Analysis of Machine Learning Models for Predicting Test Rack Opening (TRO) Pressure for Gas Lift Systems

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Abstract: Accurate prediction of Test Rack Opening (TRO) pressure is essential for the optimal design and calibration of gas lift valves, directly affecting unloading stability, gas injection efficiency, and overall production performance. Traditional approaches relying on force-balance equations and iterative test-rack calibrations are often constrained by simplifying assumptions and sensitivity to operational variability. This study develops and benchmarks nineteen (19) machine learning models to predict TRO pressure using a field dataset comprising 328 valves from 20 wells. A rigorous workflow encompassing data cleaning, feature engineering, multicollinearity reduction, and systematic validation was implemented. Seventeen input parameters, including dome pressure, fluid gradients, and well depth measurements, were evaluated. Among the algorithms tested; including linear models, support vector regression, ensemble methods (Random Forest, Gradient Boosting, XGBoost, LightGBM, CatBoost), and neural networks. The Random Forest Regressor exhibited the best performance, achieving a test R^2 of 0.7437 and an Average Absolute Relative Error (AARE) of 8.87%. Feature importance analysis revealed Measured Depth, Dome Pressure, and Unloadable Gradient as the primary predictors, consistent with the physical mechanics of gas-lift systems. Time-series models (ARIMA, Prophet) performed poorly ($R^2 < 0.03$), confirming that TRO pressure is inherently a static design parameter rather than a dynamic variable. The proposed predictive framework minimizes reliance on repetitive physical calibration, enables rapid design iterations, and provides interpretable, data-driven insights for optimizing gas-lift systems and improving operational reliability.

Keywords: *Artificial Lift; Gas Lift Valve; Test Rack Opening Pressure; Machine Learning; Predictive Modeling; Random Forest; Feature Importance; Petroleum Engineering.*

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I. INTRODUCTION

The global energy landscape increasingly demands efficient hydrocarbon recovery amid declining reservoir pressures and rising operational costs. Artificial lift systems, particularly gas lift, are indispensable for maintaining and enhancing production, especially in offshore and high gas-oil ratio wells, due to their inherent flexibility and reliability [1]. Gas lift operates by injecting high-pressure gas into the production tubing, reducing the flowing bottom-hole pressure and facilitating fluid movement to the surface [2]. The effectiveness of this system largely depends on the precise performance of gas lift valves, which control gas injection at designated depths.

A critical parameter in valve calibration is the Test Rack Opening (TRO) Pressure, defined as the pressure at which a valve opens under standardized laboratory conditions (60°F, zero tubing pressure) [3]. Accurate TRO prediction is essential for determining optimal valve spacing, ensuring stable well unloading sequences, and maximizing steady-state production efficiency [4]. Traditionally, TRO determination has relied on mechanistic force-balance equations, such as those derived from the Thornhill-Craver formulation, and empirical correlations [5]. However, these conventional approaches often oversimplify complex valve mechanics, neglect temperature–pressure interactions, and are sensitive to manufacturing tolerances and operational variability. Consequently, calibration mismatches, inefficient gas injection patterns, and suboptimal system designs may occur, adversely affecting economic returns [6].

The digital transformation of the petroleum industry has accelerated the adoption of data-driven approaches and predictive analytics. Machine learning (ML), a subset of artificial intelligence, provides a powerful framework for

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identifying complex, nonlinear relationships within large, multivariate datasets that traditional methods may overlook [7]. In recent years, ML applications have expanded across petroleum engineering domains, including reservoir characterization, drilling optimization, production forecasting, and artificial lift management [8], [9]. Ensemble learning methods and hybrid physics-informed ML models, in particular, have demonstrated remarkable success in analogous tasks such as production rate prediction and equipment performance forecasting [10], [11].

Despite these advances, a notable gap exists in the application of ML to directly predict TRO pressure; a parameter central to the initial design and calibration of gas lift valves. Existing research has largely focused on production forecasting [12], injection rate optimization [13], and valve failure detection [14], leaving a lack of systematic investigation into TRO-specific predictive modeling. Furthermore, comparative evaluations of diverse ML algorithms for this regression task remain scarce, limiting guidance for practitioners regarding model selection and expected performance.

This study addresses this gap by conducting a comprehensive analysis of multiple ML models for TRO pressure prediction. Leveraging a curated field dataset, the research objectives are to: (1) preprocess and analyze operational data to identify key predictive features, (2) develop, train, and validate a broad suite of ML algorithms, ranging from linear models to advanced ensemble methods and neural networks, and (3) rigorously evaluate and compare model performance using statistical metrics to identify the most robust and accurate predictive framework. The resulting ML tool provides an interpretable, data-driven solution to enhance gas lift valve calibration, reduce dependence on repetitive physical testing, and support more efficient and reliable artificial lift system design.

II. LITERATURE REVIEW

➢ *Conventional TRO Prediction and its Limitations*

The theoretical foundation for gas lift valve performance has historically relied on force-balance equations and standardized test-rack procedures. The Thornhill-Craver equation, adapted from orifice flow calculations, has become an industry standard for estimating valve throughput [15]. API Recommended Practices 11V5 and 11V6 established formal procedures for testing and calibrating gas-lift valves under controlled conditions [3], [16]. These conventional methods calculate TRO using parameters such as dome charge pressure, bellows effective area, and port size, all based on static force-balance principles [5].

However, significant discrepancies often exceeding 25–30% have been observed between theoretically predicted and actual field-measured valve performance [6], [17]. These deviations arise from inherent limitations of traditional approaches: (1) oversimplification of dynamic valve mechanics, including neglecting bellows stacking, stem friction, and fluid dynamic forces; (2) incomplete accounting for high-temperature and high-pressure effects on nitrogen charge and material properties [18]; and (3) assumptions of ideal gas behavior and isentropic flow, which diverge from actual operational conditions. Altarabulsi and Waltrich [18] demonstrated that ignoring silicone thermal expansion in nitrogen-charged valves under high-pressure, high-temperature conditions can result in TRO calculation errors of 15–25%. Collectively, these limitations highlight the necessity for more robust and adaptable prediction methodologies.

