithm, the support vector machine (SVM) framework is fine-tuned to analyze data and discern correlations among mud density, molecular weight, solid percent, Funnel viscosity, and temperature with SVM outputs. The resulting model achieved coefficients of determination of 0.990 and 0.938, with root-mean-square errors (RMSE) of 1.5821 and 1.2261 for yield point and plastic viscosity data, respectively, affirming its efficiency and effectiveness. Pioneering the application of sensitivity analyses in this context, Marsh funnel viscosity and molecular weight emerge as key factors for yield point and plastic viscosity, demonstrating relevancy factors of 74% and 47%, respectively. Comparative assessments reveal the superior accuracy of the proposed model over existing machine learning frameworks in the literature. The study enhances drilling methods by demonstrating the importance of sensitivity analysis for better predictions.
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1) Introduction

A drilling fluid represents a fundamental drilling component. In light of oil and gas advances, researchers have increasingly developed drilling fluids (Dindoruk & Zhang, 2024; Sun et al., 2024). Water-based drilling fluids are widely used as drilling muds because they are cost-effective and facilitate effective control of wellbore-related challenges (Rasool et al., 2024; Riazi et al., 2022; Rooki et al., 2012). The efficiency and effectiveness of a drilling mud could be substantially improved through rheological control (Alizadeh et al., 2021). Additionally, drilling cuttings in the wellbore could be more efficiently transferred to the surface (Bourgoyne Jr et al., 1991; Parizad et al., 2019). It is crucial to investigate rheological properties, such as the yield point, plastic viscosity, and apparent viscosity, to evaluate drilling hydraulics in terms of optimization and cleaning efficiency (Abdelgawad et al., 2019; Jondahl & Viumdal, 2018). As a result, the rheology of a drilling mud should be subjected to periodic evaluations in the operation so that its variations could be consistently controlled (Elkatatny et al., 2019; Stroud, 1926). The growing emphasis on sustainability has also encouraged the evaluation of alternative engineering materials, such as carbon geocrete as a substitute for Portland cement concrete (Monfaredi & Memari, 2026).

Although a variety of variables are exploited in the rheological evaluation of a drilling mud in an oil/gas field, plastic viscosity has the largest influence on drilling optimization (Ajieh et al., 2023; Weikey et al., 2018). Furthermore, it could be assumed to represent a definite parameter above the yield point (Lahalih & Dairanieh, 1989; Razi et al., 2013). This suggests that drilling performance could be influenced by the solid content of the mud above certain limits (Gowida et al., 2019; Paiaman et al., 2009). The yield point is dependent on inter-particle electrochemical interactions (Misbah et al., 2023). It is used to investigate fluid efficiency in the removal of annulus cuttings (Khandaker et al., 2023). Hence, hole cleaning efficiency control requires yield point optimization (Razi et al., 2013; Tchameni et al., 2019; Weikey et al., 2018). Moreover, apparent viscosity represents a combination of the yield point and plastic viscosity; i.e., apparent viscosity increases as the yield point and/or plastic viscosity rise (Poudel et al., 2023). In general, it is essential to monitor apparent viscosity to prevent problems in drilling and boost the cleaning performance (Al-Khdheawi & Mahdi, 2019; Gowida et al., 2019; Marsh, 1931; Razi et al., 2013).

The models developed in this research offer numerous practical applications within the drilling industry (Al-Obaidi et al., 2024). Accurate prediction of drilling fluid rheological parameters enables the optimization of drilling operations, including improved cuttings removal rate control, reduced risk of drill string sticking, and enhanced wellbore stability (Elkatatny et al., 2016; Naseri et al., 2025; Zadeh Naseri & Ershaghi, 2026). Furthermore, these models can be integrated into online rheology monitoring systems, allowing operators to gain real-time awareness of the fluid's rheological condition and implement corrective actions as needed. Finally, these models can serve as a valuable tool for training and educating drilling personnel, helping them develop a better understanding of drilling fluid behavior (Abdelaal et al., 2023).

Zhang et al. (2015) studied rheological properties of drilling muds. They reported that these properties had essential contributions to rig hydraulics. Pitt (2000) introduced a correlation to convert Marsh funnel viscosity (MFV) into apparent viscosity in a drilling fluid. The flow performance of drilling muds within a Marsh funnel was numerically modeled (Balhoff et al., 2011; Pitt, 2000). Balhoff et al. (2011) suggested that the yield point may be accurately obtained using

MFV. Razi et al. (2013) investigated rheological estimations of water-based drilling fluids. The Levenberg–Marquardt algorithm and a multilayer perception were used (Almahdawi et al., 2014). Almahdawi et al. (2014) enhanced the correlation investigated by Pitt (2000). The enhanced correlation was found to have higher performance than the original correlation in apparent viscosity prediction (SM Elkatatny, 2016).

Elkatatny (2019) performed a real-time rheological investigation of an invert emulsion-based mud through the artificial neural network (ANN) approach to develop a model for implementing real-time predictions of MFV, solid percent, and MW.

Da Silva Bispo et al. (2017) employed solid percent, MFV, and MW to implement real-time rheological predictions of water-based drilling fluid with NaCl. The authors introduced a soft sensor based on an ANN to estimate the apparent viscosity of water-based drilling fluids. An ANN-based framework for the rheological characterization of water-based drilling fluids was proposed (Elkatatny et al., 2018; Shankar et al., 2020). Elkatatny et al. (2018) characterized the rheological properties of water-based drilling fluids with KCl using the caliper parameters. The ANN model was found to be efficient in accurate real-time rheological predictions (Al-Azani et al., 2018). Al-Azani et al. (2018) adopted an ANN approach and exploited solid percent, MW, and MFV to predict the rheology of oil-based muds. Tomiwa et al. (2019) employed a hybrid artificial intelligence method to estimate the rheological parameters of spud drilling fluids.

Tchameni et al. (2019) developed an ANN framework to implement rheological estimations of water-based drilling fluids modified with biodiesel. They efficiently predicted the yield point, plastic viscosity, and apparent viscosity. Tomiwa et al. (2019) employed a biopolymer of solanum tuberosum formulation to enhance water-based drilling fluids. Furthermore, they sought to predict the rheology of the mud using an ANN technique. They focused on the rheological regeneration and estimation of the mud (the yield point, plastic viscosity, and apparent viscosity) using the ANN technique and experimental data.

