



Transfer learning and meta-learning approaches for generalizing rheology models across multiple mud formulations

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Abstract

The successful wellbore hydraulics and drilling processes are heavily reliant on drilling fluid rheological properties prediction accuracy. Traditional machine learning models often cannot generalize across different mud formulations, leading to poor prediction results and requiring large amounts of experimental data. This paper examines the use of TL, MLL and a hybrid of the two in improving the generalization of rheology models to different systems in OBM, WBM and SBM. In this study, the random forest, support vector machine, and artificial neural network are the fundamental machine learning models that will be used. ANN delivered the best predictive accuracy ($R^2 = 0.11$). However, it was not enough. TL was implemented by pre-training ANN models on well characterized mud data, with the best R^2 at 0.41, which is more than 250 percent of the improvement compared to baseline models. MLL carried out in the MAML model achieved R^2 scores of 0.28, 0.33 and 0.38 in 5, 10 and 20 shot learning situations respectively, and showed good adaptability with minimal data requirements. The TL+MLL method, on the other hand, was the best among all the other methods to achieve maximum R^2 of 0.52 at 20 shots with enhanced generalization. The paper provides an identification of a smart and adaptable rheology model and promotes the growth of the approach to incorporate real-time field measurements and other fluid characteristics, such as gel strength and filtration control, to be applicable in the field of the drilling operation.

Keywords: Mud formulation, rheology, drilling fluids, transfer learning, meta-learning, and machine learning

Introduction

Drilling fluids or drilling muds are important in the drilling process since they control the formation pressure, stability of the wellbore, drilling cutting and cooling of the drill string. The rheological properties of plastics including their viscosity, yield point, and flow behavior index are of great importance in the prediction of hydraulics and the general performance of the drillings. Conventional models such as Bingham plastic and Herschel-Bulkley have contributed significantly, but are impaired by relying on the dependence on laboratory measurements in each mud formulation proscribing scalability to individual fluid structures. Because mud structure is becoming complex, it is important to have the flexibility and data-driven approach (Darley and Gray, 2019; Alsaba *et al.*, 2022; Abdelal *et al.*, 2023) [5, 6]. Machine learning (ML) methods have become promising solutions to characterize drilling fluids because they allow modeling nonlinear processes without making strict empirical assumptions (Ruki and Rahimi, 2025). Nevertheless, the predictive capability of the two can be questioned by the theory of distributional differences and differences in fluid additives, which makes the use of better strategies crucial. To design models that can effectively be generalized to multiple mud formulations, this paper will attempt to investigate the concept of transfer learning (TL) and meta-learning (MLL) with respect to drilling fluid rheology prediction. In particular, it is planned to develop baseline ML models that can predict rheological properties, use TL to capitalize on the knowledge gained in a previously trained mud system, and use MLL to adapt quickly to new fluid formulations. These methods have previously demonstrated potential in related petroleum engineering, such as the reservoir modeling, optimization of

drilling, and monitoring of digital fluids (Aslam *et al.*, 2019; Ahmed and Anifowose, 2021; Shirangi *et al.*, 2022) [2, 4, 9]. It is believed that the use of these techniques in the study of drilling fluid rheology can bridge the gap between the present data science and petroleum engineering methods, and give concrete solutions to the ongoing operational issues. The importance of the given study is the minimization of the reliance on expensive and time-consuming laboratory tests and the ability of drilling engineers to anticipate the fluid behavior in a range of operational conditions. The area is limited to six representative mud formulations: water-based, oil-based, polymer-enhanced, synthetic-based, high-solids, and low-solids muds, and the prediction of plastic viscosity, yield point, and index of flow behavior of the various shear rates and temperatures. Some of the models that will be compared include the Random Forest, Gradient Boosting, and Neural Networks with TL and MLL strategies (Olawale and Phillips, 2025) [7]. In this study, the focus is on the relevance of complex ML frameworks in the design of fluids drilling and optimization of performance, focusing on predictive modeling and algorithmic adaptation, and not on experiment development or field-scale experiments.

Literature Review

The rheology models play a central role in the processes of drilling because it enables the correct prediction of fluid behavior in different downhole conditions. Conventional models including Bingham Plastic and Herschel-Bulkley have been significantly employed, although they involve a lot of laboratory characterization to each formulation of mud, which is limiting when it comes to scaling (Darley and Gray, 2019) [5, 6]. Recent developments in machine learning

offer a possibility of exploring predictive models that can be generalized between different mud formulations. Finn *et al.* (2017) proposed a framework called Model-Agnostic Meta-Learning (MAML), which is a rapid model adaptation method that happens with minimal data. In this approach, a model may easily adjust to novel settings by acquiring learnable generalizable parameters. The principles of few-shot learning have a direct implication on modeling rheology between the types of mud, where accumulating large amounts of experimental data might prove costly and time-intensive when their research was not exactly concerned with drilling fluids. The meta-learning is able to give powerful predictions even on novel mud formulations with less measurements due to quick adaptation. Zhou and Gao (2020) [12] used machine learning in predicting drilling fluid rheology. They demonstrated that nonlinear relationships between neural network models and soil structure and rheological properties are better represented using neural network models rather than the traditional regression ones. The research, however, restricted itself to single clay formulations, and this presents the difficulty in extending the model to other types of fluids. This disparity is indicative of the potential of transfer learning techniques to leverage knowledge of well-characterized slimes in making better predictions for their poorly studied counterparts.