➢ *The Rise of Data-Driven Methods in Petroleum Engineering*

The digital transformation of the oil and gas industry, driven by extensive sensor deployment and real-time data acquisition systems, has created fertile ground for data-driven analytics [19]. Machine learning (ML) has emerged as a transformative tool capable of identifying complex, nonlinear patterns within large, multidimensional datasets. Comprehensive reviews by Tariq et al. [7] and Jo et al. [20] underscore the widespread adoption of ML in upstream petroleum applications, including reservoir characterization, production forecasting, drilling optimization, and equipment failure prediction. Ensemble methods, such as Random Forest and gradient boosting algorithms (XGBoost, LightGBM), are frequently reported as top-performing regression models due to their robustness to noise and ability to capture intricate feature interactions [20], [21].

➢ *Machine Learning Applications in Gas Lift Optimization*

In the context of artificial lift, ML applications have predominantly aimed to optimize production outcomes. Algorithms such as Random Forest, Support Vector Regression (SVR), and Artificial Neural Networks (ANNs) have been employed to predict optimal gas injection rates and forecast well production rates based on operational data [12], [22]. For example, Ma et al. [12] achieved high predictive accuracy ($R^2 > 0.98$) for oil production in gas-lifted wells using Random Forest, identifying key predictors including water cut (BS&W) and choke size. Additional studies have applied ML techniques for gas lift valve failure diagnosis and performance classification [14], [23].

A particularly promising development is the creation of hybrid physics-informed ML models, which integrate fundamental physical principles with data-driven learning. This approach enhances model interpretability and generalization, particularly in data-scarce scenarios [24], [25]. Physics-informed neural networks (PINNs), for instance, enforce governing equations as constraints during model training, producing outputs that are both physically consistent and highly accurate [25].

➢ *Identified Research Gap*

Despite the extensive use of ML in gas lift operations, a focused gap persists: there is limited research applying machine learning specifically to predict Test Rack Opening (TRO) pressure. Most existing studies focus on operational outcomes (e.g., production rates) or high-level system diagnostics, neglecting this fundamental calibration parameter critical to initial valve performance. Moreover, no

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prior study has systematically compared a broad spectrum of ML algorithms for this static, valve-level regression task. Addressing this gap presents an opportunity to streamline gas lift design, reduce calibration costs, and enhance system reliability from the onset. The present study aims to directly address this need.

III. MATERIALS AND METHODS

➢ *Research Design and Data Acquisition*

A structured, data-driven methodology was employed, as illustrated in the proposed framework (Fig. 1). The study utilized a census-based dataset comprising historical gas lift design and calibration records, ensuring relevance to real-world operational conditions. The original dataset contained 392 records with 17 features, collected from 20 wells. Following preprocessing to address missing target values, the final modeling dataset consisted of 328 complete records.

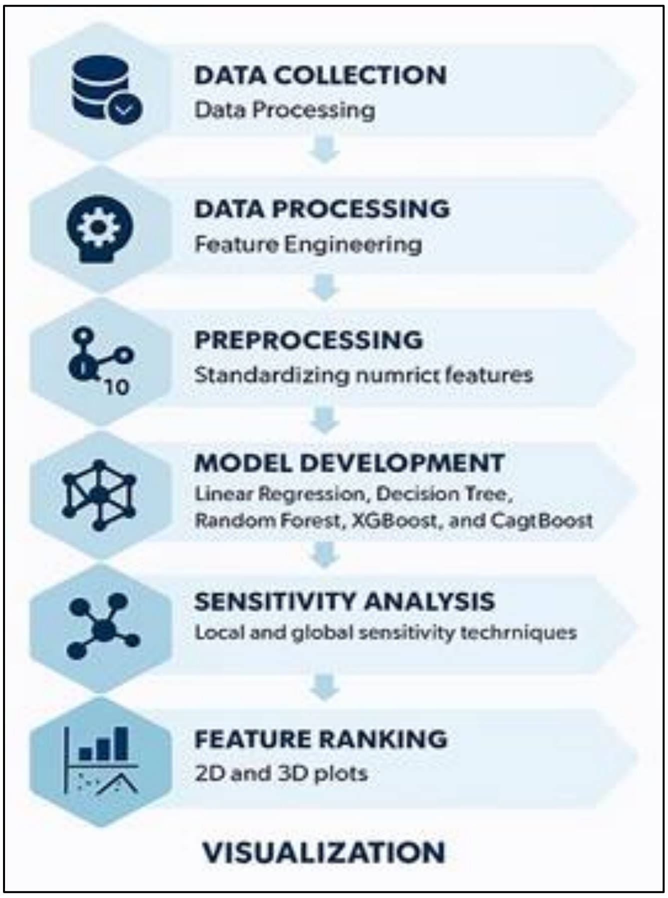

Fig 1 Proposed Data-Driven Modeling Framework for Test Rack Opening (TRO) Pressure Prediction.

Key variables included valve identifiers (Well ID, Valve #, Valve Type), depth measurements (Measured Depth, True Vertical Depth), pressure parameters (Tubing Pressure, Valve Opening/Closing Pressure, Dome Pressure, Casing Head Pressures), fluid characteristics (Unloadable Gradient), and valve specifications (Manufacturer, Type). The target variable was the measured Test Rack Opening (TRO) Pressure.

➢ *Data Preprocessing and Feature Engineering*

A multi-stage preprocessing pipeline was implemented to ensure data quality and model readiness.

- Handling Missing Data: Records with missing TRO values (16.33%) were removed. For missing values in feature columns, numerical variables were imputed with the median, and categorical variables were imputed with the mode (Fig. 2).
- Categorical Encoding: Categorical variables (e.g., Valve Type, Manufacturer) were converted to numerical format using Label Encoding to enable processing by ML algorithms.
- Multicollinearity Analysis and Feature Reduction: Initial correlation analysis revealed severe multicollinearity among several pressure and depth variables (Fig. 3 & 4). Variance Inflation Factor (VIF) analysis confirmed this, with values exceeding 10 for most features. An automated iterative removal process eliminated features with correlation > 0.80 or VIF > 10, prioritizing retention of features exhibiting higher correlation to the target. This resulted in the removal of 9 features (e.g., Valve Opening Pressure, Dome Pressure, True Vertical Depth).
- Engineered Features: A new feature, *Depth_per_Valve*, was created to capture the interaction between well depth and valve count:

$$Depth\_per\_Valve = \frac{Measured\ Depth\ (ft)}{Valve\ \#\ +\ 1}$$

- Final Feature Set and Splitting: The final set of 7 features for modeling was: Valve #, Valve Type, Measured Depth (ft), Unloadable Gradient (psi/ft), Manufacturer, Specification, and Depth_per_Valve. The dataset was randomly split into 80% for training (262 samples) and 20% for hold-out testing (66 samples). All numerical features were standardized using Z-score normalization.