Al-khdheawi and Saleh Mahdi (2019) empirically predicted the apparent viscosity of water-based drilling fluids. Moreover, they employed an ANN to perform the predictions. The average absolute error (AAE) was found to be 8.6% for the empirical model and 10.6% for the ANN. Gowida et al. (2019) introduced an ANN model to measure MFV and MW for the rheological evaluation of water-based drilling fluids with CaCl_2 . Moreover, the rheological parameters were treated as dependent on MFV and MW and were empirically predicted. The models were found to be accurate enough. Elkatatny et al. (2019) developed a few empirical ANN models to implement the real-time rheological (MFV and MW) estimations of water-based drilling fluids with NaCl.

2) Materials and Methods

2.1) Data Description

In this study, a comprehensive rheological dataset was meticulously collected from water-based drilling fluids obtained from 20 wells in the Aghar Gas Field, located in southwestern Iran (Jafarifar & Najjarpour, 2021). The dataset encapsulates a diverse array of conditions, with temperature fluctuations ranging from 71°C to 100°C. Simultaneously, the pressure exhibited variations between

4,500 to 6,000 psi, and the target drilling depths ranged from 12,460 to 14,430 ft. The selected input parameters for the model encompass temperature, solid percentage, Marsh Funnel Viscosity (MFV), and Molecular Weight (MW), while the desired outcomes are the yield point, plastic viscosity, and apparent viscosity. It is noteworthy that rheological measurements were conducted with respect to the drilling mud temperature, ensuring the relevance and accuracy of the acquired data in reflecting real-world drilling conditions.

2.2) Support Vector Machine (SVM)

Today, artificial intelligence has been applied in many sciences (Aziz et al., 2026). SVMs are an efficient and effective learning approach that has been widely used to address numerous engineering problems (Daryasafar et al., 2019; Meybodi et al., 2015; Razavi et al., 2018). SVMs have efficient and effective formulations on the basis of empirical risk minimization (ERM) and structural risk minimization (SRM) (Ahangari et al., 2022; Kardani & Baghban, 2017). For function $f(x)$ relating dataset (X_i, Y_i) , in which $X = [x_1, x_2, \dots, x_n]$ represents inputs, where $x_i \in R^d$ and n denotes the dataset size, and $Y = [y_1, y_2, \dots, y_n]$ represents the real target outputs, the formulation in an SVM is given as (Al-Khdheawi & Mahdi, 2019):

$$f(x) = w \cdot \varphi(x) + b \quad (1)$$

Where $\varphi(x)$ stands for the kernel function, w is the weight vector, and b denotes the bias.

To obtain b and w , it is necessary to solve the constrained minimization problem proposed by Vapnik (Cortes & Vapnik, 1995):

$$\text{minimize } \frac{1}{2} w^T w + C \sum_{i=1}^n (\xi_i^+ + \xi_i^-) \quad (2)$$

$$\text{s.t. } \begin{cases} y_i - (w \cdot \varphi(x) + b) \leq \varepsilon + \xi_i^+ \\ (w \cdot \varphi(x) + b) - y_i \leq \varepsilon + \xi_i^- \\ \xi_i^+, \xi_i^- \geq 0, i = 1, 2, \dots, n \end{cases} \quad (3)$$

Where w^T denotes the transposed weight matrix, while constant $C > 0$ controls penalization for error ε . Moreover, ξ_i^+ represents the positive upper excess deviation, whereas ξ_i^- represents the negative lower excess deviation. Equation (2) becomes a dual space by incorporating Lagrange multipliers as (Rostami et al., 2016):

$$f(x) = \sum_{i=1}^n (\alpha_i - \alpha_i^*) \varphi(x_i, x_j) + b \quad (4)$$

Where both α_i and α_i^* stand for Lagrange multipliers. They are to meet constraints $\alpha_i \geq 0$ and $\alpha_i^* \leq C$. Also, $\varphi(x_i, x_j)$ represents the kernel function.

The most popular kernel functions include the radial basis function (RBF) and Gaussian kernel.

2.3) Grey wolf optimization (GWO)

The gray wolf optimization (GWO) algorithm is a populated-based metaheuristic optimization method introduced by Mirjalili et al., (2014). As a population-based framework, GWO generates an initial population of wolves reflecting the possible solution (Ullah et al., 2023; Zamouche et al., 2023). The wolves are classified into (1) alpha, (2) beta, (3) delta, and (4) omega groups based on their levels of responsibility to make decisions and lead the hunt. The alpha, beta, and delta wolves have the first-, second-, and third-highest fit, respectively. The omega wolves are directed toward more efficient solutions by the alpha, beta, and delta wolves (Makhadmeh et al., 2023).

Once initialization has been completed, the prey is circled. The mathematical formulation of this process is written as (Deng et al., 2023):

$$X(t + 1) = X_p(t) - A \cdot D \quad (5)$$

Where t denotes the current iteration, and $t + 1$ stands for the next iteration. Also, $X_p(t)$ represents the prey vector to indicate the probable position of wolf α . Furthermore, D is calculated as (Dharmegowda et al., 2023):

$$D = |C \cdot X_p(t) - X(t)| \quad (6)$$

It should be noted that A and C are given by:

$$A = 2 \cdot r_1 - a \quad (7)$$

$$C = 2 \cdot r_2 \quad (8)$$

Where $X(t)$ is the position of the grey wolf, a typically undergoes a linear reduction from 2 to 0, and r_2 represents random vectors in the range of $[0, 1]$. The wolf with a position of (X, Y) or (X, Y, Z) can perform repositioning around the prey, as A and C enable random repositioning.

