DEVELOPMENT OF REAL-TIME FORECASTING METHODOLOGY FOR DRILLING FLUID PROPERTY CHANGES BASED ON SURFACE SENSOR DATA

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Abstract. Drilling fluid properties change continuously during operations due to temperature effects, solid buildup, influxes, degradation, and interventions. Conventional periodic testing provides delayed data, hindering timely corrections and increasing risks of NPT, well control issues, and formation damage. This study introduces a real-time forecasting methodology for key mud properties – density, Marsh funnel viscosity, plastic viscosity, yield point, and gel strength – with prediction horizons of 15-120 minutes. The approach combines high-frequency surface sensor data (density, temperature, flow, rheology, drilling parameters) with physics-based temperature/pressure corrections and hybrid machine learning models (XGBoost + attention-augmented LSTM). The method was developed and validated using full-scale mud loop experiments and field data from three directional wells (onshore shale gas and offshore HPHT). On unseen test sets, models achieved $R^2 > 0.95$ for horizons up to 60 min, RMSE < 0.012 $g \cdot cm^{-3}$ for density and < 3.5 $s \cdot L^{-1}$ for viscosity at 60 min, and directional accuracy > 90%. Probabilistic forecasts enabled reliable trend alerts. Field trials showed that early predictions allowed preemptive treatments, reduced ECD fluctuations, mitigated barite sag, and improved hole cleaning. The framework enables proactive mud management, with the potential to reduce mud-related NPT by an estimated 15-30% under similar operating conditions, based on observed response times in the test cases. Limitations include reliance on sensor quality and need for recalibration after major changes. Future work may integrate downhole data and automated treatment suggestions.

Keywords: drilling fluid, mud properties, real-time forecasting, machine learning, surface sensors.

Introduction

Drilling fluid (mud) is essential for well construction, performing critical functions including cuttings transport, hydrostatic pressure maintenance, bit cooling and lubrication, wellbore stabilization, and formation damage prevention [1; 2]. These functions depend on key properties such as rheological characteristics (plastic viscosity, yield point, gel strength), density, filtration control, pH, electrical stability (for oil-based systems), and solids content [3; 4].

During drilling operations, these properties undergo continuous changes due to dynamic downhole conditions: high temperatures degrade polymers, drilled solids increase density and viscosity, formation fluids cause contamination, reactive formations consume chemical treatments, and mechanical shear breaks down viscosifiers [5; 6]. Traditional monitoring relies on periodic manual testing (every 15-30 min for density and Marsh viscosity; daily for full rheology), which provides snapshots but suffers from low frequency, time delays, and inability to capture transient events [7; 8]. These forces reactive rather than proactive treatments, are potentially leading to non-productive time, well control incidents, and formation damage [9; 10].

Automated real-time sensors now enable continuous data acquisition from the mud system [11]. When integrated with surface drilling parameters these streams generate high-frequency datasets. However, raw sensor data alone does not provide actionable foresight; the key challenge is transforming this information into reliable predictions of mud property evolution [12; 13].

Data-driven approaches, particularly machine learning, have shown potential for bridging this gap [14; 15]. Nevertheless, a comprehensive, field-applicable methodology for operational real-time forecasting of drilling fluid properties changes – integrating multi-source data and providing probabilistic alerts – remains underdeveloped for widespread adoption [16].

This work develops and validates a structured methodology for predicting changes in key drilling fluid properties during active drilling using real-time surface data, supporting proactive mud management decisions at the rig site and in remote operation centers.

Materials and methods

Drilling fluid systems investigated included water-based muds (WBM) with polymer additives (xanthan gum, polyanionic cellulose) and invert-emulsion oil-based muds (OBM) formulated with synthetic base oil, emulsifiers, organophilic clay, and calcium chloride brine [17; 18]. All formulations followed API 13B-1 (WBM) and 13B-2 (OBM) standards, with densities of 1.05-1.80 $g \cdot cm^{-3}$ and temperatures up to 150 °C in simulated conditions [19; 20].