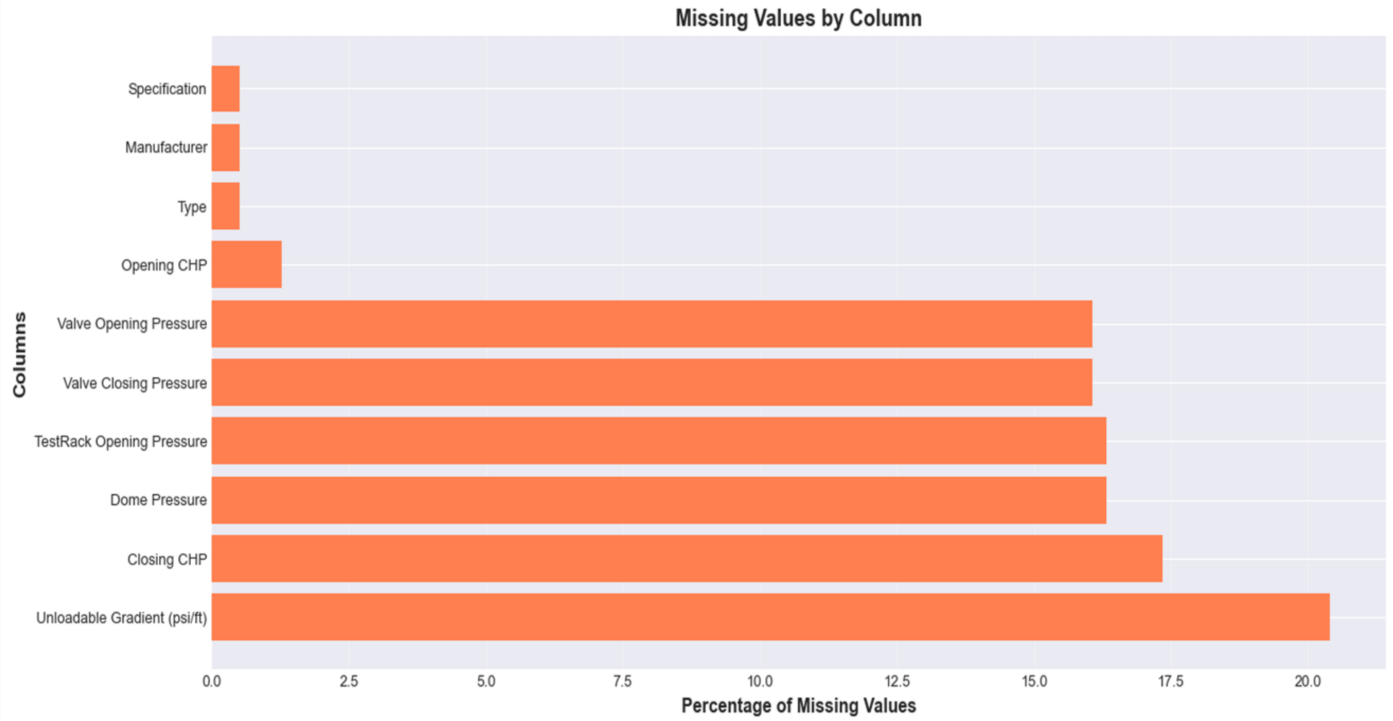

Fig 2 Percentage of Missing Values in the Original Dataset before Preprocessing.