Based on the positions of the alpha, beta, and delta wolves, the omega wolves undergo repositioning as (Mirjalili et al., 2014):

$$X(t + 1) = \frac{X_1 + X_2 + X_3}{3} \quad (9)$$

In which X_1 , X_2 , and X_3 can be found as:

$$X_1 = X_\alpha(t) - A_1 \cdot D_\alpha \quad (10)$$

$$X_2 = X_\beta(t) - A_2 \cdot D_\beta \quad (11)$$

$$X_3 = X_\delta(t) - A_3 \cdot D_\delta \quad (12)$$

Where X_α , X_β , and X_δ represent the positions of the alpha, beta, and delta wolves, respectively. Moreover, D_α , D_β , and D_δ can be obtained as (Sharifzadegan et al., 2023):

$$D_\alpha = |C_1 \cdot X_\alpha(t) - X(t)| \quad (13)$$

$$D_\beta = |C_2 \cdot X_\beta(t) - X(t)| \quad (14)$$

$$D_\delta = |C_3 \cdot X_\delta(t) - X(t)| \quad (15)$$

Where C_1 , C_2 , and C_3 stand for random vectors, and $X(t)$ denotes the current solution (Ravi & Kumar, 2023).

Once all the wolves have undergone the above-mentioned steps in a given iteration, it is required to calculate fitness. A solution that outperforms the current optimal solution becomes the new optimal solution. The iterations are discontinued once the discontinuance criteria are met. The present work adopted GWO to optimize SVM control parameters (see Figure 1).

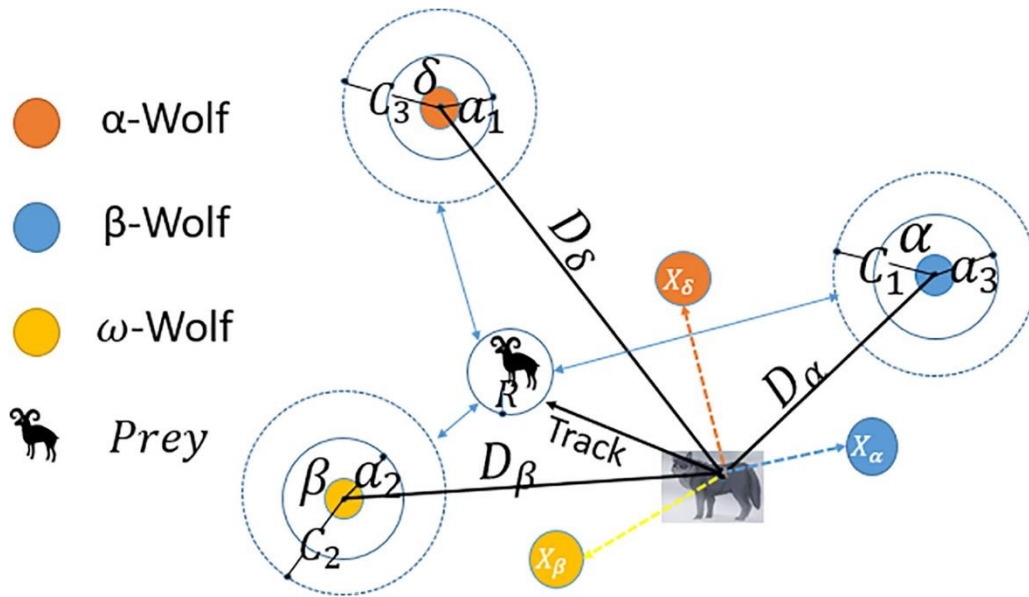


Figure 1. Grey Wolf Optimization Algorithm Results for Positions, Distances, and Predation Activities of α , β , and γ (Yang et al., 2022)

3) Result and Discussion

This section rigorously assesses the proposed model's efficiency and effectiveness in predicting the target output by employing various comprehensive analyses. The goal is to thoroughly evaluate the model's performance, ensuring its reliability and accuracy in estimating the desired output. The analyses conducted in this section aim to provide a holistic understanding of the model's predictive capabilities and its ability to capture the intricacies of the target variable.

3.1) Sensitivity Analysis

A sensitivity analysis is a crucial step in understanding how variations in input parameters impact the target output (Setiawan et al., 2021). This analysis is essential for identifying critical regions and potential methodological errors, aiding in efficient prioritization (Baghban et al., 2019). Sensitivity analyses can be conducted at both global and local levels. Local sensitivity analysis isolates the impact of a single input while keeping others constant, while global sensitivity analysis assesses the overall effects and interactions between inputs and outputs (Baghban et al., 2017; Soleimani & Saeedi Dehaghani, 2023).

Figure 2 provides a visual representation of the input effects on the output. Notably, molecular weight emerges as the most influential factor on plastic viscosity, with a relevancy factor of 47%. Conversely, Marsh funnel viscosity, solid percent, and temperature exhibit negligible effects, with relevancy factors of 17%, 43%, and 20%, respectively. Additionally, Marsh funnel viscosity emerges as the most influential factor on yield point, with a relevancy factor of 74%. Conversely, molecular weight, solid percent, and temperature exhibit negative effects, with relevancy factors of -16%, -18%, and -6%, respectively. This comprehensive exploration illuminates the varying degrees of influence each input parameter holds over the target output, offering valuable insights for refining and optimizing the model.

