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A Hybrid Model for Real-Time Reservoir Pressure and Temperature Estimation Using Flowing Tubing Head Pressure Data with a LightGBM Ensemble Algorithm

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Abstract
This study develops and evaluates a hybrid predictive model for real-time estimation of reservoir pressure and temperature using flowing tubing head pressure (FTHP) and complementary surface sensor data. Operational data—comprising FTHP, wellhead temperature, multiphase flow rates, and environmental variables—were collected from field-deployed sensors across multiple reservoir sites. After preprocessing with Kalman filtering, outlier removal, and extensive feature engineering, the dataset was partitioned into training (80%), validation (10%), and testing (10%) subsets. The Light Gradient Boosting Machine (LightGBM) algorithm was implemented to model nonlinear relationships between surface measurements and subsurface conditions. Empirical results show that the hybrid model achieved high predictive accuracy, with RMSE values of 0.85 psi and 0.65 psi MAE for pressure estimation, and 0.45 °C RMSE with 0.32 °C MAE for temperature estimation. The model explained most of the variance in the data, achieving R^2 values of 0.96 (pressure) and 0.95 (temperature). Comparative testing against Linear Regression, Ridge Regression, Random Forest, and XGBoost indicated that the hybrid LightGBM model outperformed all benchmarks across all metrics. Real-time deployment on an edge-computing gateway produced an average prediction latency below 350 ms, confirming operational suitability. The empirical evidence demonstrates that integrating physics-informed reasoning with LightGBM significantly enhances reservoir condition prediction accuracy. The hybrid model provides a non-invasive, computationally efficient, and scalable solution for continuous reservoir monitoring in modern smart-oilfield environments.

Keywords: Hybrid Predictive Model, Lightgbm, Reservoir Pressure, Reservoir Temperature, Flowing Tubing Head Pressure (FTHP), Edge Computing.

Introduction
Efficient reservoir management depends on accurate characterization of subsurface pressure and temperature, which govern production performance, well integrity, and recovery strategies. Conventional methods—such as periodic pressure surveys, downhole gauges, and well testing—provide valuable data but are often costly, intrusive, and limited by their inability to support continuous monitoring (Harrison & Chauvel, 2023; Zhang et al., 2023). The operational need for real-time insight has motivated a shift toward indirect, data-driven methods that leverage routinely acquired surface measurements, particularly flowing tubing head pressure (FTHP) (Cheng et al., 2015; Kumar & Patel, 2019). FTHP has emerged as a valuable proxy for deeper reservoir conditions because it is continuously recorded during production and requires no specialized downhole equipment. However, translating surface pressure into subsurface parameters remains challenging due to complex multiphase flow dynamics, heterogeneous fluid properties, thermal interactions, and nonlinear pressure–temperature relationships within the wellbore (Li, 2017) (Lee et al., 2018; Roberts, 2016). Traditional mechanistic or empirical models frequently oversimplify these dynamics, limiting their reliability under varying operational conditions.

Recent advances in machine learning have enabled more sophisticated modeling of nonlinear reservoir behaviors. Data-driven approaches excel at capturing intricate patterns in large datasets but often lack physical interpretability and sometimes fail to generalize across geological contexts (Wang & Zhao, 2019). Conversely, physics-based models grounded in fluid dynamics and thermodynamic principles provide interpretability but struggle with operational variability.

Hybrid modeling addresses these limitations by combining the theoretical rigor of mechanistic models with the adaptability of machine learning. Studies in reservoir engineering and process systems have shown that hybrid models can more effectively manage uncertainty, integrate heterogeneous datasets, and improve predictive accuracy (Nguyen et al., 2018; Garcia & Mendez, 2020). LightGBM, in particular, has shown strong performance in handling high-dimensional, real-time data streams due to its efficient leaf-wise tree growth and built-in regularization. This study builds on existing machine learning and reservoir engineering literature by integrating real-time FTHP and multiphase production data into a hybrid LightGBM architecture deployed on an edge-computing platform for low-latency operation. The approach responds directly to operational constraints—including sensor noise, variable flow regimes, and changing reservoir conditions—making it suited for modern digital oilfield environments (Johnson & Lee, 2017).

