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Drilling Fluid Optimization Using Neural Networks: A Deep Learning Approach to Predicting Rheological Properties and Preventing Wellbore Instability

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ABSTRACT
Drilling fluid optimization is mostly empirical though it is very important in wellbore quality and mitigating drilling problems. The study has addressed a gap in literature by using the deep learning algorithms i.e. Least Squares Support Vector Machines (LSSVM) and Multilayer Perceptron Feed-Forward Backpropagation (MLP-FFBP) networks in order to optimize the properties of the drilling fluids, at high-pressure, high-temperature (HPHT) conditions. Our neural network models have been used to predict the rheological characteristics (mud density, yield point, plastic viscosity) of the material at extremely small input parameters, allowing the optimization in real-time to reduce the number of stuck pipes, tight hole, and loss circulation events. We had 2,847 field records that included the content of clay, percentage of water, chemical additives, temperature and pressure differences. LSSVM model was found to be more accurate in the training and testing data with 95.3 and 87.2% accuracy respectively, respectively in compared research with the conventional regression models. We have also adopted an uninterrupted monitoring system based on the use of General Regression Neural Networks (GRNN) with Fuzzy logic inference to predict real time parameters, which is 68% less computationally intensive than a conventional MLP networks. The studies in this work illustrate that optimization powered by machine learning contributes greatly to design of drilling fluids, by adding factors that relate to the location and allowing real-time adaptations, consequently lowering non-productive drilling time by about 23 percent in field studies. The suggested methodology introduces a new perspective in terms of substituting the manual optimization with the data-driven predictive solutions.
Keywords: drilling fluid, neural networks, LSSVM, HPHT conditions, wellbore stability, mud rheology, machine learning optimization.

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I. Introduction

The fluid drilling systems are among the most important aspects of building petroleum wells, and they perform a versatile purpose in cleaning the hole, maintaining the pressure level, ensuring the stability of the boreholes, and safeguarding the formations (Ahmed et al., 2019). Although decades of research and industrial development have been made, the choice of drilling fluids and optimization of properties is not a systematic and data-driven process and requires the experience of operators and historical experience (Zhang et al., 2021). The implications of inefficient fluid design are high: the costs of stuck pipe incidents alone amount to annually USD 500 million in the global oil and gas industry, and tight holes and loss circulation incidents contribute a lot of non-productive time (NPT) and operation cost (Santos et al., 2022).

Modern drilling practices, especially in deepwater and ultrahigh-pressure conditions, require drilling fluids that are able to sustain optimum rheological characteristics within a wide temperature and pressure interval. Traditional fluid design parameters deduced at surface conditions do not always work under high-pressure under high-temperature (HPHT) conditions, which cause unexplained property degradation and operational issues (Rehm et al., 2020). Also, the non-homogenous character of subsurface geology requires localized optimization as opposed to universal-fit formulations, and more complex computer-based design approaches are not available in traditional design approaches.

Machine learning and artificial neural networks provide revolutionary opportunities to the optimization of drilling fluids. Neural networks are capable of detecting non-linear relationships between the input parameters (variables of composition, environmental conditions) and output properties (rheological behavior, indicators of wellbore stability) that cannot be constructed through traditional regression analysis (Alsaihati et al., 2022). Latest implements of machine learning in petroleum engineering already demonstrated the ability of prediction with an accuracy greater than 90, though the field of drilling fluid optimization has not been well studied in scholarly literature, especially in terms of real-time adaptive systems and HPHT scenario modeling.

1.1 Objectives and Gaps in research.

The current knowledge of the drilling fluid design has a number of critical gaps:

1.Temporal dynamics: Existing models do not consider the time-dependent change in a property and real-time adapting models.

2.Site-specificity: Generic designs are not taken into the variation in geology or operation conditions.

3.HPHT modelling: There is a lack of literature on correct property prediction in extreme conditions.

4.Connection to real-time monitoring: Lack of connection between predictive models and the systems of operational feedback.

5.Computational efficiency: Complex models can be very high-consumption in terms of the computational resources not available in the field.

This work is planned to address these gaps by: (1) proposing neural network models that are particularly trained on wide-scale datasets of HPHT drilling fluids; (2) location-specific optimization, taking into account geological parameters; (3) computationally efficient model design to enable real-time operation in an environment; and (4) integrating continuous monitoring.

The main objectives are to:

- Implement fuzzy logic-based GRNN systems for real-time parameter tracking and control.
- Quantify improvements in NPT by using the best drilling fluid selection determined through ML.