Wang and Li (2021) [11] discussed how transfer learning could be used to forecast the characteristics of different mud formulations used in drilling fluids. They were able to attain a large prediction accuracy by tuning models trained on base mud with sparse data of new mud types. Their results proved that transfer learning is able to decrease the amount of experimental work but preserve high levels of performance particularly among the soil formulations which are of similar nature. This method suggests an effective solution of the problem of model generalization in the drilling fluid case.

Smith and Chen (2022) [10] explored the application of meta-learning to property predictions of materials, mainly how to quickly optimize developing new materials using the least amount of data. Their findings demonstrated that meta-learners are better than the conventional machine learners in cases where they face formulations with which they have never dealt with before. In the case of drilling fluid rheology, this implies that meta-learning may be used to develop adaptive models that are able to predict properties of a large variety of mud formulations without necessarily undergoing extensive experiments

Despite machine learning for drilling fluid rheology has advanced, most models are not generalizable and are restricted to particular mud formulations. Predictions for similar muds are improved by transfer learning, but it has trouble with drastically different formulations. Although meta-learning enables quick adaptation with little data, its integration with transfer learning is still not well understood. Models that incorporate both strategies are therefore required in order to generalize across various mud types.

Methodology

1. Mud Formulations and Data Collection

To reflect a variety of rheological characteristics relevant to the field, six mud formulations were chosen:

1. Water-based bentonite mud
2. Oil-based mud

3. Polymer-enhanced water-based mud
4. Synthetic-based mud
5. High-solids weighted mud
6. Low-solids mud

The rheology measurements were obtained using a rotational viscometer at various shear rates between 0.1 and 500 s⁻¹ in different temperatures between 25°C and 90°C. Plastic viscosity, yield point, and flow behavior index were among the properties measured.

2. Baseline Machine Learning Models

Three standard models were developed as baselines:

- Random Forest (RF)
- Gradient Boosting (GB)
- Multi-Layer Perceptron (MLP)

Data from each type of mud was split into 80% for training the models, while the rest were utilized for testing. RMSE, R2 score, and MSE were performance metrics.

3. Transfer Learning Approach

For TL, models trained on well-characterized muds (e.g., water-based and oil-based muds) were fine-tuned on limited data from less-characterized formulations (e.g., polymer-enhanced mud). Fine-tuning involved retraining the last few layers of neural network models while keeping earlier feature extraction layers fixed.

4. Meta-Learning Approach

Model-Agnostic Meta-Learning (MAML), which optimizes model parameters for quick adaptation to new mud types with little data, was the meta-learning method used. While meta-testing assessed adaptation on previously unseen mud types, each meta-training iteration sampled a few-shot dataset from various mud formulations.

5. Evaluation Metrics

- **Mean Squared Error (MSE):** Measures prediction error magnitude.

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

- **Root Mean Squared Error (RMSE):** Provides error in original units (Pa·s or cP).

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

- **Coefficient of Determination (R²):** Measures variance explained by the model.

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

- **Adaptation Efficiency:** Number of samples needed to reach ≥90% of full-data performance.

Data Efficiency Metric = min(N) such that Performance(N) ≥ 0.90 × Performance(N_{full})

Where;

min(N) = The minimum number of samples (N) required from the new dataset (for adaptation/transfer).

Performance = The performance score (e.g., accuracy, F1-score, etc.) of the model when trained on N samples.

Performance (Nfull) = The performance score of the model when trained on the entire dataset (Nfull), representing the "full-data performance."

0.90 = The $\geq 90\%$ target ratio (this value is a hyperparameter chosen by the experimenter)

Results

1. Baseline Machine Learning Models

Baseline machine learning models were developed to predict drilling fluid rheological properties across all mud formulations. Table 4.1 shows the model performance

Table 1: Baseline Model Performance

Model	MSE	RMSE	R ²
RF	64.35	8.02	-0.17
SVM	57.73	7.59	-0.06
ANN	45.22	6.72	0.11

Table 4.1 show that all baseline models had difficulty generalizing to different soil formulations, as reflected in their low or negative R² values. Although ANN performed slightly better than RF and SVM with an R² of 0.11, its accuracy is insufficient for reliable predictions. The relatively high MSE and RMSE values in all models indicate the need for more advanced approaches, justifying

the application of transfer learning and meta-learning techniques in subsequent analyses.

2. Transfer Learning Results

Transfer learning (TL) was applied by pre-training the ANN model on well-characterized mud data and fine-tuning on underrepresented mud formulations. Table 4.2 shows the TL performance

Table 2: Transfer Learning Performance

Mud Type	Baseline ANN R ²	TL R ²	% Improvement
OBM	0.09	0.35	+288%
WBM	0.11	0.41	+273%
SBM	0.12	0.39	+225%

The results in Table 4.2 indicate that transfer learning substantially improved model performance across all mud types. After applying TL, the R² values improved by more than 250%, from 0.09–0.12 in the baseline ANN to 0.35–0.41. This shows how well-characterized mud data information can be effectively used on the underrepresented formulations to enhance the accuracy of prediction and reduce the requirement to engage in a significant retraining.