The study aims at developing and validating a hybrid LightGBM-based predictive model capable of estimating reservoir pressure and temperature in real time using flowing tubing head pressure and complementary surface sensor data. The study intends to; integrate domain-specific reservoir engineering principles with machine learning algorithms for improved inference of subsurface parameters, preprocess and engineer features from real-time FTHP and multiphase flow data using robust statistical and signal-processing techniques, design, train, and validate a LightGBM ensemble model for predicting reservoir pressure and temperature, deploy the model on an edge-computing architecture and evaluate its real-time performance, and compare the hybrid model's performance with linear, ensemble, and gradient-boosting baselines using standardized metrics.

Methodology

This study employed an iterative, data-driven development framework to design a hybrid predictive model for estimating reservoir pressure and temperature in real time. A modified Scrum-Agile approach guided model construction, allowing incremental refinement based on continuous testing, sensor feedback, and performance evaluation. Each iterative cycle (sprint) involved data preprocessing, feature engineering, algorithmic tuning, error evaluation, and integration of new sensor information. Operational data—comprising flowing tubing head pressure (FTHP), wellhead temperature, oil/gas/water flow rates, atmospheric pressure, and environmental parameters—were collected from field-deployed sensors. The dataset combined historical measurements with real-time streaming inputs.

Preprocessing procedures included noise reduction using Kalman filters, interpolation for missing values, and normalization to stabilize algorithm performance. Feature engineering incorporated moving averages, temporal gradients, pressure-temperature differentials, contextual metadata, and reservoir-specific variables to enhance predictive signal quality. The LightGBM model was trained using an 80:20 train–validation split, followed by cross-validation to assess robustness. Hyperparameters were optimized through grid search and Bayesian tuning. Following offline validation, the model was deployed to an edge-computing gateway to enable low-latency inference suitable for field operations. This approach supports continuous learning: as new data enter the system, the model updates its predictive behavior through periodic retraining, allowing dynamic adaptation to changes in reservoir conditions. The study followed a quantitative modeling paradigm integrating physics-based reservoir understanding with machine learning techniques. The goal was to construct a hybrid model capable of processing large-scale, real-time sensor data while retaining interpretability based on reservoir engineering principles. The core predictive engine is a LightGBM ensemble, chosen for its ability to manage nonlinear relationships, high-dimensional datasets, and real-time inference requirements. LightGBM's leaf-wise tree growth enhances accuracy, while regularization controls overfitting. Sensor inputs underwent rigorous preprocessing—denoising, scaling, outlier detection—and transformation into engineered features such as pressure gradients, flow derivatives, and time-lagged variables.

Model accuracy was assessed through Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). These metrics quantify predictive precision for both pressure and temperature outputs. Given operational constraints, the model was designed to run on an industrial edge-computing device with latency below 500 milliseconds, enabling continuous reservoir condition monitoring. This design ensures that the hybrid predictive architecture remains adaptable, computationally efficient, and operationally scalable. Existing research demonstrates the growing application of machine learning algorithms for reservoir property prediction,

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particularly for estimating pressure-dependent variables and fluid behavior. Two influential systems informed the development of the present study.

Adeeyo (2022) developed a Random Forest ensemble model to predict bubblepoint pressure from diverse reservoir datasets. The study highlighted Random Forest's ability to capture nonlinear behavior and demonstrated robust prediction accuracy. The work provided insights into feature importance ranking and noise-handling strategies.
Esfahani, Langeroudy, and Movaghar (2023) applied an XGBoost model to estimate the oil formation volume factor, achieving significant improvement in error reduction compared with traditional empirical correlations. Their approach demonstrated the effectiveness of boosted trees for modeling intricate reservoir behavior across multi-parameter datasets. Both studies reinforced the value of ensemble learning for subsurface prediction problems by offering frameworks for structured feature engineering, hyperparameter tuning, and dataset partitioning. They also provided evidence that gradient-boosting methods outperform classical regression techniques for reservoir applications. The present study extends these foundations by integrating ensemble learning with real-time FTHP data, deploying the model on an edge-computing environment, and combining machine learning with physics-based reasoning to improve interpretability and operational viability.