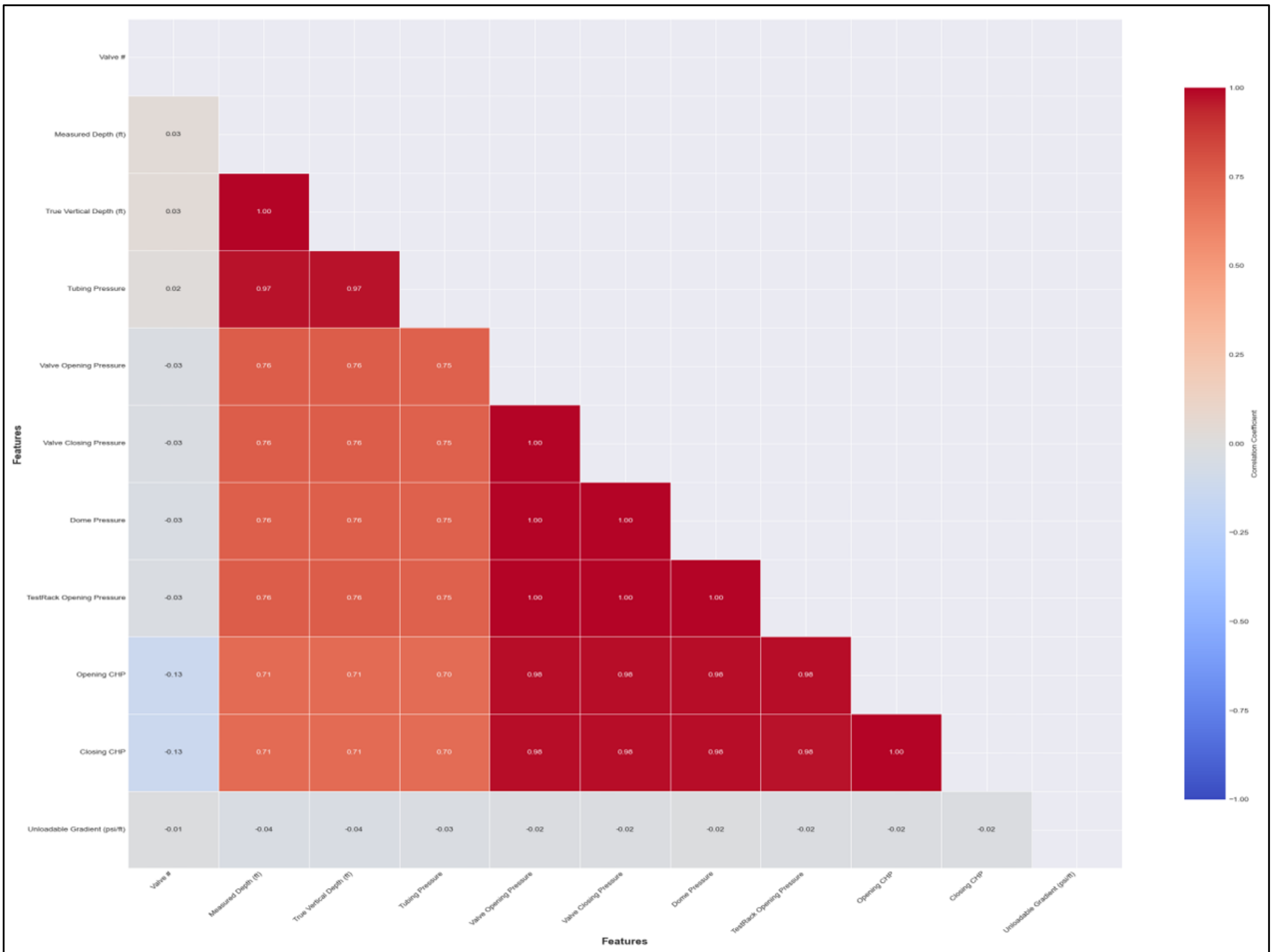

Fig 3 Correlation Matrix Heatmap Showing Strong Linear Relationships (Multicollinearity) Among Original Numerical Features.

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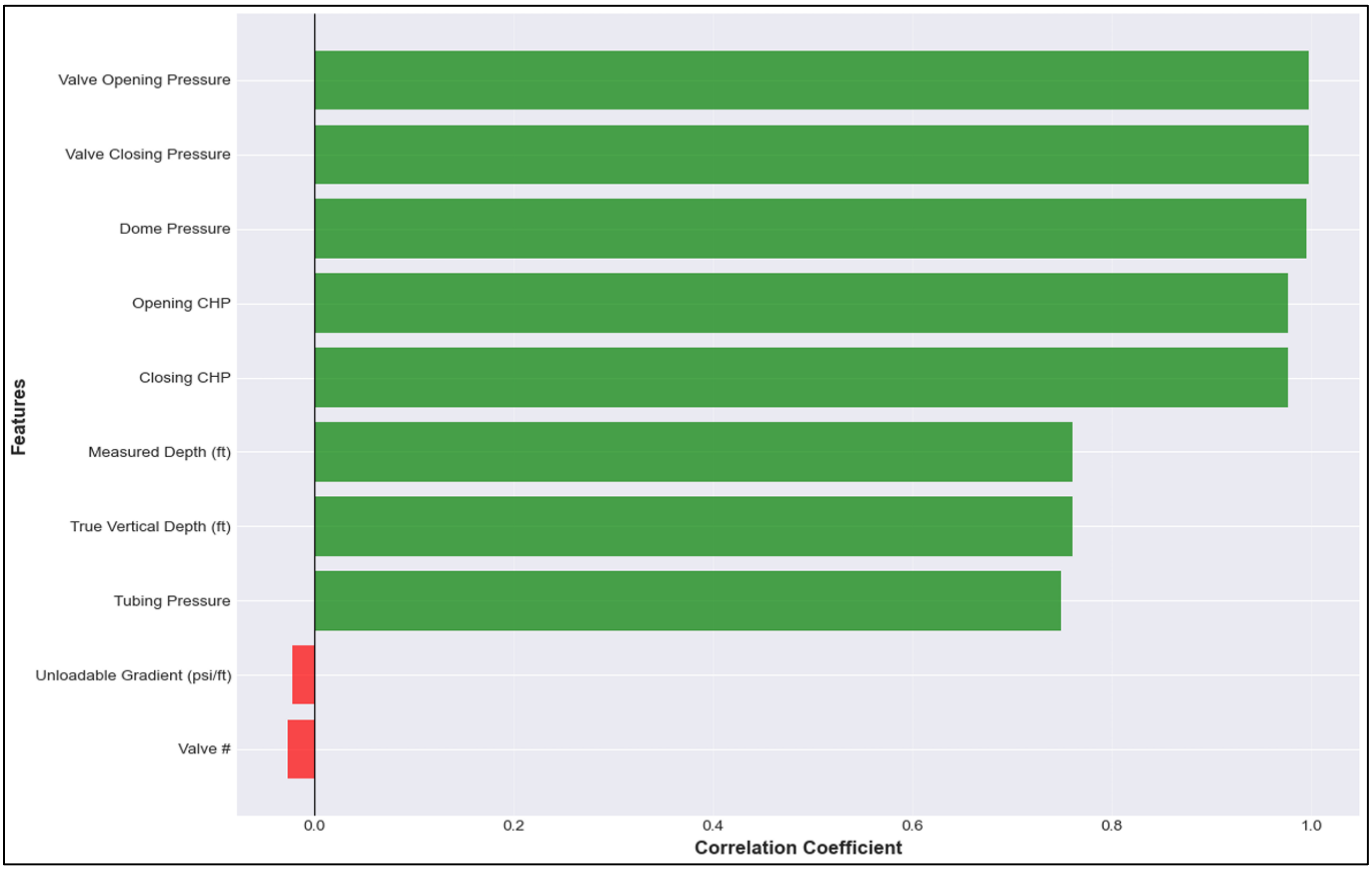

Fig 4 Bar Chart of the Top 15 Features Most Correlated with the Target Variable (Test Rack Opening Pressure).

- *Model Development and Training*

Nineteen machine learning models, spanning diverse algorithmic families, were implemented using Python's scikit-learn, XGBoost, LightGBM, CatBoost, and Keras/TensorFlow libraries (Table 1).

Hyperparameter tuning was performed for the top tree-based models (XGBoost, LightGBM, CatBoost, Random Forest, Decision Tree) using RandomizedSearchCV with 3-fold cross-validation. A final advanced ensemble, Ensemble_Tuned, was constructed by combining the predictions of the five individually tuned models.

- *Model Evaluation Framework*

Model performance was evaluated on an unseen test dataset using a comprehensive suite of statistical accuracy and error metrics to ensure a robust and objective assessment. The coefficient of determination (R^2) was employed to quantify the proportion of variance in Test Rack Opening (TRO) pressure explained by each model, providing an overall measure of goodness-of-fit. Complementing this, the root mean square error (RMSE) was used to capture the dispersion of prediction errors in psi, thereby emphasizing the impact of larger deviations, while the mean absolute error (MAE) quantified the average magnitude of prediction errors without bias toward their direction.