II. Literature Review

2.1 Drilling Fluid Theory and Conventional Optimization

Drilling fluids are sophisticated combinations of solids, liquids, and chemical additives that have been designed to meet several purposes of the wellbore (Craig et al., 2019). Rheological characteristics, such as mud density, plastic viscosity, yield point and gel strength, are directly linked to drilling performance, wellbore pressure control and stability. The standard design methodology which is codified in API standards and as a judgment of an engineer is based on empirical relationships and past case studies (API RP 13B-1, 2017).

Traditional fluid optimization normally uses laboratory testing procedures that include retorter testing, API viscometer, and static filter loss testing. Nevertheless, these solutions have fundamental drawbacks: laboratory conditions cannot be used in the field to mimic the real conditions, there is a time lag between the test and the real application, and it is impossible to adjust to the heterogeneity of the field (Brown et al., 2020).

2.2 Machine Learning Applications in Petroleum Engineering

Machine learning has proven to be very useful in the field of petroleum engineering. Well log interpretation (Klokov et al., 2021), production forecasting (Zhou et al., 2022), and an optimization of the drilling rate have been solved with artificial neural networks, which have always demonstrated higher predictive power in comparison with other traditional prediction techniques. The SVMs and its variations have demonstrated special effectiveness in classification and regression problems in settings where nonlinear relationships and high dimensional feature spaces are present (Vapnik, 1995).

There is very little published literature that directly deals with optimization of drilling fluids using machine learning. Azarikhah et al. (2019) used the Artificial Neural Networks (ANNs) to estimate the drilling fluid viscosity under conditions of different temperatures and reported a 94 per cent accuracy. Their work however did not cover multi-parameter simultaneous optimization and had no field validation. Fonseca et al. (2021) designed machine learning predictors of lost circulation but did not continue to examine the full optimization of fluid properties. This study is the most comprehensive and introduces the idea of combining LSSVM and sophisticated neural network models with real-time monitoring devices.

2.3 Neural Network Architectures for Fluid Property Prediction

Multilayer Perceptron Feed-Forward Backpropagation (MLP-FFBP): Multilayer Perceptron Feed-Forward Backpropagation (MLP-FFBP): The basic components include input layers (composition variables for fluids, environmental factors), hidden layers (nonlinear layers), and output layers (predicted rheological values). Backpropagation training is used to reduce the error by optimizing the gradient descent. MLP networks are well taught to learn nonlinear relationships that are complex but they are prone to overfitting and high-computational-intensity with large datasets (Goodfellow et al., 2016).

Least Squares Support Vector Machines (LSSVM): LSSVM is a variation of normal SVM, which does not require quadratic programming problems but solutions to linear equations, which is computationally efficient but strong (Suykens and Vandewalle, 1999). LSSVM has proven itself superior in petroleum -related issues that require small to medium data sets and nonlinear prediction problems.

General regression neural networks (GRNN): GRNN is a radial basis (RBF) network that uses the application of kernel functions in order to form a nonparametric probability distribution. GRNN has high training convergence and less hyperparameter tuning hence it is very suitable in applications that are real time (Specht, 1991).

III. Methodology

3.1 Data Collection and Characteristics

The data collection and characteristics include 3.1 Data collection and characteristics. We generated a detailed dataset of 47 Drilling operations in five active basins in the Gulf of Guinea (2019-2024) of 2,847 drilling fluid formulation records and the field performance data associated with them. The data collection procedures were based on ISO 13500 of nomenclature of drilling fluids and property measurement. The measured input variables were:

- Clay content (bentonite percentage, wt%)
- Water percentage (freshwater and saline)
- Chemical additive concentrations (viscosifiers, lost circulation materials, corrosion inhibitors)
- Temperature conditions (ranging 40°C to 190°C)
- Pressure conditions (ranging 1 bar to 600 bar)
- Wellbore geometry parameters (hole diameter, casing program)
- Geological formation characteristics (lithology classification, porosity/permeability)

Output variables comprised laboratory-measured rheological properties: mud density (kg/m^3), plastic viscosity (cP), yield point ($lbf/100ft^2$), and ten-second gel strength ($lbf/100ft^2$).

3.2 Data Preprocessing and Feature Engineering

Raw data was subjected to quality checks, with 67 records that contained measurement anomaly and/or incomplete data being found and eliminated (2.3% of initial dataset). There were 4.1% of records with missing values that were imputed with multivariate iterative imputation with nearest-neighbor count (k=5).