3.2) Outlier Analysis

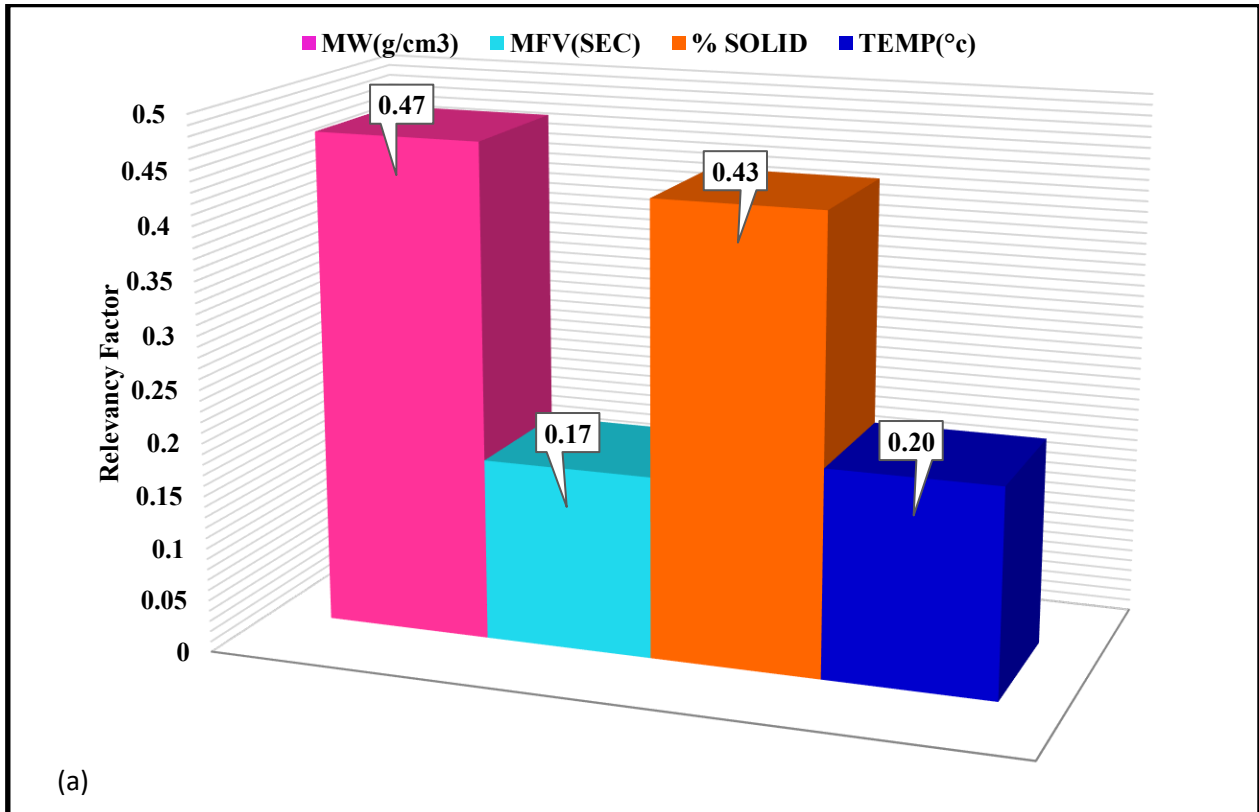
The present work utilized outlier analysis to detect outliers. Outlier analysis is essentially employed to identify data points of different behavior from the dataset (Daneshfar et al., 2020; Setiawan et al., 2021). Outliers are found using the leverage method through the critical leverage limit H^* , Hat

indices H , and standardized residuals R^2 . The Hat index and critical leverage limit are given by Daneshfar et al. (2020), and Mousazadeh et al. (2021):

$$H = X(X^t X)^{-1} X^t \quad (16)$$

$$H^* = \frac{3n}{(p + 1)} \quad (17)$$

Where X is an $n \times k$ matrix, and t represents the transposed matrix. Moreover, p is the number of inputs, whereas n denotes the number of training data points. Hat solutions are likely to involve the main diagonal space of H . The outlying candidates are identified using William's R-H plot. Subsequently, the squared feasible data area is obtained for limiting the warning leverage at the vertical and horizontal axes and cutoff value (typically ± 3) (Yousefmarzi et al., 2024). Both R and H are treated as outliers because they lie outside the valid area; i.e., $[-3, 3]$ and $[0, H^*]$, respectively. William's plot is illustrated for the GWO-SVM outputs in Figure 3. As can be seen, the data points mostly lied within the valid area. A total of sixteen data points exceeded H^* . Therefore, the GWO-SVM model is proved to be efficient and effective in detecting inherent correlations between the inputs and the output.