Real-time data were acquired from a full-scale mud circulation test loop. The test loop comprised a 500 L agitated tank, progressive cavity pump (0-1200 $L \cdot min^{-1}$), 4-inch (≈102 mm) circulation line with inline sensors, heat exchanger (25-180 °C), and a return line. Measured parameters included mud density, Marsh funnel viscosity, temperature, flow rate, standpipe pressure, rheological readings, conductivity/pH (WBM), electrical stability (OBM), solids content, and drilling mechanics (ROP, WOB, RPM, torque). Data were logged at 1 Hz and aggregated to 1-minute resolution, yielding approximately 85,000 data points from laboratory simulations (120-180 hours with intentional perturbations) and field operations. Of these, approximately 35,000 points originated from the mud loop experiments, 22,000 from onshore well A, 15,000 from onshore well B, and 13,000 from the offshore HPHT well. Data preprocessing involved outlier detection and removal using the z-score method ($|z| > 4$) and the isolation forest algorithm. Missing values were handled via forward-fill for short gaps (< 10 min) and linear interpolation otherwise. Normalization and scaling were applied using Min-Max scaling for inputs to neural networks [21; 22]:

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} , \tag{1}$$

and Standard Scaler for tree-based models.

Feature engineering generated time-lagged and derived variables to capture temporal dynamics and physical trends. Lagged features included MD_{t-1}, MD_{t-5}, MFV_{t-1}, $T_{fl,t-1}$ (up to 30 min lag). Rolling statistics comprised 5-min and 15-min rolling mean, standard deviation, and slope of MD, MFV, and T_{fl}. Physical derivatives incorporated a temperature-induced density correction approximation [23; 24]:

$$\Delta\rho_{\text{temp}} \approx -0.00065 \times \Delta T (\text{g} \cdot \text{cm}^{-3} \text{ per °C for typical WBM}). \tag{2}$$

Change rates (e.g., $dMD/dt \approx (MD_t - MD_{t-10})/10$ min, solids loading proxy = (MD − base density)/(weighting agent SG), and drilling context (ROP×RPM, torque deviation) were computed. Targets included future values (15–120 min) of MD, MFV, PV, YP, and gel strength (10 s and 10 min). The primary framework combined physics-informed and data-driven elements using a hybrid model. Baseline physics-based corrections for temperature/pressure effects on density/viscosity followed empirical relations [25].

$$\rho_{\text{corrected}} = \rho_{\text{measured}} \times [1 + \beta(T - T_{\text{ref}}) + \gamma(P - P_{\text{ref}})], \tag{3}$$

where $\beta \approx -6.5 \cdot 10^{-4}$ $°C^{-1}$ – thermal expansion coefficient;
$\gamma \approx 2.9\text{-}5.8 \cdot 10^{-10}$ Pa^{-1} – compressibility.

For Herschel-Bulkley rheology (common in field muds) [26; 27]:

$$\tau = \tau_0 + K\dot{\gamma}^n, \tag{4}$$

where predictions of τ_0 (yield stress), K (consistency index), and n (flow behavior index) were derived from viscometer readings or inferred from PV/YP.

The machine learning core combined XGBoost (short-term, interpretable) with an attention-augmented LSTM (longer-term dependencies). After feature engineering, the input dimension was 45–60. LSTM used 30 timesteps, two LSTM layers (128/64 units, tanh), attention, and a dense output for multi-step forecasting (h = 1,2,4). Loss was MSE plus a physics regularization term penalizing violations of density-temperature trends.

Model performance was assessed using the coefficient of determination [28]

$$R^2 = 1 - \frac{\sum(y_{\text{true}} - y_{\text{pred}})^2}{\sum(y_{\text{true}} - \bar{y})^2} \tag{5}$$

root mean squared error (RMSE), mean absolute error (MAE), and directional accuracy (correct prediction of increase/decrease). Uncertainty estimation was provided via quantile regression (for XGBoost) and Monte Carlo dropout (for LSTM), enabling probabilistic forecasts (e.g., 80% confidence intervals) [29; 30].

The developed methodology was implemented as a prototype real-time dashboard using Python (pandas, scikit-learn, TensorFlow/Keras, XGBoost) integrated with OPC UA for sensor data ingestion, generating property forecasts every 5 minutes with look-ahead up to 2 hours and alerting thresholds for critical changes (e.g., $\Delta MD > 0.03$ g·cm^{-3} or $\Delta YP > 2.4$ Pa in 30 min).