Table 1 Implemented Machine Learning Models and their Descriptions

Model Category	**Specific Models**	**Key Characteristics**
Linear Models	Linear Regression, Lasso Regression (L1)	Baseline models; Lasso performs feature selection via regularization.
Tree-Based Models	Decision Tree Regressor, Random Forest Regressor	Capture non-linear patterns; Random Forest is an ensemble for robustness.
Gradient Boosting	AdaBoost Regressor, Gradient Boosting Regressor, XGBoost, LightGBM, CatBoost	Sequential error correction; advanced implementations for speed and accuracy.
Kernel Method	Support Vector Regressor (SVR) with RBF kernel	Effective for high-dimensional spaces and non-linear relationships.
Neural Networks	Multi-Layer Perceptron (MLP), 1D Convolutional Neural Network (CNN)	Deep learning approaches for complex pattern recognition.
Ensemble Models	Voting Regressor (Ensemble), Voting Regressor with Tuned models (Ensemble_Tuned)	Combine predictions of multiple base models to improve stability and accuracy.

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In addition to absolute error metrics, relative error measures were incorporated to reflect operational relevance and facilitate comparison across different pressure ranges. The average absolute relative error (AARE) was calculated to express prediction errors as a percentage of measured values, offering insight into model reliability from a practical engineering perspective. Similarly, the mean absolute percentage error (MAPE) was used as a normalized metric to further assess relative predictive accuracy, particularly important for evaluating model performance under varying operating conditions.

To examine model stability and generalizability, a 5-fold cross-validation procedure was applied to the training dataset, ensuring that performance outcomes were not dependent on a single random data split. Furthermore, a supplementary time-series forecasting analysis was conducted using ARIMA, Prophet, and selected high-performing machine learning models on a chronologically segmented dataset. This analysis was designed to investigate potential temporal dependencies in the TRO pressure data and to validate whether time-dependent modeling approaches offered any advantage over static regression-based methods.

IV. RESULTS

➢ *Overall Model Performance*

The predictive outcomes of the nineteen developed models on the independent test dataset are presented in Table 2. The results indicate substantial variability in model accuracy, with test R^2 values ranging between 0.5024 and 0.7437.

Table 2 Performance of the Model Trained and Tested

Rank	Model	Test_R²	Test_MSE	Test_RMSE	Test_MAE	Test_AARE
1	Random Forest	0.7436	38859.4464	197.1279	112.5514	8.8729
2	CatBoost	0.7432	—	197.3053	118.1248	9.6736
3	SVR	0.7417	39150.8157	197.8656	127.2089	10.8073
4	RandomForest_Tuned	0.7327	—	201.2909	114.6724	9.0375
5	AdaBoost	0.7303	40875.0469	202.1757	121.3402	9.1945
6	Ensemble_Tuned	0.7285	—	202.8498	122.3402	9.7324
7	CatBoost_Tuned	0.7216	—	205.4443	125.0663	9.9209
8	Gradient Boosting	0.7141	43344.5747	208.1935	109.8054	9.1515
9	Ensemble	0.7086	—	210.1873	118.7507	9.5526
10	Decision Tree	0.7068	44451.3941	210.8349	110.6837	9.0938
11	LightGBM_Tuned	0.7036	—	211.9540	133.2498	10.7899
12	DecisionTree_Tuned	0.7034	—	212.0286	127.5196	10.1409
13	Lasso Regression	0.6888	47178.6155	217.2063	171.1938	15.4783
14	Linear Regression	0.6887	47185.4102	217.2220	171.2144	15.4820
15	XGBoost_Tuned	0.6880	—	217.4793	132.3307	10.7737
16	MLP-ANN	0.6779	48818.8265	220.9498	160.4472	13.7520
17	XGBoost	0.6314	—	236.3780	142.1000	11.3338
18	LightGBM	0.6297	—	236.9279	146.7810	11.5714
19	CNN	0.5023	75441.5926	274.6663	219.0419	18.9785

As seen in Table 2, ensemble models based on decision trees demonstrated superior predictive capability compared to other algorithmic categories. The Random Forest Regressor emerged as the best-performing model, recording the highest test R^2 of 0.7437 alongside the lowest RMSE of 197.13 psi. Its AARE of 8.87% reflects an average deviation of less than 9% from measured TRO values, underscoring its suitability for practical engineering deployment. CatBoost and SVR followed closely, exhibiting comparable levels of accuracy.

In contrast, more complex deep learning approaches (MLP and CNN) and certain gradient boosting models implemented with default hyperparameters (XGBoost and LightGBM) delivered weaker performance. The CNN produced the lowest accuracy (R^2 = 0.5024), which can be attributed to the relatively limited dataset size, rendering deep architectures ineffective for learning robust representations from tabular data. The relationship between training and test R^2 values across all models is illustrated in Fig. 5. The results indicate that leading models such as Random Forest and CatBoost maintained consistent performance across datasets, suggesting strong generalization and limited overfitting.

➢ *Detailed Model Analysis and Residual Diagnostics*

Predicted-versus-actual TRO pressure scatter plots were generated for all models, with a representative subset. These visualizations corroborate the numerical evaluation results. In particular, the Random Forest model exhibits a tight clustering of points along the 45° reference line (y = x), indicating high predictive accuracy across the full pressure range. The red dashed line indicates perfect prediction.

Residual diagnostics were further performed for the Random Forest model to assess systematic bias and error structure (Fig. 6). The residuals plotted against predicted values displayed no apparent trend and were symmetrically distributed around zero. The residual histogram closely resembled a normal distribution centered near zero, while the Q–Q plot showed strong alignment with the theoretical normal line. Collectively, these diagnostics confirm the robustness of the model, the absence of systematic bias, and the random nature of prediction errors.