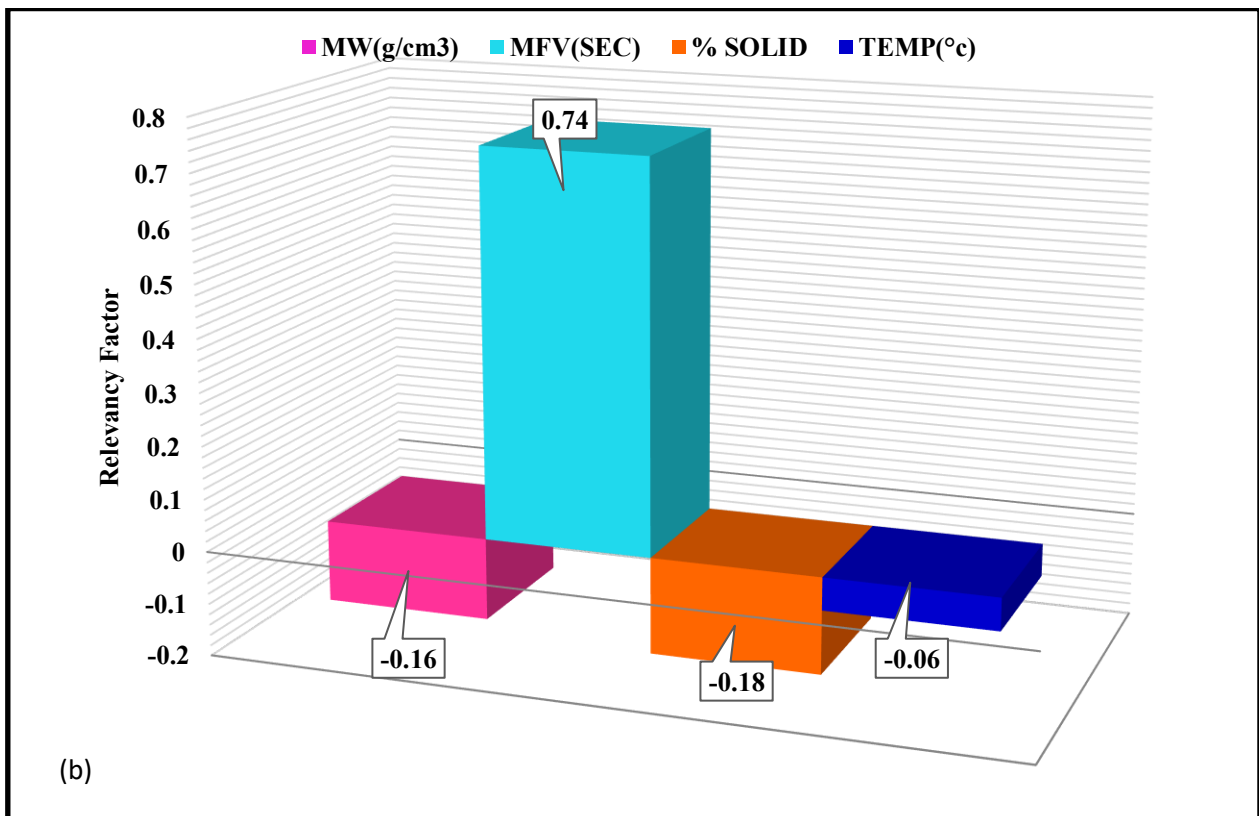
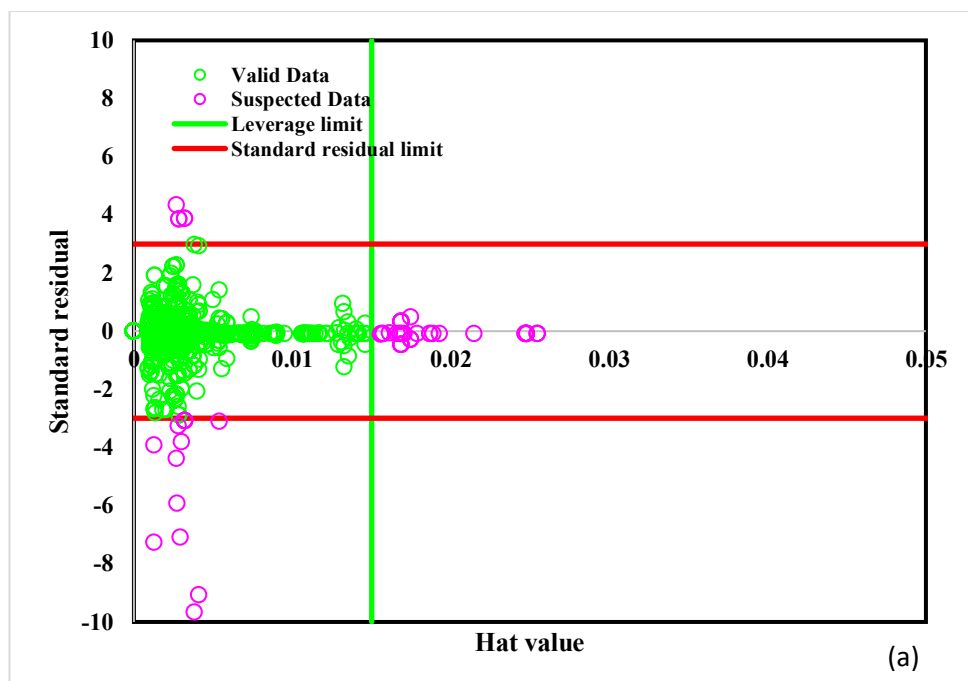


Figure 2. Sensitivity Analysis on All Input Parameters Affecting the Target Output Parameters: (a) Plastic Viscosity, (b) Yield Point



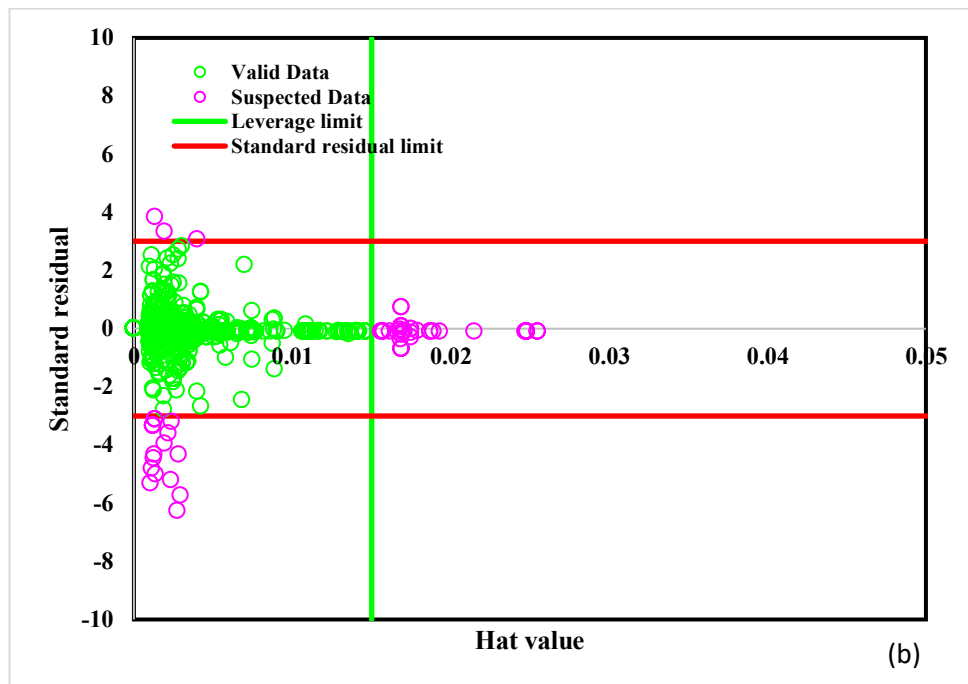


Figure 3. Williams' Standard Residual-Hat Value (R-H) Plot for the GWO-SVM Outputs to Identify and Eliminate Suspicious Data Points for: (a) Plastic Viscosity, (b) Yield Point

3.3) Model Assessment

The evaluation of the model involves a comprehensive analysis of its performance using the target values derived from both the training and testing phases. This assessment is visually represented in Figure 4, where the target values are plotted against the corresponding data index. The graphical representation clearly indicates the model's high predictive power. The close alignment of the predicted values with the actual target values underscores the accuracy and efficacy of the model across both the training and testing datasets. This visual confirmation substantiates the robustness and reliability of the developed model, validating its capability to make accurate predictions in diverse scenarios.