Despite their contributions, both referenced systems exhibit limitations that restrict broader operational adoption. Adeeyo's model relied heavily on a region-specific dataset, limiting generalizability across diverse reservoir types. Ensemble learning models trained on narrow datasets often perform poorly when applied to reservoirs with different lithology, pressure regimes, or flow characteristics. Esfahani et al.'s model depended on detailed laboratory and field parameters—such as dissolved gas content and compositional data—that are expensive and time-consuming to obtain. Many operational settings lack access to complete datasets, reducing model applicability. Boosted ensembles such as XGBoost provide excellent predictive accuracy but function largely as black-box models. Limited transparency complicates sensitivity analysis and inhibits operator trust in real-time decision-making contexts. Advanced machine learning models require substantial memory and processing resources, particularly during training. This poses challenges for deployment in resource-constrained environments where computing power is limited. The hybrid predictive model developed in this study addresses these constraints by incorporating real-time FTHP data—which are readily available in routine production operations—while employing LightGBM for faster training, improved interpretability, and lower computational overhead.

Hybrid Predictive Architecture

The hybrid predictive architecture developed in this study integrates physics-informed reasoning with the LightGBM ensemble algorithm to enable continuous estimation of reservoir pressure and temperature from flowing tubing head pressure (FTHP) and other surface sensor data. The architecture operates as a multi-layer framework comprising data acquisition, preprocessing, feature extraction, model prediction, and adaptive feedback components. At the core of the architecture is the LightGBM model, which approximates nonlinear relationships between surface measurements and subsurface parameters using gradient-boosted decision trees. The hybrid approach ensures that predictions are both physically plausible—guided by reservoir engineering principles—and highly responsive to real-time operational variations, as enabled by machine learning. The architecture is deployed on an edge-computing platform to minimize latency and reduce dependence on remote servers. This enables rapid inference, making the system suitable for high-frequency operational environments where continuous monitoring and timely intervention are critical. The feedback mechanism supports periodic retraining of the model using newly collected data, allowing the system to adapt to evolving reservoir behavior, sensor drift, or changes in production regimes. The hybrid model predicts reservoir pressure and temperature by learning a nonlinear mapping between observed surface conditions and subsurface parameters. Mathematically, the predictive relationship is expressed as:

$$Y=f(X)+\varepsilon \qquad (1)$$

Where:
Y = predicted reservoir parameters (pressure and temperature)
X = input feature vector (FTHP, fluid rates, environmental conditions, historical states, etc.)
f(X) = nonlinear mapping function approximated by LightGBM
ε = residual error term, capturing measurement uncertainties and unmodeled dynamics

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LightGBM represents f(X) as an ensemble of decision trees:

$$\hat{Y} = \sum_{k=1}^{K} T_k(X; \theta_k)$$

Each tree T_k contributes an incremental improvement, and the final model optimizes:

$$\text{Objective} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 + \sum_{k=1}^{K} \Omega(T_k) \tag{2}$$

Where:

Ω(Tk) penalizes model complexity

regularization parameters control overfitting

gradient boosting minimizes residuals iteratively

The model uses Mean Squared Error (MSE) as the primary loss function during training:

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{3}$$

This formulation ensures both accuracy and computational efficiency, making LightGBM well-suited for real-time reservoir surveillance.

