



Real-time machine learning model for rheology and viscoelastic behavior under dynamic pressure variation

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Abstract

Measured forecast of the rheological and viscoelastic behavior under dynamic pressure changes will be important in enhancing the efficiency of the processes and also in avoiding operational problems in the drilling, polymer processing and pipeline systems. This paper set out to create a real-time machine learning (ML) model to predict viscosity, shear stress, yield point and viscoelastic behavior at different pressure and temperature levels. Measurements in high pressure rheometer were measured at pressures: 0-10,000 psi and temperatures: 25-120°C and pre-processed by outlier removal and normalization and feature engineering (including pressure derivatives and shear history). The hybrid type of model that is a combination of gradient boosting regression (GBR) and long short-term memory (LSTM) networks were trained and validated. The outcome is that the hybrid model had an R² value of 0.97 and a RMSE of 3.14 in the prediction of rheological parameters, whereas the traditional Herschel-Bulkley model had an R² value of 0.78. The model similarly estimated viscoelastic modulus with R² = 0.95 of storage modulus (G) and R² = 0.93 storage modulus (G''). On-line measurements indicated a mean estimation latency of 78ms, which means that the system can be used in the sub-second control mode, and thus there is great prospect of applying it in industries and making upstream decisions

Keywords: Rheological behavior, viscoelastic properties, dynamic pressure, machine learning, hybrid model, Gradient Boosting Regression (GBR), Long Short-Term Memory (LSTM)

Introduction

In such industries as polymer processing, oil and gas, and pharmaceutical, rheology plays a very important role (Bautista *et al.*, 2023) [2]. Rheological and viscoelastic behaviour in the presence of dynamic variation of pressure is of significance to predict its behaviour more accurately and ensure stability of the process and optimization of its overall performance. The non-Newtonian fluid behavior under rapidly varying pressure and temperature fields is often not well modeled by the simpler rheological models, including Bingham plastic, Herschel-Bulkley and Power Law models. The models also lead to inadequate process control in dynamic systems due to their reliance on the steady-state flow assumption and the neglect of the short-term effects (Liang *et al.*, 2021) [5]. Recent progress in the field of machine learning (ML) and, specifically, in the deep learning (DL) and hybrid models, allow predicting rheological properties in real-time with the help of streaming sensor data (Ahmed *et al.*, 2023) [1]. An example of this is that the predictive performance of ML algorithms used to predict viscosity and flow properties of hybrid nanofluids with respect to different operational conditions are outstanding when using Gradient Boosting Regression and Random Forest (Hussain *et al.*, 2023; Salinas-Rodriguez *et al.*, 2024) [3, 6]. Nevertheless, there is a lack of research to incorporate the viscoelastic response prediction under dynamic pressure profiles in a real-time ML.

This paper will fill this gap by designing and confirming an effective prediction model on the ML platform that can forecast the rheological parameters and the viscoelastic behavior of non-Newtonian fluids under dynamic pressure changes accurately. To achieve this purpose, the study involves gathering and pre-treating high-quality rheological measurements at different dynamic pressure and

temperature loads, creation of a hybrid GBR + LSTM machine learning framework to forecast the viscosity, shear stress, yield point, and viscoelastic moduli, and comparing its efficiency with both conventional rheological models and individual machine learning methods. The paper tries to evaluate the real time predictability of the model and whether it is suitable to use in industries. The existing industry standards are based on the use of some laboratory tests instead of real-time prediction devices, although previous studies have highlighted the significance of real-time drilling fluid rheology monitoring to enhance drilling efficiency, minimise downtime and wellbore instability (Kumar *et al.*, 2021; Wang *et al.*, 2022) [8, 4].

he researchers restrict the study to non-Newtonian drilling fluids and polymer-based fluids subjected to pressure variations ranging between 0 and 10,000 psi and temperatures ranging between 25 and 120 degC. The training and validation data are obtained out of experimental high-pressure rheometer data. Although multiphase flow systems, chemical degradation and full-scale industrial implementation are out of this work, they offer valuable guidelines to be followed in the future studies. The research was significant as it had the potential to change the real-time management of processes in a variety of industries where rheology plays a vital role. The model can reduce pressure surges and mechanical failures in pipelines, improve cuttings transport and wellbore stability in drilling, improve the performance of polymer processing in production and decreases the operational costs through the replacement of reactive changes with predictive control. Ultimately, it will provide a solution to the divide between data-driven modeling and optimization of real processes, allowing smarter, more effective, and safe industrial processes.

Literature Review

Rheological and viscoelastic behavior in different pressure conditions have been well researched, and most studies are still based on empirical modeling. Several researchers have tried to combine data-driven methods in order to have better accuracy in prediction.

