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Dynamic Young's modulus prediction from drilling parameters: A case study of CT oil field, offshore Vietnam

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ABSTRACT

Real-time prediction of dynamic Young modulus (E_{dyn}) during drilling is crucial for optimizing operational efficiency and mitigating geohazards, particularly in complex geological settings such as offshore Vietnam. While conventional methods like core analysis and wireline logging are accurate, they are often costly, time-consuming, and disruptive to operations. This study investigates the feasibility of using machine learning (ML) models to predict E_{dyn} from real-time drilling parameters, applying to the CT oil field, offshore Vietnam. Six standard drilling parameters were utilized as model inputs: weight on bit, torque, rotary speed, rate of penetration, mud flow rate, and standpipe pressure. The target variable, E_{dyn} was computed from compressional (V_p) and shear (V_s) wave velocities, measured by dipole sonic tools, which served as the ground truth. Three algorithms-Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF)-were trained and cross-validated using 1061 data points from Wells A and B. Evaluation based on Correlation Coefficient (R) and Root Mean Square Error (RMSE) showed that the ANN model yielded superior predictive accuracy compared to both SVM and RF during training and testing phases. On a blind test (Well C), the optimized ANN achieved high correlation ($R = 0.912$) and low error ($RMSE = 0.134$ GPa), confirming its robustness for real-time operational support. Although this study focuses on E_{dyn} as a primary geomechanical indicator, these real-time estimates serve as a critical first step toward comprehensive geomechanical assessment. It provides a reliable proxy for rock stiffness trends; thus, the static modulus could be potentially derived through established empirical correlations in future stages of the research. This methodology also provides a feasible, data-driven workflow for estimating rock strength continuously (meter-by-meter) while drilling.

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1. Introduction

Young's modulus, which quantifies formation stiffness and governs rock behavior under applied forces (Brady & Brown, 2006), is a fundamental parameter for safe and efficient oil and gas operations. Accurate determination of this modulus is essential for borehole stability design, drilling parameter optimization, and mitigating geomechanical risks such as wellbore instability and sand production (Malkowski & Ostrowski, 2017).

The modulus varies considerably across geological formations, ranging from megapascals in unconsolidated sands to tens of gigapascals in compacted carbonates. This variation is controlled by mineral composition, porosity, cementation, and in-situ stress conditions (Hoek & Brown, 1980; Castagna et al., 1993). Sandstone formations typically exhibit Young's modulus values between 10-50 GPa, while carbonate rocks may reach 70-90 GPa. Shale formations show intermediate values of 5-30 GPa, often with significant anisotropy. This high degree of geological variability highlights the limitations of relying on discrete, single-point measurements and underscores the need for continuous formation characterization.

Conventional determination of Young's modulus relies on laboratory core testing and wireline logging. While laboratory testing of core specimens via uniaxial compression can achieve high accuracy, the method suffers from significant practical limitations. Core retrieval is expensive, provides limited spatial coverage, and is often unviable in fractured or poorly consolidated formations where recovery rates can drop below 50% (Mansoor, 2017; Palmstrom & Singh, 2001). Furthermore, laboratory testing requires considerable preparation and analysis time, typically delaying results for several weeks.

Although sonic logging provides continuous measurements, the value it determines is the dynamic modulus. The conversion from dynamic to static modulus (the value required for most geomechanical models) introduces significant uncertainties due to strain amplitude effects and formation heterogeneity (Małkowski & Ostrowski, 2017; Sharifi et al., 2023). Dynamic values derived from logs are typically 20÷50% higher than static laboratory values, necessitating empirical correction factors that are highly lithology-dependent. Crucially, both conventional logging and core analysis are post-drilling operations, precluding their use for real-time decision-making. In contrast, drilling parameters-such as weight on bit (WOB), rotary speed (RPM), rate of penetration (ROP), and torque-are recorded continuously and reflect real-time rock-bit interactions. These parameters are known to correlate strongly with formation mechanical properties; for example, stiffer formations generally exhibit lower ROP and require higher torque under consistent operational inputs (Tariq et al., 2016).