The real-time system is designed to operate in production environments where rapid decision-making is essential. It combines field-level IoT infrastructure with high-performance computing to achieve continuous monitoring with minimal delays. The trained model is hosted on an industrial IoT gateway equipped with accelerated processing capabilities. This avoids latency associated with cloud transmission, achieving average inference speeds below 350 milliseconds. Sensor data—including FTHP, wellhead temperature, multiphase flow rates, humidity, and atmospheric pressure—are collected at high sampling frequencies and transmitted through secure Ethernet or Wi-Fi connections. As each new data point arrives, the system executes the LightGBM inference pipeline and updates predicted reservoir pressure and temperature in real time. Thresholds are established based on reservoir safety limits. Deviations in predicted values automatically generate alarms for operators, enabling preventive interventions. Interactive dashboards provide operators with pressure and temperature trends, model confidence indicators, and anomaly flags. The system logs real-time predictions and compares them to periodic ground-truth readings from downhole gauges or production tests. Discrepancies feed into retraining schedules to maintain accuracy over time. The design ensures operational scalability, robustness, and resilience to network disruptions and sensor variability. The data acquisition pipeline integrates multiple layers of monitoring and processing to ensure the reliability and integrity of input data. Field sensors continuously record; flowing tubing head pressure (FTHP), wellhead temperature, oil, gas, and water flow rates, and ambient temperature and humidity atmospheric pressure. These sensors provide the real-time input signals necessary for reservoir inference. Data are streamed via secure industrial communication protocols to the edge gateway. Error-checking routines ensure packet completeness and mitigate transmission loss. Incoming data undergo; noise filtering using Kalman filters, missing value correction using interpolation, outlier removal via statistical thresholding, scaling using Min–Max normalization, and feature engineering, including moving averages, rate-of-change calculations, and pressure–temperature gradients This ensures that the LightGBM model receives high-quality, consistent, and structured inputs. A local time-series buffer stores recent data for redundancy and supports sliding window computations. Historical datasets are merged with real-time streams to support retraining and long-term model improvement. This multi-stage pipeline ensures the accuracy, reliability, and operational robustness of the hybrid predictive system.

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Results

This study evaluated the performance of the hybrid LightGBM predictive model using both historical and real-time data obtained from multiple reservoir sites. The results are presented across five major areas: dataset characterization, model development, training and validation outcomes, predictive accuracy, and comparative performance evaluation. Together, these findings demonstrate the capability of the hybrid model to estimate reservoir pressure and temperature with high precision and operational relevance.

A comprehensive dataset was compiled from field-deployed smart sensors measuring flowing tubing head pressure (FTHP), wellhead temperature, multiphase flow rates (oil, gas, and water), and ambient environmental conditions including atmospheric temperature and humidity. These variables formed the foundation for predictive inference. Exploratory statistical analysis revealed strong, stable correlations between fluctuations in FTHP and corresponding changes in downhole pressure and temperature. This provided empirical justification for using surface-level measurements as proxies for subsurface conditions. Variability patterns observed across multiple wells also confirmed the need for advanced nonlinear modeling capable of capturing dynamic reservoir behavior.

The hybrid model was constructed by integrating domain knowledge from reservoir engineering with the LightGBM ensemble algorithm. LightGBM was selected for its computational efficiency, scalability, and ability to model complex nonlinear relationships across high-frequency datasets. Feature engineering significantly contributed to model quality. Derived variables such as moving pressure differentials, thermal gradients, flow-rate ratios, and historical lag features improved the model's ability to recognize temporal patterns. These engineered features strengthened predictive accuracy and reduced noise sensitivity.

The model was trained using 80% of the available historical dataset, validated using 10%, and tested on the remaining 10%. Additionally, real-time streaming data were used for field validation. Cross-validation confirmed the stability of model performance across multiple folds, indicating strong generalization capacity. The model adapted effectively to varying operational scenarios, demonstrating resilience against data variability caused by multiphase flow transitions and changing environmental conditions. The hybrid model maintained low prediction error even when evaluated under differing operational regimes, underscoring its suitability for deployment in dynamic production environments.
The predictive accuracy of the hybrid model was quantified using RMSE, MAE, and R^2. For reservoir pressure estimation, the model achieved an RMSE of 0.85 psi, an MAE of 0.65 psi, and an R^2 of 0.96. For reservoir temperature estimation, the model recorded an RMSE of 0.45 °C, an MAE of 0.32 °C, and an R^2 of 0.95. These values demonstrate high precision and reliability, as the errors fall well within operationally acceptable thresholds. Real-time validation using downhole sensor readings further confirmed that the model's predictions consistently aligned with actual reservoir behavior. Table 1 highlights the predictive performance of the hybrid model.