Zhao and Sun (2022) [9] examined the weaknesses of the traditional rheological models including Bingham Plastic and Herschel-Bulkley when used under transient downhole pressure conditions. They concluded that these models cannot well represent pressure induced changes in yield stress and apparent viscosity, especially when high-pressure ramping occurs. Their effort advised application of adaptive or data-driven models to enhance prediction fidelity in the process of drilling. The model created by Ahmed *et al.*, (2023) [1] is a supervised machine learning model that is used to forecast drilling fluid viscosity using pressure, temperature and shear rate as input features. They obtained a high $R^2 = 0.91$ using random forest regression, which is much higher than the conventional curve-fitting techniques. His work showed that ML was useful in modelling nonlinear interactions of thermodynamic variables though it did not include viscoelastic behavior, including storage and loss moduli. Liang *et al.* (2021) [5] paid attention to viscoelastic characterization of polymer-based fluids in high pressure, high temperature (HPHT) conditions. They did oscillation tests to measure the storage modulus (G') and loss modulus (G'') as high as 8,000 psi. Their analysis revealed that it is the pressure that exerts a great hardening influence on the polymer network, and this needs to be considered during the design of fluids in the deep wells. Nevertheless, they performed work based on laboratory measurements, but did not incorporate predictive modeling. Bautista and Hernandez (2023) [2] presented a hybrid approach that couples experimental rheology and neural network modeling. Their research involved a feedforward neural network that was trained with both shear stress and shear rate data and the result was that the accuracy of the prediction of the flow curve was enhanced by 30 percent as compared to the traditional rheological models. Their model, however, had a limitation with regards to applicability in industry as it was not proven under dynamically varying pressure conditions and in real time. Smith *et al.* (2020) [7] investigated the application of RNNs for predicting the viscoelastic behavior of polymer extrusion processes at varying pressures. Their model of time-dependent behavior LSTM showed a high capacity in predicting the stress relaxation and creep compliance curves. Their work has provided a basis on which temporal deep learning architecture can be applied to rheological model based on pressure but only applied to polymer melt and not drilling fluids.

Taken together, these studies point to the direction of a transition of the completely empirical models to the hybrid models of experimental-machine learning. Nonetheless, a knowledge gap exists in the development of models that can be used to predict the rheological and viscoelastic properties in real-time at the dynamically varying pressure and temperature conditions. It is this gap that gives the rationale behind the current study where feature-engineered data and hybrid ML modeling are combined to overcome these issues.

The majority of the available research concentrates on steady-state rheological framework and does not describe

fluid with high-frequency variations in pressure. Machine learning methods employed so far do not pay much attention to viscoelastic properties such as storage and loss moduli. Moreover, very few models are confirmed to work with low-latency and real-time prediction in dynamic pressure conditions. In the case of industrial use, this requires the resulting creation of a hybrid machine learning model that will be able to predict rheology and viscoelasticity in real time with accuracy.

Methods

1. Data Acquisition

The experimental data was given through tests of a high-pressure, high-temperature (HPHT) rheometer of water-based and polymer-based drilling fluids. Among the data obtained were pressure, temperature, shear rate, shear stress, viscosity, and viscoelastic moduli (G' , G''). The dataset consisted of approximately 200,000 data points over a variety of different fluids, temperature changes (25-120°C), and pressure steps (0-10,000 psi).

2. Data Preprocessing

Data preprocessing was done to enhance the quality of data and enhance the performance of the model. Outliers were eliminated using the inter quartile range (IQR); the interquartile range was calculated as:

$$IQR = Q_3 - Q_1 \quad (1)$$

and the points in the data set were designated as outliers when they met.

$$x < Q_1 - 1.5 \times IQR \text{ or } x > Q_3 + 1.5 \times IQR \quad (2)$$

Q_1 and Q_3 are the first and third quartile respectively. Having been cleaned, Min-Max normalization of the features within the range [0,1] was done using.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (3)$$

Where

x = original value,

x_{min} and x_{max} = minimum and maximum value of the feature,

x' = normalized value.

Further feature engineering was done to enhance predictive capability such as the derivatives of pressure which was calculated as:

$$\frac{dP}{dt} = \frac{P_i - P_{i-1}}{t_i - t_{i-1}} \quad (4)$$

Where P_i and P_{i-1} are successive pressure measurements at times t_i and t_{i-1} . Shear history features and interaction terms between temperature and pressure were also developed in order to obtain the combined effects of these variables on rheological behavior. To guarantee the objective evaluation of the model and the best hyperparameter tuning, the dataset was divided into 70% of training, 15% of validation, and 15% of testing data

3. Model Development

A hybrid machine learning framework was designed to work well in capturing nonlinear feature-target relationships as well as the time-dependence in rheological behavior. The initial application of Gradient Boosting Regression (GBR) was made to estimate the nonlinear complex interactions of pressure, temperature and rheological responses. The model was a successive formation of a decision tree each aimed at minimizing the residual error of the last decision tree, thus enhancing the accuracy of prediction with each boosting. The GBR model produced outputs that were learned nonlinear trends that were in turn used as supplementary input features to a Long Short-Term Memory (LSTM) model. The LSTM had the task of modeling the time-dependence and memory effects in the data which is especially significant in the case of dynamic changes in pressure where the previous states affect behavior in the future. The hybrid model based on the combination of the static feature-learning capacity of GBR and the sequence-modeling power of LSTM enabled the production of stronger and more accurate predictions. The process of model training was the optimization of network parameters with Adam optimizer and with early stopping to avoid overfitting. Monitoring of model performance in the training process was done through validation data which makes sure that the model performs well on unknown data. This hybrid GBR-LSTM fusion eventually led to a more valid predictive structure than when either of the models are used alone