Early analytical models, such as those based on specific energy (SE), attempted to correlate drilling energy with rock strength but were limited by oversimplified assumptions (Sharifi et al., 2023). SE calculations, for instance, often presume linear relationships that fail in heterogeneous formations. Furthermore, these models struggle to account for complexities like formation anisotropy, where horizontal and vertical moduli can differ significantly. The estimation is further complicated by operational factors. Bit wear, for example, alters cutting efficiency and thus the relationship between WOB and ROP. Formation damage and mud cake buildup can mask the true rock response. Moreover, in-situ temperature and pressure conditions modify mechanical properties; Young's modulus, for instance, is typically 10÷30% higher at depth compared to surface measurements. These factors introduce complex, non-linear interdependencies that simple analytical models cannot adequately capture.

Machine learning (ML) models, including neural networks (ANN), support vector machines (SVM), and random forests (RF), ... are increasingly applied in well log analysis. These methods have been used to predict Young's modulus from sonic, density, and porosity logs, often outperforming traditional correlations, especially in heterogeneous formations (Gong et al., 2019; Ajah et al., 2020). ANNs, for example, have proven effective at capturing the non-linear relationships between acoustic properties and mechanical behavior.

A more recent development is the extension of ML to real-time drilling parameters, which bypasses the need for post-drilling logs. This application is challenging because the relationships between drilling parameters and rock properties are highly non-linear and convoluted by operational variables (e.g., bit type, mud properties) and in-situ conditions (Mahmoud et al., 2019; Mahmoud et al., 2022). However, ML models are well-suited for this task, as they can identify complex patterns from multi-dimensional data without requiring explicit physical formulas (Tu et al., 2024; Jonas, 2002). Previous work has already demonstrated promising accuracy, provided the models are calibrated with sufficient core or log data (Elkatatny et al., 2019).

To address the growing need for cost-effective, real-time geomechanical characterization in complex geological settings, this study develops machine learning models to predict dynamic Young's modulus directly from drilling parameters. The investigation focuses on the CT oil field, offshore Vietnam, a setting characterized by complex, interbedded sandstone-shale sequences. In this approach, real-time drilling parameters serve as the model inputs, while dynamic Young's modulus values, derived from density and sonic logs, are used as the reference targets.

Three algorithms address this regression problem: Artificial Neural Networks (ANN), Random Forest (RF), and Support Vector Machine (SVM). Each algorithm offers distinct advantages for different aspects of the prediction task, with comparative evaluation determining the most suitable approach for CT oil field conditions. The following sections present methodology development including data preprocessing, model training, and validation, followed by results and implications for real drilling scenarios. Implementation considerations for field deployment and recommendations for future research are also discussed, providing a complete framework for practical application of the developed approach.

Despite the availability of various geomechanical assessment methods, a comprehensive comparison of advanced machine learning architectures validated on strictly unseen field data remains limited for the Cuu Long Basin. The novelty of this study lies in the systematic comparison of ANN, SVM, and RF models developed using data from Wells A and B. By utilizing Well C as an independent blind test, this research aims to provide a reliable tool for real-time Young's modulus prediction, bridging the gap between theoretical modeling and practical application in the CT oil field.

2. Database

2.1. Study Area

The CT oil field covers 5,559 km^2 within Block 09-3/12 at the southeastern margin of the Cuu Long Basin, offshore Vietnam's continental shelf. The field is located approximately 160 km southeast of Vung Tau city (Figure 1) and borders several adjacent blocks including 09-1, 09-2/09, 03, 04-2, 10, and 17.