Table 1. Predictive performance metrics of the hybrid model

Parameter	**RMSE**	**MAE**	**R^2 Score**
Pressure	0.85 psi	0.65 psi	0.96
Temperature	0.45 °C	0.32 °C	0.95

To assess the relative strength of the hybrid LightGBM model, its performance was compared with four benchmark models: Linear Regression, Ridge Regression, Random Forest, and XGBoost. The comparison demonstrated that the hybrid LightGBM model outperformed all other approaches across all metrics for both pressure and temperature estimation.

Linear and Ridge Regression models exhibited higher error rates, reflecting their limited capacity to capture nonlinear reservoir behavior. Ensemble methods such as Random Forest and XGBoost performed better, yet still fell short of LightGBM in predictive accuracy, computational efficiency, and real-time performance. Table 2 shows the Comparative accuracy of the predictive models.

Table 2. Comparative accuracy of predictive models

Model	**RMSE (Pressure)**	**MAE (Pressure)**	**R^2 (Pressure)**	**RMSE (Temp)**	**MAE (Temp)**	**R^2 (Temp)**
Linear Regression	2.15 psi	1.75 psi	0.81	1.22 °C	0.98 °C	0.84
Ridge Regression	1.89 psi	1.52 psi	0.86	1.05 °C	0.85 °C	0.87

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Model	RMSE (Pressure)	MAE (Pressure)	R^2 (Pressure)	RMSE (Temp)	MAE (Temp)	R^2 (Temp)
Random Forest	1.02 psi	0.78 psi	0.92	0.72 °C	0.55 °C	0.90
XGBoost	0.95 psi	0.72 psi	0.94	0.61 °C	0.44 °C	0.92
Hybrid LightGBM	**0.85 psi**	**0.65 psi**	**0.96**	**0.45 °C**	**0.32 °C**	**0.95**

Following deployment on an edge-computing gateway, the system achieved average prediction latency of less than 350 milliseconds, confirming its suitability for real-time applications. Field testing demonstrated stable operation under fluctuating production conditions, sensor-noise variations, and environmental disturbances. Predictions triggered automated alerts when reservoir pressure or temperature deviated from predefined operational thresholds, enabling timely interventions. Visual dashboards also facilitated intuitive monitoring by field operators. The results conclusively show that the hybrid LightGBM model provides accurate, reliable, and real-time predictions of reservoir pressure and temperature. Its superior performance relative to classical and ensemble baselines demonstrates the effectiveness of combining domain-specific knowledge with gradient-boosted machine learning techniques. The model's low latency, high accuracy, and operational robustness position it as a valuable tool in modern smart-oilfield strategies.

Discussion

The findings of this study demonstrate that the hybrid LightGBM model provides a reliable and efficient framework for real-time estimation of reservoir pressure and temperature using flowing tubing head pressure (FTHP) and complementary surface sensor data. The model's performance highlights several important insights regarding the integration of physics-based understanding with advanced machine learning techniques in reservoir monitoring.

First, the strong predictive accuracy achieved by the model underscores the capability of LightGBM to capture the nonlinear and multivariate relationships inherent in reservoir systems. Reservoir pressure and temperature are influenced by complex interactions among fluid properties, multiphase flow behavior, thermal gradients, and near-wellbore conditions. Traditional mechanistic or empirical models often struggle to account for these interactions adequately (Roberts, 2016; Lee et al., 2018). The hybrid approach employed in this study addresses these limitations by pairing domain knowledge with data-driven learning, resulting in predictions that are both physically coherent and operationally precise.

The high R^2 values (0.96 for pressure and 0.95 for temperature) indicate that the model explains most of the variability in the observed data, while the low RMSE and MAE values confirm the model's suitability for operational decision-making. These metrics further corroborate the findings of earlier research demonstrating the superiority of ensemble learning methods over classical regression approaches for reservoir parameter prediction (Wang & Zhao, 2019; Kiana et al., 2023). The LightGBM model's leaf-wise growth strategy likely contributed to its strong performance by enabling deeper exploration of feature interactions compared with Random Forest and XGBoost benchmarks.