4. Model Evaluation

The performance of the models was assessed at 15 percentage hold-out test set when it had been trained using 70 percent of the data and tuned using 15 percent validation data. Regression measures were standard and they were the coefficient of determination. Equation 5,6, and & were used for the model evaluation

$$R^2 = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \tag{5}$$

$$MAE = \frac{100}{n} \sum_{i=1}^n | \hat{y}_i - y_i | \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \tag{6}$$

\bar{y} are true values, y_i are predicted values and \bar{y} is mean of the observed values

Generalization was done with 5-fold cross-validation and an ablation analysis of removing GBR outputs and then the LSTM input (subsequently) was done to measure the hybrid design contribution. Lastly, inference latency was timed to ensure real-time applicability, with sub-second response times being the target with which the rapid deployment to dynamic pressure monitoring settings can be implemented.

Results

Table 4.1 indicates the performance of the model on rheological parameters of the various ML models.

1. Model Performance on Rheological Parameters

| Model | R ² Score | RMSE | MAPE |
|------------------|----------------------|-------|------|
| Herschel–Bulkley | 0.78 | 11.24 | 8.1% |
| GBR | 0.92 | 5.56 | 3.6% |
| LSTM | 0.94 | 4.82 | 3.2% |
| Hybrid GBR+LSTM | 0.97 | 3.14 | 1.9% |

2. Prediction of Viscoelastic Behavior

The prediction of viscoelastic behavior is demonstrated in Table 4.2

Table 2: Viscoelastic Behavior Prediction

| Metric | G' (Storage Modulus) | G'' (Loss Modulus) |
|----------------------|----------------------|--------------------|
| R ² Score | 0.95 | 0.93 |
| RMSE | 2.41 Pa | 2.86 Pa |
| MAPE | 2.2% | 2.7% |

3. Real-Time Latency Test

The latency test has yielded a result presented in Table 4.3.

Table 3: Real-Time Latency Test

| Parameter | Result |
|------------------------|---------------------------------------|
| Average Inference Time | 78 ms per prediction |
| Maximum Latency | 105 ms |
| Real-Time Suitability | Suitable for sub-second control loops |

Discussion

The hybrid GBR+LSTM model when compared to empirical models, such as Bingham Plastic and Herschel-Bulkley demonstrated an improvement over the conventional rheological modeling tools to reduce the overall error of the predictions to more than 40 per cent.

The Gradient Boosting Regression (GBR) was in a position to learn the intricate nonlinear association across pressure, temperature, and the price of shear, whereas the Long Short-Term Memory (LSTM) network could learn the temporal relationship, which occurs in dynamic drilling settings. These components combined were strong predictive frameworks capable of being faithful to fluid conduct in reality.

This performance was important in the incorporation of engineered features such as shear history and pressure derivatives that allow the model to capture transient behaviors that are normally not feasible in the traditional steady-state models. These features enhanced the model in predicting yield stress and apparent viscosity at varying down hole conditions as it can detect minute differences in fluid response when changing pressure ramping and shear rate variations.

This predictability of models in terms of the storage modulus (G') as well as the loss modulus (G'') viscoelastic moduli is a significant advancement towards the drilling fluid design and monitoring. Proper estimation of these parameters gives an insight about the balance between elastic and viscous contributions to flow behavior that is significant to the study of phenomena related to the development of gel strength, stress relaxation and recovery of fluids after pressure increase. Such an ability helps to formulate and adjust drilling fluid properties more accurately and in real-time, eventually enhancing the flow assurance and minimizing the potential of operational failures. The practical usefulness of the proposed model is also supported by the fact that real-time estimation results

are less approximate. The model generated sub-second predictions consistently, which were consistent and thus it was applicable in direct integration in the process control systems.

This facilitates the proactive operation decision making process and the drilling engineers are able to factor in and avoid problems, like barite sag, over-pressure surge or inefficient transportation of cuttings before they turn into wasted productive time (NPT). These predictive control may result in safer drilling, less material waste and a better wellbore stability. The findings attest to the fact that the feature-engineered data combined with hybrid learning architectures is an effective method of real-time rheological and viscoelastic prediction. Besides the limitations of the empirical model, the study also shows that the implementation of solutions based on advanced ML is possible in time-sensitive industrial environments.

Conclusion

In this study, a real-time machine learning model to predict rheological and viscoelastic behaviour at varying pressure dynamics was developed successfully. The hybrid GBR+LSTM model can be useful in real-time process monitoring and control, where the high accuracy ($R^2 > 0.97$) and low-latency prediction are required.

Recommendations

- Extend the study to include multiphase and compressible fluid systems.
- Integrate uncertainty quantification for better risk assessment.
- Conduct field-scale validation to confirm real-world applicability.

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