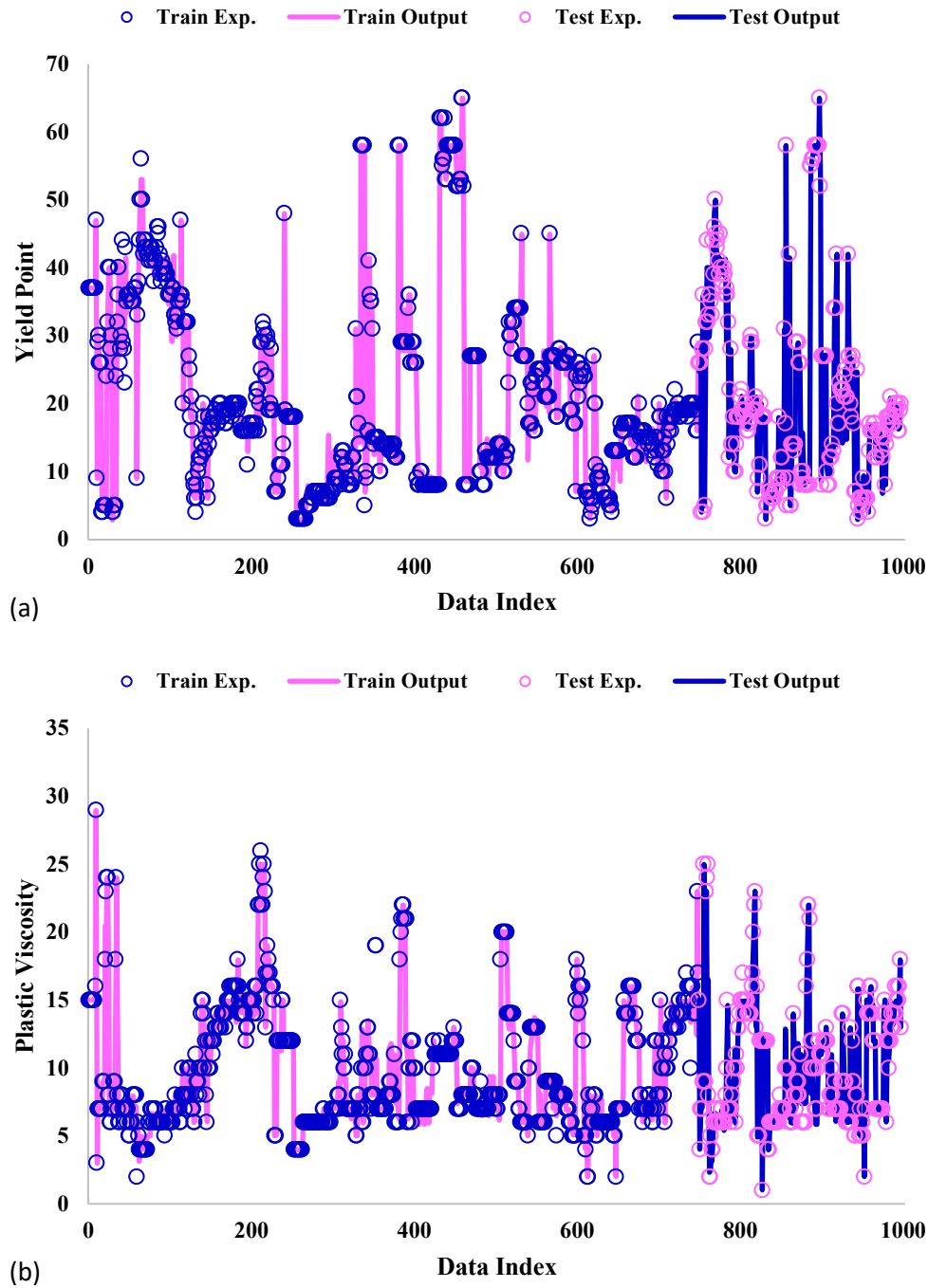


Figure 4. The Modeling Phases During Training and Testing Phases for Parameters of: (a) Plastic Viscosity, (b) Yield Point Based on the Data Index

The assessment of model accuracy is quantified through the utilization of the coefficient of determination (R^2), a statistical measure evaluating the goodness of fit between predicted and actual values (Daryasafar et al., 2019; Meybodi et al., 2015). In this study, the R^2 values obtained for both the training and testing phases were exceptionally high, reaching a near score of 1. This signifies an outstanding level of accuracy in the model's predictions, as it explains the entire variability in the observed data (Deymi et al., 2023). Figure 5 represents this remarkable accuracy, depicting a plot of model predictions against actual observations. The close alignment of the data points in the plot reinforces the high predictive accuracy of the model, confirming its capability to precisely capture and reproduce the patterns present in the training and testing datasets.