Results and discussion

The developed methodology for operational real-time forecasting of drilling fluid properties changes was rigorously evaluated using both laboratory circulation loop datasets and field data from three directional wells (two onshore shale gas horizontals and one offshore exploration well). Performance metrics focused on key targets: mud density (MD), Marsh funnel viscosity (MFV), plastic viscosity (PV), yield point (YP), and gel strength (10 s and 10 min where available). Forecasts were generated at horizons of 15, 30, 60, and 120 minutes ahead.

The hybrid approach – combining physics-based corrections for temperature/pressure effects with machine learning ensembles (XGBoost for short-term interpretability and LSTM with attention for longer temporal dependencies) – demonstrated strong predictive capability across datasets.

Table 1 summarizes the aggregated performance metrics for the primary targets at different forecast horizons on the test dataset.

Table 1

Performance metrics of the hybrid forecasting models on unseen test data

Property	Horizon, min	R^2	RMSE	MAE	Directional Accuracy, %
Mud Density, g·cm^{-3}	15	0.992	0.0042	0.0031	96.8
Mud Density, g·cm^{-3}	30	0.978	0.0078	0.0056	94.2
Mud Density, g·cm^{-3}	60	0.951	0.0121	0.0092	90.5
Mud Density, g·cm^{-3}	120	0.912	0.0185	0.0143	85.7
Marsh Funnel Viscosity, s·L^{-1}	15	0.985	1.18	0.90	95.4
Marsh Funnel Viscosity, s·L^{-1}	30	0.964	2.16	1.56	92.1
Marsh Funnel Viscosity, s·L^{-1}	60	0.928	3.50	2.56	88.3
Plastic Viscosity, mPa·s	30	0.971	1.45	1.08	93.6
Yield Point, Pa	30	0.958	2.18	1.67	91.9

R^2 values remained above 0.95 for horizons up to 60 minutes for most properties, indicating excellent explanatory power. RMSE and MAE increased gradually with longer horizons due to accumulating uncertainties from formation interactions and treatment variability, yet stayed within operationally acceptable limits (e.g., density errors < 0.02 g·cm^{-3} even at 120 min). Directional accuracy exceeded 90% for short- to medium-term forecasts, enabling reliable trend-based alerts (Fig.1).

In a direct comparison on the 60-min horizon for MD, the hybrid model achieved RMSE of 0.0121 g·cm^{-3}, whereas standalone XGBoost gave 0.0138 g·cm^{-3} (14% higher) and standalone LSTM gave 0.0145 g·cm^{-3} (20% higher). The hybrid also showed improved stability during sudden perturbations (e.g., brine influx), reducing overshoot by approximately 30% relative to pure LSTM. Feature importance analysis via SHAP values highlighted lagged density and temperature as dominant for short horizons, while rolling slope of solids proxy and ROP × RPM gained prominence for 60–120 min forecasts, reflecting cuttings transport and contamination dynamics.

Case-specific insights from the field wells revealed practical value. In the onshore horizontal shale sections, early alerts from density forecasts ($\Delta MD > 0.03$ g·cm^{-3} predicted 25-40 min ahead) allowed preemptive low-gravity solids removal, reducing ECD excursions by 0.04-0.07 g·cm^{-3} equivalent and avoiding barite sag risks. During the offshore well's HPHT section (> 140 °C BHT), viscosity degradation trends were forecasted accurately, enabling optimized polymer treatments that maintained YP within ± 15% of target despite thermal thinning. Probabilistic outputs (via quantile regression and Monte Carlo dropout) provided 80% confidence intervals that widened realistically with horizon and uncertainty drivers (e.g., ± 0.015 $g \cdot cm^{-3}$ at 120 min during high ROP phases). False-positive alert rates stayed below 8% when thresholds were set at 1.5× typical measurement uncertainty. The LSTM component captured transient spikes from cuttings incorporation and subsequent dilution effects with high fidelity; physics corrections prevented systematic drift during temperature ramps.