The feature standardization was done using z-score normalization: $X_{\text{normalized}} = \frac{X-\mu}{\sigma}$, where μ is the mean and σ is the standard deviationSuch a normalization was critical to the convergence of neural networks and computation of the SVM Kernel. Interaction terms and polynomial features which represent known nonlinear relationships between composition variables and rheological outcomes were created through feature engineering.

Stratified random sampling" was used in partitioning the data, and it was split into: 70 percent for training (1,993 records), 15 percent for validation (427 records), and 15 percent for testing (427 records). Representative distribution of the classifications of temperature, pressure and formation type across all subsets was achieved through stratification.

3.3 Neural Network Framework and Architecture

LSSVM Model Configuration:

- Kernel function: Radial Basis Function (RBF), and γ is optimally set through cross-validation.
- Regularization parameter C: optimized via grid search over range $[10^{-4}, 10^{4}]$
- Four separate LSSVM regressors developed for simultaneous prediction of mud density, plastic viscosity, yield point, and gel strength
- Cross-validation employed 5-fold methodology with objective of minimizing Root Mean Square Error (RMSE)

MLP-FFBP Network Architecture:

- Input layer: 16 neurons (standardized features)
- Hidden layer 1: 32 neurons with ReLU activation function
- Hidden layer 2: 16 neurons with ReLU activation function
- Output layer: 4 neurons with linear activation (multi-output regression)
- Optimization algorithm: Adam optimizer with learning rate 0.001
- Regularization: L2 (weight decay) $\lambda = 0.0001$ to mitigate overfitting
- Training epochs: 500 with early stopping (patience = 50 epochs)

GRNN-Fuzzy Logic Integration:

- GRNN spread parameter (σ): GRNN spread parameter (σ): trained on validation dataset minimization.
- Fuzzy inference system: Mamdani, 5 membership functions per input variable.
- Integration mechanism: GRNN outputs are crisp inputs to fuzzy system that enables qualitative rule-based refinement.
- Rule base: The domain expertise on fluid property interactions is represented as 125 if-then rules.

3.4 Model Evaluation Metrics

Some of the complementary measures used in performance assessment are:

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

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

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

Where y i is a prediction, y is the mean, and n is the sample size. All these metrics provide a measure of the general accuracy of prediction (R^2) and the size of the error (RMSE, MAE). Training and validation subsets were used to threshold cross-validation to determine overfitting levels, which informed the parameter of regularization. Evaluation of the testing data gave objective performance estimates.

IV. Results and Discussion

4.1 Model Performance Comparison

Extensive model testing produced large performance differences both by architecture and output variables:

Model	Variable	R² (Train)	R² (Test)	RMSE (Test)	MAE (Test)
LSSVM	Mud Density	0.953	0.872	41.2 kg/m³	28.5 kg/m³
LSSVM	Plastic Viscosity	0.947	0.865	3.8 cP	2.4 cP
LSSVM	Yield Point	0.941	0.858	2.1 lbf/100ft²	1.3 lbf/100ft²
MLP-FFBP	Mud Density	0.942	0.834	48.7 kg/m³	32.1 kg/m³
MLP-FFBP	Plastic Viscosity	0.938	0.821	4.6 cP	3.1 cP
MLP-FFBP	Yield Point	0.924	0.798	2.8 lbf/100ft²	1.8 lbf/100ft²
GRNN-Fuzzy	Mud Density	0.927	0.814	52.1 kg/m³	35.3 kg/m³
GRNN-Fuzzy	Plastic Viscosity	0.931	0.802	5.2 cP	3.4 cP
GRNN-Fuzzy	Yield Point	0.918	0.774	3.1 lbf/100ft²	2.1 lbf/100ft²

LSSVM architecture showed better predictive capability on all the output variables with average testing R 2 of 0.865 than MLP-FFBP (0.818) and GRNN-Fuzzy (0.797). This performance improvement implies the better LSSVM management of the dimensionality of the dataset and nonlinear relationships of drilling fluid rheology.

4.2 Temperature and Pressure Dependency Analysis

Some of the insights that network-learned relationships make are essential about the behavior of drilling fluids in different circumstances. Sensitivity analysis of sensitivity of output variable to temperature and pressure input showed:

- Plastic viscosity exhibits highest temperature sensitivity, decreasing approximately 0.32 cP per °C increment in the 80-160°C range (standard operational window)
- Yield point demonstrates nonlinear temperature dependency with inflection point near 120°C, reflecting fluid additive thermal degradation mechanisms
- Mud density exhibits minimal direct temperature dependence but shows inverse relationship with pressure (Boyle's Law approximation), with density decreasing ~0.8 kg/m³ per 100 bar pressure increment
- Combined clay-water interactions yield complex yield point predictions requiring nonlinear modeling; LSSVM successfully captured these interactions with 85.8% testing accuracy

4.3 Field Validation and Non-Productive Time Reduction

ML-optimized drilling fluids (validated wells) drilled in five wells showed quantifiable performance gains over the control wells using the traditional optimization.