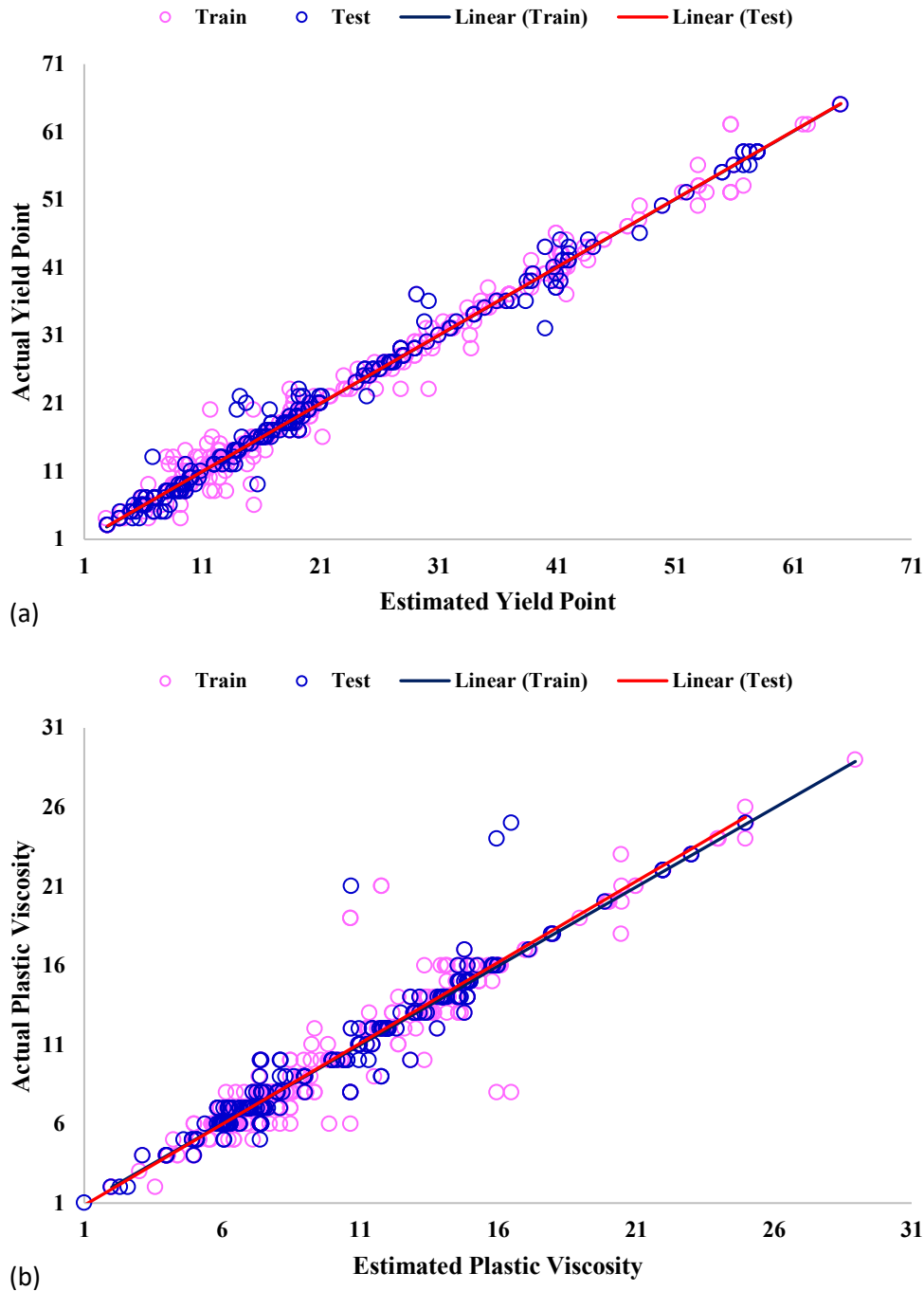


Figure 5. Model Predictions Against Actual Observations for Target Parameters of: (a) Plastic Viscosity, (b) Yield Point

This visual indication underscores the efficiency and effectiveness of the proposed model in making accurate predictions, as its closeness to the bisector line suggests minimal deviation between predicted and observed values. Moreover, the calculated deviation, measuring below 0.6% for the model, as illustrated in Figure 6, adds another layer of confirmation to the accuracy of the model. The low deviation indicates that the model's predictions closely match the actual values, reinforcing its reliability and precision. The comprehensive evaluation of the proposed model's

performance is encapsulated in Table 1, where detailed statistical results provide a thorough insight into its predictive accuracy and reliability in the realm of biomass chemical exergy prediction.

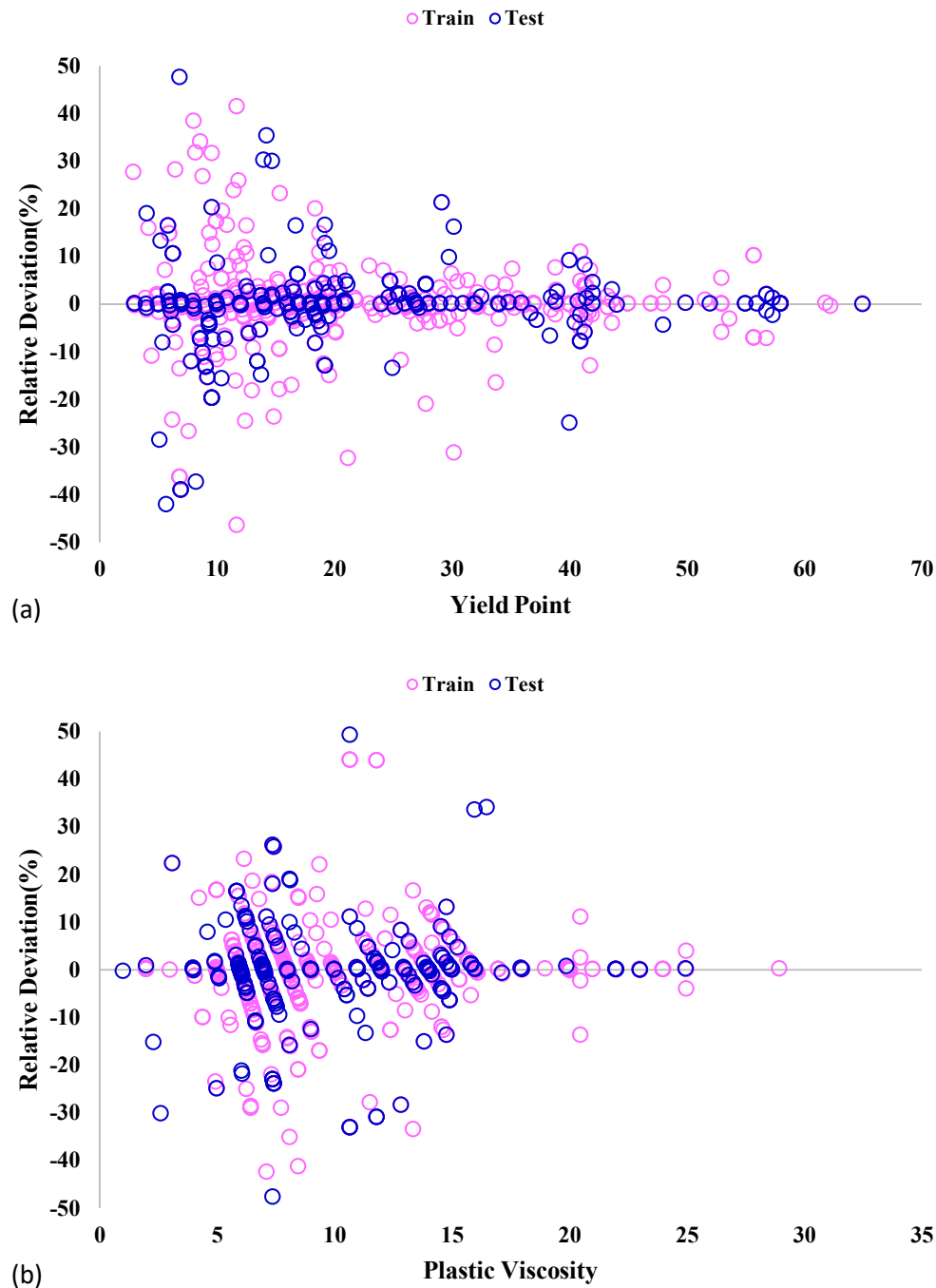


Figure 6. Relative Deviations for Target Parameters: (a) Plastic Viscosity, (b) Yield Point