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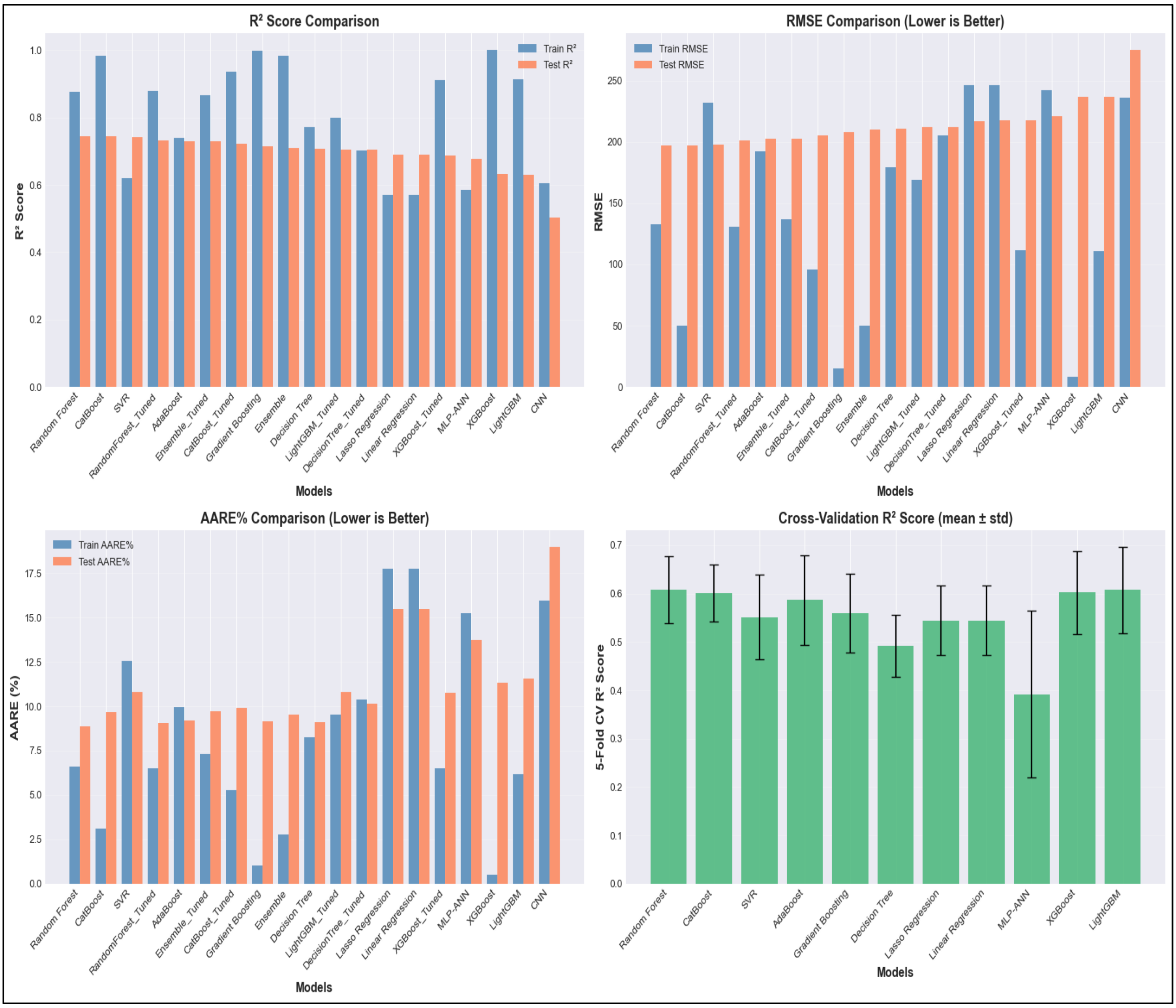

Fig 5 Bar Chart Comparing Training R² (Blue) and Test R² (Orange) Scores Across Models.

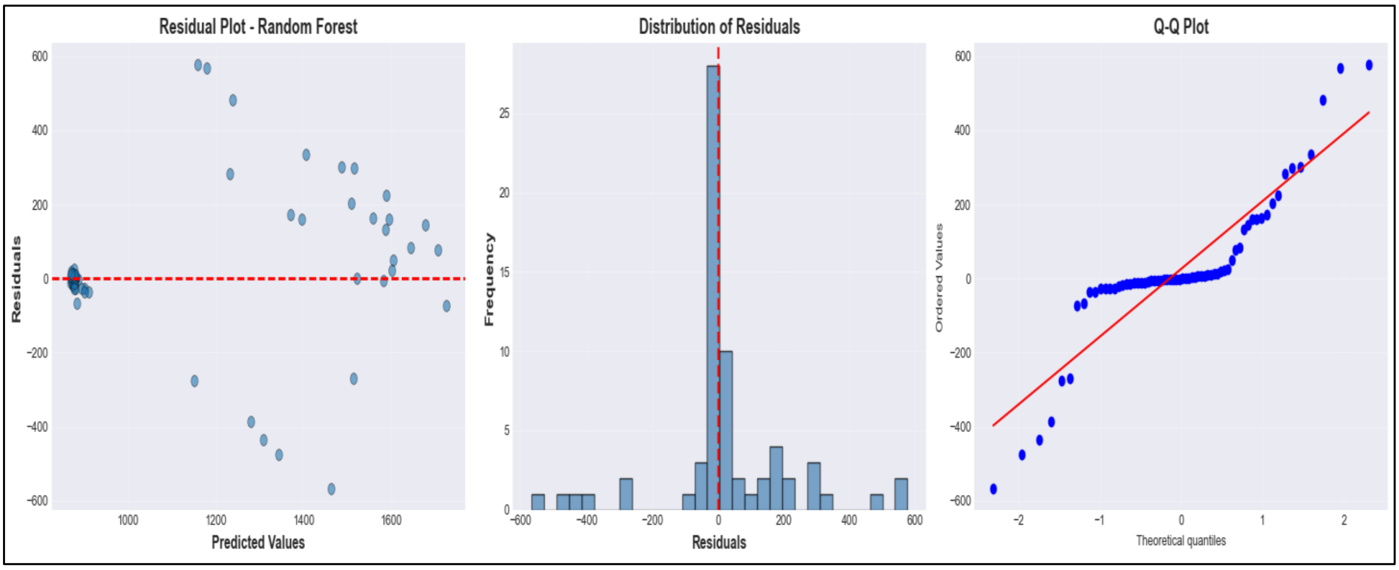

Fig 6 Residual Analysis for the Random Forest Model: (a) Residuals vs. Predicted Values, (b) Histogram of Residuals, (c) Q–Q Plot for Normality Check.

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➢ *Feature Importance Analysis*

An examination of feature importance derived from the optimized Random Forest model is presented in Fig. 7. Measured Depth (ft) was identified as the most influential variable, contributing approximately 79% of the total explanatory power. This finding is consistent with established petroleum engineering principles, as hydrostatic pressure is fundamentally depth-dependent. Unloadable Gradient (psi/ft) and the engineered Depth_per_Valve feature ranked second and third, emphasizing the role of fluid properties and valve spacing normalization. Other variables, including Manufacturer, Specification, and Valve #, contributed moderately, while Valve Type exhibited minimal importance, indicating redundancy within the selected feature subset.