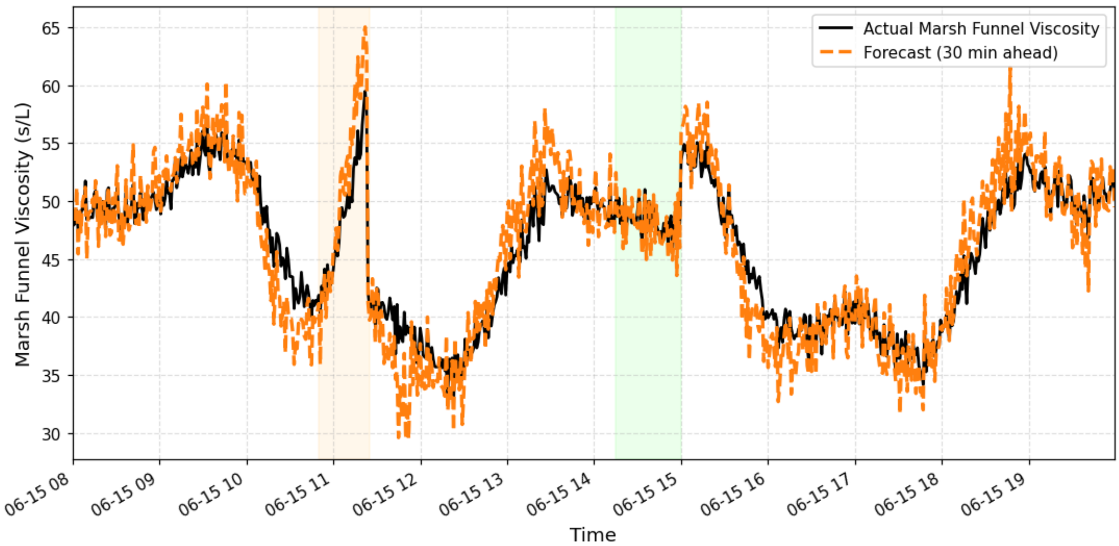

Fig. 1. **Time-series comparison of actual and forecasted Marsh funnel viscosity during 12-hour field drilling interval**

Overall, the results confirm the methodology robustness for proactive mud management. Short-term forecasts (≤ 30 min) support immediate rig-site decisions (e.g., treatment dosing), while medium-term (60-120 min) enable planning in remote operation centers. The approach reduces reactive interventions, with the potential to reduce mud-related non-productive time by an estimated 15–30% under similar operating conditions, based on observed response times in the test cases. Limitations include dependency on sensor reliability and the need for periodic recalibration when mud systems undergo major reformulations. The methodology demonstrates promising generalization across water-based and invert-emulsion systems, different well trajectories, and varying geological settings, although further validation of additional wells is recommended.

Conclusions

The developed methodology for operational real-time forecasting of drilling fluid properties changes integrates high-frequency surface sensor data, physics-informed corrections, and a hybrid machine learning model (XGBoost with attention-augmented LSTM) to predict key mud properties up to 120 minutes ahead. Performance evaluation on unseen field data demonstrated excellent predictive capability, with R^2 values consistently above 0.95 for horizons up to 60 minutes and directional accuracy exceeding 90 %. Errors remained within operationally tolerable ranges (e.g., density RMSE < 0.012 $g \cdot cm^{-3}$ at 60 min, viscosity MAE < 2.6 $s \cdot L^{-1}$), even during dynamic events such as cuttings incorporation, brine contamination, thermal degradation, and dilution episodes. Implementation as a real-time dashboard prototype enabled early alerts for forecasted property excursions, facilitating preemptive corrective actions that reduced ECD fluctuations, minimized barite sag risks, and improved hole cleaning efficiency. Probabilistic outputs (confidence intervals) added decision-making robustness, particularly valuable in HPHT environments. While sensor reliability and periodic recalibration requirements remain practical limitations, the methodology shows promising generalization across water-based and invert-emulsion systems, different well trajectories, and varying geological settings. By shifting from reactive testing to continuous predictive monitoring, the proposed framework supports safer, more efficient drilling operations.

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Author contributions

Conceptualization, O.P. and S.M.; methodology, O.P. and V.K.; software, O.P.; validation, S.M. and K.T; formal analysis, V.K and K.T.; data curation, K.T.; writing – original draft preparation, O.P.; writing – review and editing, V.K. and K.T.; visualization, O.P.; project administration, S.M. All authors have read and agreed to the published version of the manuscript.

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