Table 1 outlines the assessment of the proposed model's ability to estimate key parameters, categorizing the results into different phases: Train, Test, and Total. The statistical parameters, including R^2 (coefficient of determination), MRE (Mean Relative Error in percentage), MSE (Mean Squared Error), RMSE (Root Mean Square Error), and STD (Standard Deviation), offer a comprehensive understanding of the model's performance metrics.

For the property "Yield Point," the model demonstrates high predictive accuracy across all phases, with R^2 values of 0.990 for Train, 0.987 for Test, and a Total R^2 of 0.990. The MRE percentages are consistently low, ranging from 4.655% to 5.358%, indicating minimal relative

errors. Similarly, MSE, RMSE, and STD values are well-contained, further emphasizing the model's reliability in estimating the Yield Point.

Table 1. Evaluation of the Proposed Model's Ability to Estimate Key Parameters Based on Statistical Parameters

Property	Phase	R ²	MER (%)	MSE	RMSE	STD
Yield Point	Train	0.990	4.655	1.731874605	1.3160	1.1497
	Test	0.987	5.358	2.503135643	1.5821	1.3774
	Total	0.990	4.831	1.924303461	1.5821	1.2114
Plastic Viscosity	Train	0.943	5.047	1.097709778	1.0477	0.9480
	Test	0.924	5.451	1.503443032	1.2261	1.1176
	Total	0.938	5.148	1.198939818	1.2261	0.9928

In the case of "Plastic Viscosity," the model maintains commendable performance. The R² values for Train, Test, and Total R² are 0.943, 0.924, and 0.938, respectively, showcasing the model's ability to capture the variance in the data. The MRE percentages, MSE, RMSE, and STD values for Plastic Viscosity reinforce the consistent and accurate estimation across different phases.

The presented statistical results collectively reinforce the robustness of the proposed model, affirming its capability to accurately predict key parameters related to biomass chemical exergy.

4) Conclusion

This study demonstrates the significant potential of integrating the Grey Wolf Optimizer (GWO) with Support Vector Machines (SVM) to accurately predict the rheological properties of water-based drilling fluids. By leveraging a comprehensive dataset and employing rigorous statistical validation, we have developed a model exhibiting exceptional predictive capabilities, as evidenced by high coefficients of determination (R² of 0.990 and 0.938) and low root-mean-square errors (RMSE of 1.5821 and 1.2261) for yield point and plastic viscosity, respectively. Beyond simply achieving high accuracy, this research provides valuable insights into the key factors governing drilling fluid behavior, identifying Marsh funnel viscosity and molecular weight as primary influencers. The sensitivity analysis highlights their relative importance, offering a practical framework for optimizing fluid formulations and minimizing operational risks. Ultimately, this work contributes to a deeper understanding of drilling fluid rheology and provides a robust, data-driven tool for enhancing drilling efficiency, reducing costs, and promoting safer, more sustainable drilling practices. The demonstrated accuracy and interpretability of the model position it as a valuable tool for both research and industrial applications.

5) Limitations of the Study

Despite the accuracy and efficiency of the developed models, it is important to acknowledge the limitations of this study. The dataset used in this research is limited to data collected from a few wells in the South Zagros region, and generalizing the results to other areas with different geological conditions requires further investigation. Furthermore, these models were developed based on laboratory data and considering specific compositions of additives (green starch, limestone, PAC, NaCl, and xanthan), and their accuracy may decrease when other compounds are used. Finally, this study focused solely on predicting rheological parameters (Yield Point, Plastic Viscosity, and Apparent Viscosity) and did not explore the effects of these parameters on other

aspects of drilling operations, such as cuttings removal rate and wellbore stability. Therefore, this study seeks to develop yield point, plastic viscosity, and apparent viscosity models of high accuracy. New correlations are developed using the SVM-based grey wolf concept to predict the yield point and plastic viscosity. Green starch, limestone, polyanionic cellulose, NaCl, and xanthan are used in the water-based drilling fluid. Graphical investigation and statistical error analysis are utilized to validate the models. Eventually, the results are compared to previous works to evaluate their accuracy (Al-Khdheawi & Mahdi, 2019; Pitt, 2000).

Statements and Declarations

Ethics Statement: The author affirms that this research was carried out in compliance with recognized ethical standards and principles. All information sources have been appropriately cited and credited. Where required, ethical clearance was granted, and informed consent was obtained from all participants. No instances of plagiarism, data fabrication, or falsification were involved in this study.

Use of Artificial Intelligence: The author confirms that AI-based tools were employed exclusively for language polishing and grammatical correction. All AI-generated assistance was thoroughly examined, validated, and revised by the author, who bears full responsibility for the precision, authenticity, and integrity of the final manuscript. AI tools were not utilized to produce or alter research data or to substitute essential scholarly reasoning.

Conflicts of Interest: Any possible conflicts of interest, including financial or personal relationships that might affect the research, are disclosed. The author states that there are no competing interests.

Compliance with Regulations: The author verifies that this study adhered to all relevant institutional, national, and international rules, and that all required permissions for data usage and reproduction were secured.

Conflict of Interests: The authors affirm that there are no competing interests to disclose.

Data Availability: The data will be provided upon request to the corresponding author of this article, R. Daneshfar, via email at reza_daneshfar@ut.ac.ir.

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