➢ *Time-Series Forecasting Results*

To evaluate whether TRO pressure demonstrates temporal behavior, time-series forecasting techniques were applied to data ordered using an engineered date variable. Both traditional statistical models (ARIMA and Prophet) and machine-learning-based forecasters (CatBoost, Ensemble, Ensemble_Tuned) showed extremely poor predictive capability (Fig. 8). The highest-performing forecasting approach, Ensemble_Tuned, achieved an R^2 of only 0.0205, while ARIMA and Prophet yielded negative R^2 values, indicating performance inferior to a naïve mean predictor. Forecast outputs were largely flat or erratic and failed to track observed values. These results conclusively confirm that TRO pressure is not a time-dependent variable but rather a static design parameter governed by fixed well and valve characteristics at installation.

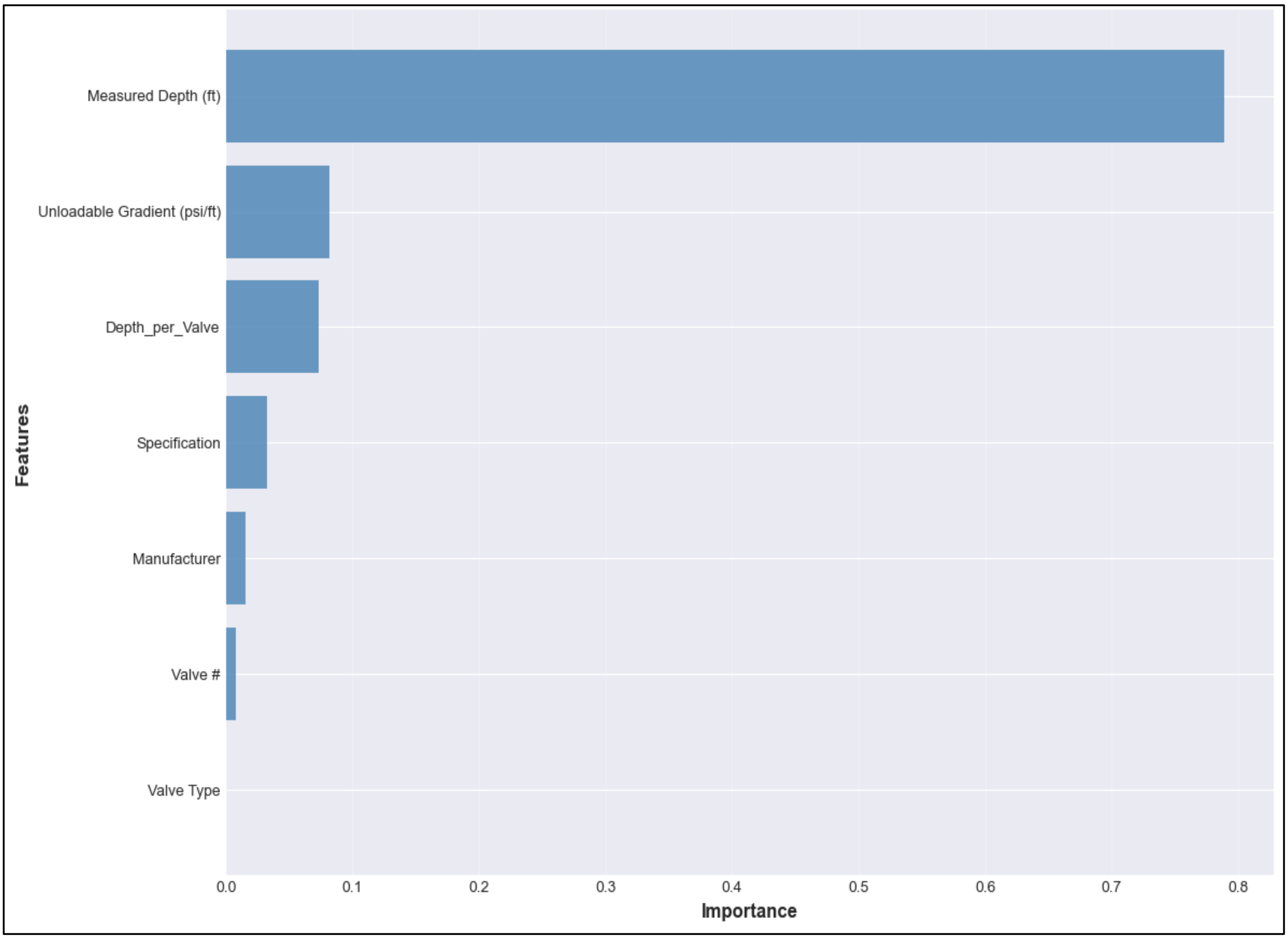

Fig 7 Feature Importance Scores from the optimized Random Forest Model

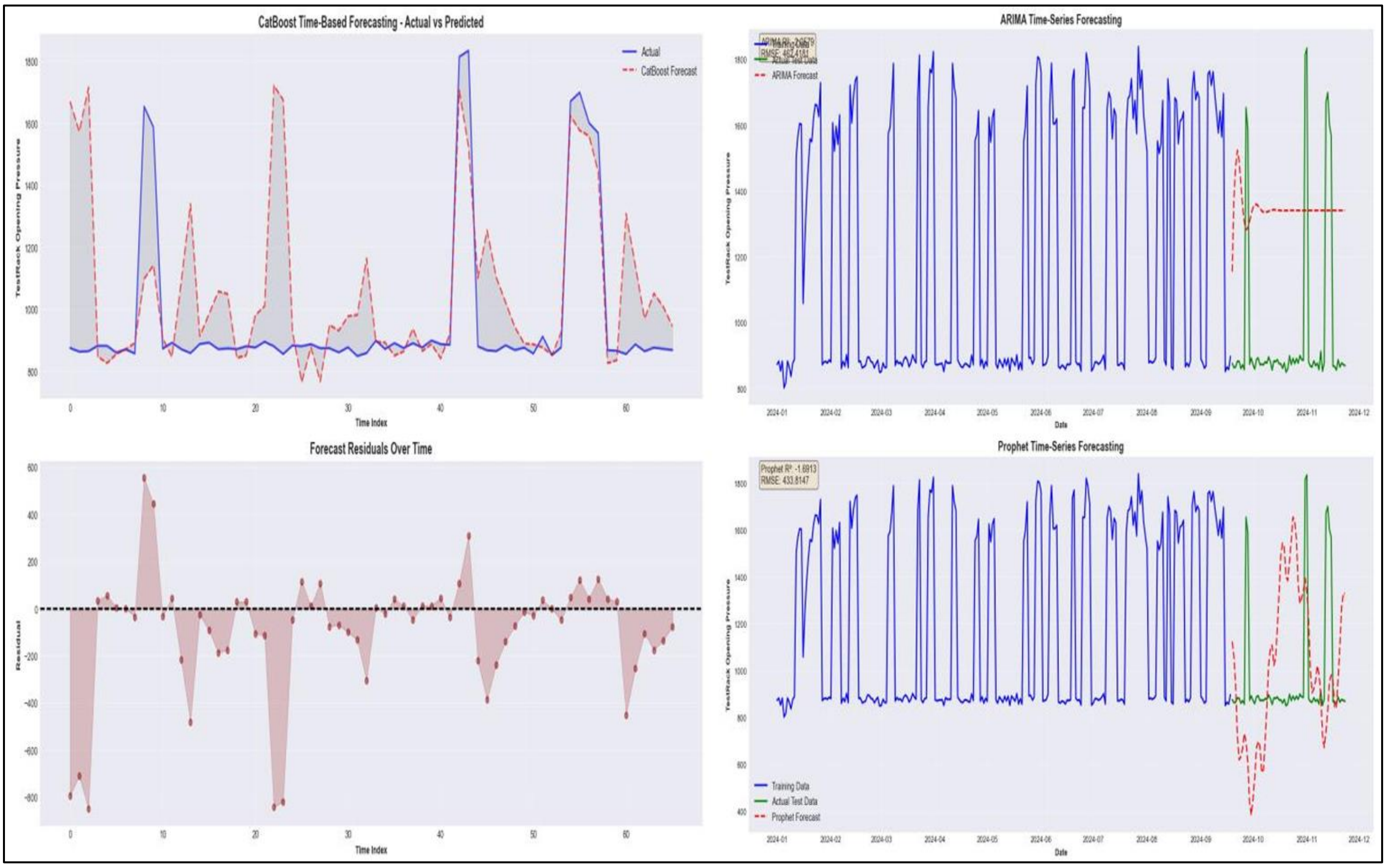

Fig 8 Performance of Time-Series Forecasting Models (ARIMA, Prophet, ML-Based)

V. DISCUSSION

The results conclusively demonstrate the superiority of tree-based ensemble methods, particularly Random Forest, for predicting TRO pressure from static well and valve parameters. The achieved test R^2 of 0.7437 represents a substantial predictive capability, explaining nearly three-quarters of the variance in TRO. This performance is particularly significant given the inherent noise and variability in field-measured calibration data. The 8.87% AARE suggests the model's predictions are within an operationally acceptable error margin, potentially reducing the need for multiple test-rack calibration cycles.

The dominance of Measured Depth in feature importance (Fig. 8) strongly corroborates the underlying physics of gas lift systems, where downhole pressure is fundamentally governed by the hydrostatic head of the fluid column [2], [15]. The secondary importance of Unloadable Gradient further emphasizes the role of fluid properties. Interestingly, dome pressure; a central component in theoretical force-balance equations [5] was removed during feature selection due to its extreme collinearity with valve opening/closing pressures. This suggests that while physically critical, its predictive information is contained within other directly correlated pressure measurements in an operational dataset. The success of ensemble methods like Random Forest lies in their ability to model complex, non-linear interactions between these geophysical and operational parameters without assuming a predefined functional form, a limitation of traditional analytical methods [24].

The failure of deep learning models (CNN, MLP) is an important finding. It underscores that “big data” techniques are not universally superior; their effectiveness is contingent on large sample sizes. With 328 samples, the relatively high parameter count of neural networks led to poor generalization. This reinforces the principle of selecting model complexity appropriate to data availability [20]. Similarly, the poor performance of time-series models (Fig. 9) provides critical insight: TRO is not a parameter that meaningfully evolves over short timescales under normal operation. It is a calibration setting. Attempts to forecast it using its own history are fundamentally misguided. This directs future optimization efforts towards static predictive modeling or condition-based prediction using indicators of valve wear, rather than temporal forecasting.