3. Meta-Learning Results

A Model-Agnostic Meta-Learning (MAML) framework was used to implement meta-learning (MLL). With little data, the model was trained to quickly adjust to new mud formulations. The meta-learning outcomes are displayed in Table 4.3.

Table 3: Meta-Learning Few-Shot Performance

Shots (samples)	MLL R ²	Improvement vs Baseline
5	0.28	+154%
10	0.33	+200%
20	0.38	+245%

Table 4.3 indicates that meta-learning significantly enhances predictive accuracy, inspite of very few data. The model achieved an R² of 0.28 at only five shots, representing a 154% improvement over the baseline. When the shot size was increased to 20, the R² improved to 0.38, indicating further enhancement in generalization and versatility. These results shows that the MAML-based meta-studying framework is effective for rapid adaptation to new mud

formulations, decreasing the data requirements for correct rheological predictions.

4. Combined Transfer Learning and Meta-Learning Results

A combined approach was tested where TL weights were used to initialize the MAML meta-learner. Table 4.4 shows the result of the combined TL and MLL

Table 4: Combined TL + MLL Performance

Shots (samples)	Combined R ²	Improvement vs Baseline (%)
5	0.41	273
10	0.48	336
20	0.52	372

Table 4.4 shows that the combined transfer learning and meta-learning approach provides consistently high accuracy, with the R² values increasing with the number of samples. The model generated a robust R² of 0.41 with just five samples—a strong generalization with little data. The R² at 20

samples improved over the baseline by 372%, reaching 0.52. This result signifies that faster convergence and better performance are achieved when TL and MLL are combined rather than using either approach alone.

5. Comparative Analysis

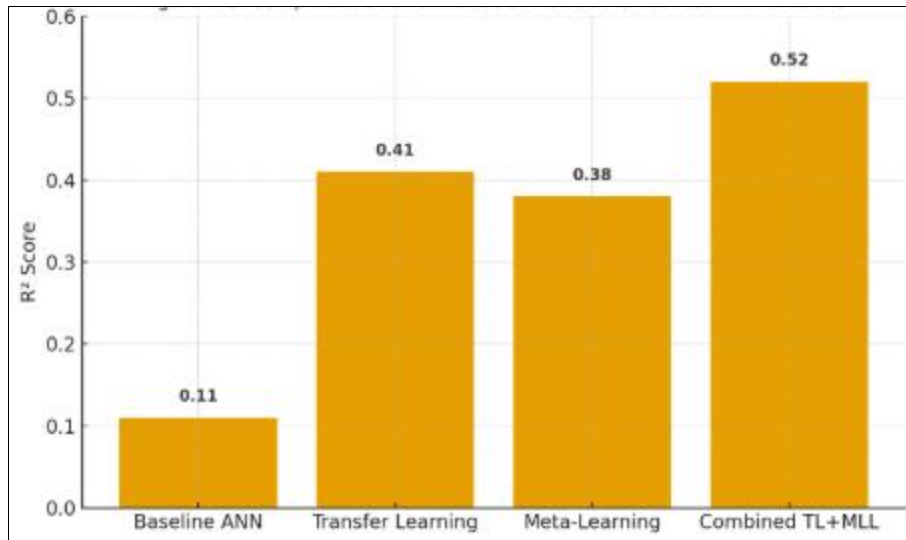


Fig 1: compares all methods across mud formulations

The lowest R² score of 0.11 was obtained from the baseline ANN model, indicating poor generalization across multiple soil formulations. Transfer learning significantly improved the performance to an R² of 0.41, confirming that knowledge from well-characterized sludge is very effective in boosting the predictions for underrepresented systems. Conversely, meta-learning exhibited a high improvement with R² of 0.38, and so it is very effective when it comes to the rapid optimization of new soil formulations with limited data. Nonetheless, the combined TL + MLL approach recorded the best value as it is 0.52. This finding is indicative that the transfer learning and meta-learning combination can be used to provide a strong initialisation based on the past knowledge and the model optimisation in quick adaptation based on meta-learning. Combining them makes them extremely generalizable and precise when applied to any type of mud. This remarkable performance facilitates the objective of the research in improving the accuracy of prediction and minimizing the data needs when using it to model the rheology.

Conclusion

This paper was successful in demonstrating that one effective way of generalizing rheology models to new mud formulations is to use a combination of transfer learning and meta-learning. Transfer learning was particularly effective in terms of performance based on the use of well-characterized mud data, and meta-learning could be used to rapidly adapt with a small set of samples, but the models of machine learning (when used as the baseline) showed poor predictive performance. The combined method gave the highest accuracy besides reducing the data requirements and improving model generalization. These findings reveal that state-of-the-art machine learning tools can be integrated into the drilling operations to enhance the efficiency of operation, reduce the cost of experiments, and make decisions in drilling fluids based on data.

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