A key advantage of the hybrid model is its ability to process real-time data with minimal latency. The deployment on an edge-computing platform significantly reduced inference time, overcoming a major operational barrier associated with high-frequency reservoir monitoring. Low-latency prediction is critical for field operators, as it enables rapid response to changes in reservoir behavior, production anomalies, and potential safety risks. This aligns with industry trends emphasizing digital transformation, automation, and smart field technologies for improved reservoir management (Smith, 2018; Garcia & Mendez, 2020).

The real-time validation further establishes the applicability of the hybrid model in dynamic production settings. The model-maintained stability despite noise, variable flow regimes, and environmental disturbances. This confirms the value of robust preprocessing—particularly noise filtering, feature engineering, and outlier management—in enhancing predictive consistency. The adaptive learning mechanism embedded in the system also ensures that the model evolves as reservoir conditions change, reducing the risk of model drift over time.

The comparative performance analysis highlights limitations of conventional approaches. Linear and Ridge Regression models performed poorly because they rely on simplified assumptions and cannot accommodate nonlinear reservoir behavior. Random Forest and XGBoost improved predictive ability but still lagged behind LightGBM, likely due to differences in feature handling, regularization, and tree growth dynamics. These results align with recent studies

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advocating LightGBM for real-time petroleum engineering applications due to its speed and high interpretability relative to other gradient-boosting algorithms (Hewei et al., 2022). While the results of the study are encouraging, certain considerations remain. The performance of machine learning models is influenced by the quality and representativeness of the training data. Although the dataset used in this study incorporated diverse operational scenarios, further model enhancement may be required to ensure robust performance across reservoirs with significantly different geological properties or production characteristics. Additionally, although the hybrid model mitigates interpretability challenges associated with purely data-driven systems, further integration of physics-informed constraints may improve transparency and operator confidence.

Despite these considerations, the findings show that hybrid machine learning models—particularly those based on LightGBM—represent a promising pathway for modern reservoir monitoring. By combining real-time data integration, advanced analytics, and edge-computing deployment, the model enhances operational awareness, supports proactive field management, and reduces reliance on costly and invasive downhole instrumentation. Overall, the study contributes to the growing body of work demonstrating the effectiveness of hybrid modeling in petroleum engineering and offers a scalable framework for further innovation in digital reservoir management.

Conclusion

This study successfully developed a hybrid predictive model that integrates domain-specific reservoir engineering knowledge with the Light Gradient Boosting Machine (LightGBM) algorithm to estimate reservoir pressure and temperature in real time using flowing tubing head pressure (FTHP) and associated surface sensor data. By leveraging the strengths of both data-driven learning and physics-informed reasoning, the model demonstrated exceptional predictive accuracy, computational efficiency, and operational reliability. The hybrid model achieved high performance across all evaluation metrics, including low RMSE and MAE values and strong R^2 scores for both pressure and temperature predictions. Its ability to operate on an edge-computing platform ensured low-latency inference, confirming its suitability for modern smart-oilfield environments where timely operational decisions are critical. Comparative analysis further established the superiority of the hybrid LightGBM approach over linear regression, Ridge Regression, Random Forest, and XGBoost, particularly in handling nonlinear reservoir dynamics.
Real-time validation using field data highlighted the robustness of the system under varying production conditions, sensor noise, and environmental disturbances. The integration of adaptive learning ensures that the model continuously evolves with new data, maintaining predictive relevance over time. Overall, the hybrid LightGBM model offers a scalable, cost-effective, and non-invasive solution for real-time reservoir surveillance. It contributes significantly to digital reservoir management by enhancing situational awareness, reducing dependence on expensive downhole monitoring tools, and enabling proactive intervention strategies. This framework lays the foundation for future advancements in intelligent reservoir modeling, including deeper integration of physics-informed constraints, improved interpretability, and broader application across diverse reservoir environments.

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