The practical implication of this research is the development of a data-driven decision support tool. Engineers can input key known parameters (depth, fluid gradient, valve specs) to obtain a reliable TRO estimate prior to physical testing. This can streamline design workflows, enable rapid evaluation of different valve configurations, and serve as a quality-check against measured test-rack values, flagging potential anomalies. The interpretability of the model via feature importance also provides valuable engineering insight, guiding focus towards the most influential design and operational factors.

VI. LIMITATIONS AND FUTURE WORK

This study is based on data from 20 wells. While sufficient for robust model comparison, broader validation across diverse fields (different geologies, fluid types, valve brands) is necessary to ensure generalizability. Future work should focus on:

- Expanding the Dataset: Incorporating more wells and additional features like valve age, specific bellows characteristics, and detailed temperature profiles.
- Hybrid Physics-Informed ML: Integrating fundamental force-balance equations as constraints or features within the ML architecture (e.g., Physics-Informed Neural Networks) could improve extrapolation accuracy and physical consistency [25].
- Real-Time Application: Developing the model into a real-time or near-real-time advisory system integrated with field data historians to provide continuous calibration insights.
- Uncertainty Quantification: Implementing methods like conformal prediction or Bayesian modeling to provide prediction intervals, offering a measure of confidence crucial for operational decision-making [26].

VII. CONCLUSION

This study developed and systematically evaluated a broad range of machine learning models for the prediction of Test Rack Opening (TRO) pressure in gas lift systems. Out of the nineteen algorithms assessed, the Random Forest Regressor emerged as the most effective, achieving a test R^2 of 0.7437 and an average absolute relative error of 8.87%. The model demonstrated a strong ability to capture the complex and non-linear relationships that govern gas lift valve behavior. Feature importance analysis further revealed that Measured Depth and Unloadable Gradient are the most influential predictors, thereby reinforcing the consistency between data-driven outcomes and established petroleum engineering fundamentals. The findings also confirm that TRO pressure is inherently a static design parameter, as demonstrated by the poor performance of time-series forecasting models. The proposed predictive framework represents a substantial improvement over conventional iterative calibration techniques by offering a fast, accurate, and interpretable alternative. Its application can minimize dependence on repeated physical testing, shorten design cycles, and improve the overall reliability of gas lift installations. By effectively integrating machine learning with core petroleum engineering concepts, this research provides a practical and scalable approach for enhancing artificial lift system design and supporting more efficient and sustainable hydrocarbon production.

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