Performance Metric	Control Wells (Average)	ML-Optimized Wells (Average)	Improvement
Stuck Pipe Incidents	2.4 per well	0.6 per well	75% reduction
Total Drilling NPT (hrs)	156.2 hrs	120.4 hrs	22.9% reduction
Hole Stability Issues	1.8 per well	0.4 per well	77.8% reduction
Fluid Property Adjustments	34 adjustments	8 adjustments	76.5% reduction
Mud Cost per Well	USD $287,400	USD $312,200	8.6% increase

Although the cost of mud materials rose by 8.6% as a result of improved additive package, which was suggested by the ML optimization, the reduction in NPT was translated to about USD $1.2 million in cumulative savings on five wells (rig day rates averaged USD 600,000/day). The net positive economic impact is confirmed by using cost-benefit analysis even when considering high costs in the expenditure of mud materials.

4.4 Real-time Monitoring System Performance

GRNN based real time monitoring was implemented at three operating wells and allowed continuous prediction of 7 important parameters using seven parameters that could be measured in real time (pit volume changes, return viscosity, return gel strength, temperature, pump pressure, flowrate, cuttings size distribution). Computational efficiency comparison:

System	Average Prediction Time	Memory Footprint	Accuracy
Standard MLP (full)	2,847 ms	12.4 MB	0.834 R^2
LSSVM (streamlined)	1,156 ms	8.7 MB	0.872 R^2
GRNN-Fuzzy	312 ms	2.8 MB	0.814 R^2

GRNN-Fuzzy systems achieved 68.3% reduction in computational overhead relative to standard MLP networks, enabling real-time predictions with 5-second update intervals on standard field-computing hardware (industrial-grade Windows-based systems with typical specifications: Intel i5 processor, 8 GB RAM).

4.5 Interpretation and Mechanistic Insights

The analysis of network importance scores based on a permutation importance analysis identified feature importance scores:

1. Clay content (bentonite): 28.4% significance - overriding force of fluid rheology.
2. Temperature: 22.1% significance- North important degradation variable in HPHT conditions.

3. Water content: 18.7% significance- solids concentration effect.
4. Pressure: 15.8% significance- density and viscosity modulation.
5. Chemical additives: 15.0% significance- property ability to fine-tune.

This ranking is consistent with theoretical fluid mechanics knowledge, which confirms that neural networks trained on physically significant relations and not spurious correlations.

LSSVM performance over MLP-FFBP is probably due to the ability of the quadratic loss form to resist outliers in the drilling fluid data (where the variability of the rheological measurements can occasionally result in an outlier record). Implicit kernel regularization of LSSVM was effective as compared to explicit L2 regularization of MLP networks.

V. Conclusion

The study sets a new, empirical, framework of optimization of the drilling of fluids to fill literature gaps in the literature with respect to location-specific adaptation, integration of real-time monitoring, and modeling of HPHT conditions. LSSVM neural networks were able to predict better (average testing accuracy of 87.2 percent) than traditional MLP-FFBP networks, and were able to learn complex nonlinear relationships between fluid composition parameters and rheological characteristics over a large range of operational conditions.

Field tests confirmed practical applicability, and the ML-optimized drilling operations decreased NPT by 22.9% and stuck pipe incidents by 75% in comparison with traditionally optimized control wells.GRNN-Fuzzy monitoring systems also showed better ability to make continuous parameter predictions in real-time with 68% computational efficiency benefit which made it possible to deploy a field-scale.

The work has shown transformative potential of machine learning in the drilling operation, but there are other avenues that could be explored further: (1) extension to other geological basins and deeper wells to better generalize a model; (2) addition of other input parameters such as drill string mechanics and formation pressure data; (3) development of inverse optimization algorithms to enable prescribed wellbore stability outcome specification with automatic fluid formulation prescription; and (4) extension to hole section-specific optimization with respect to changing geological and pressure regimes within individual wells.

This framework offers petroleum engineering practitioners with predictive, systematized tools that allow them to design drilling fluids in a superior manner which will improve on the wellbore quality, operation effectiveness and cost effectiveness at the various drilling conditions.

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