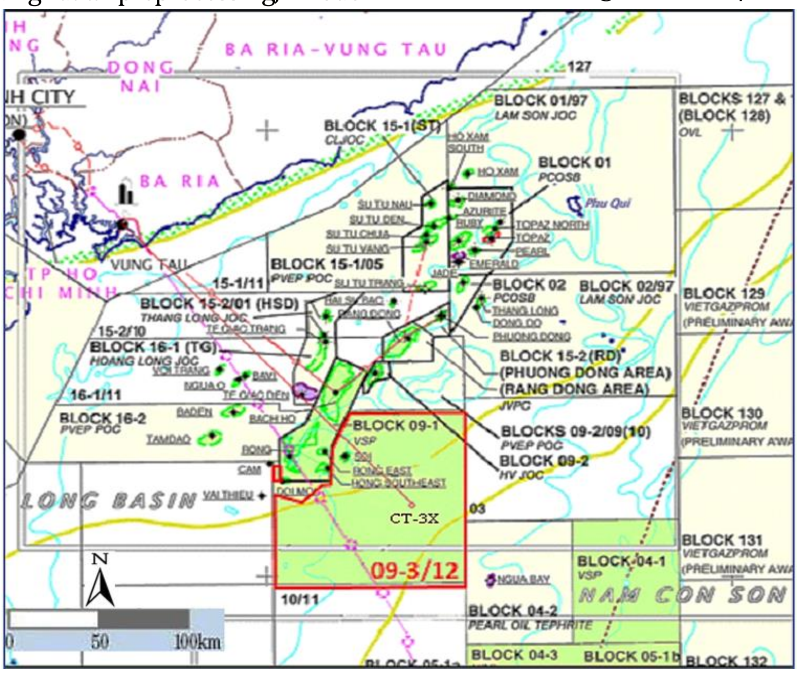

Figure 1. Red rectangle shows the study area.

Drilling targets include Lower Miocene and Upper Oligocene formations with complex geological structures. These formations contain interbedded sandstone layers and highly reactive clay zones. The heterogeneous nature of these formations creates significant drilling challenges and wellbore instability risks. Accurate mechanical property prediction is therefore essential for selecting optimal drilling parameters and reducing operational risks.

2.2. Data Collection

The dataset comprises 1061 samples from two wells (A and B) at the CT oil field, incorporating six drilling parameters: Rate of Penetration (ROP), Rotary Speed (RPM), Weight on Bit (WOB), Standpipe Pressure (SPP), Pump Flow Rate (FLOWIN) and Torque (TORQUE).

These parameters were continuously recorded during drilling operations, providing real-time formation response data (Table 1).

Table 1. Statistical analysis of drilling parameters in the dataset.

Parameters	Min	Max	Mean	StdDev
ROP	6.32	95.76	38.1	21.25
RPM	54.85	141.6	136.09	5.34
SPP	87.02	200.92	172.92	18.76
TORQUE	789.91	2227.25	1767.95	182.01
WOB	1.04	6.85	4.15	1.11
FLOWIN	27.09	39.02	37.92	0.91

- Rate of Penetration (ROP) measures drilling advancement speed (m/hr). ROP correlates inversely with rock stiffness - formations with higher Young's modulus resist bit penetration, resulting in lower ROP values. This relationship makes ROP a key indicator for Young's modulus prediction;

- Rotary Speed (RPM) controls bit rotation rate. Hard formations with high Young's modulus often require adjusted RPM to maintain cutting efficiency. RPM variations reflect formation mechanical properties and contribute to Young's modulus estimation;

- Weight on Bit (WOB) applies downward drilling force (tons). The WOB-ROP relationship varies significantly with formation stiffness. Higher Young's modulus formations require different WOB optimization strategies;

- Standpipe Pressure (SPP) monitors system pressure (atm). SPP changes reflect formation transitions and drilling resistance variations. These pressure signatures help identify formations with different Young's modulus values during drilling;

- Flow Rate (FLOWIN) controls mud circulation (l/s). While primarily for cooling and cuttings removal, flow rate adjustments often correlate with formation changes;

- Torque (TORQUE) represents rotational force needed to turn the bit (m*kg). Stiffer formations with higher Young's modulus generate increased torque resistance during drilling.

Dynamic Young's modulus values from well logging data provide reference targets for model training and validation. We compare machine learning predictions against log-derived values to evaluate model performance and determine whether real-time drilling data can replace expensive well logging for formation characterization.

During the model development phase, we utilized a 5-fold Cross-Validation (CV) approach on this subset. This means that for each hyperparameter trial, the data from A and B was internally split, ensuring that the model's performance was validated on data it hadn't seen in that specific training fold.

To simulate a real-world drilling scenario, Well C was completely withheld from the training and optimization process. This blind test set consists of 832 data points. No data from Well C was used for feature scaling, hyperparameter tuning, or model selection. This "blind" evaluation provides an unbiased estimate of the model's ability to generalize to new, unseen data.

2.3. Outlier Detection and Removal

Real-time drilling data often contains considerable noise, measurement uncertainties, and non-Gaussian distributions that reduce analytical reliability. These drilling parameters frequently exhibit non-normal statistical behavior because of geological heterogeneity, varying borehole conditions, and equipment constraints.

Figure 2 shows frequency distribution histograms and box plots for six drilling parameters. The histograms display the distribution patterns needed for model development. Most parameters show approximately normal distributions with

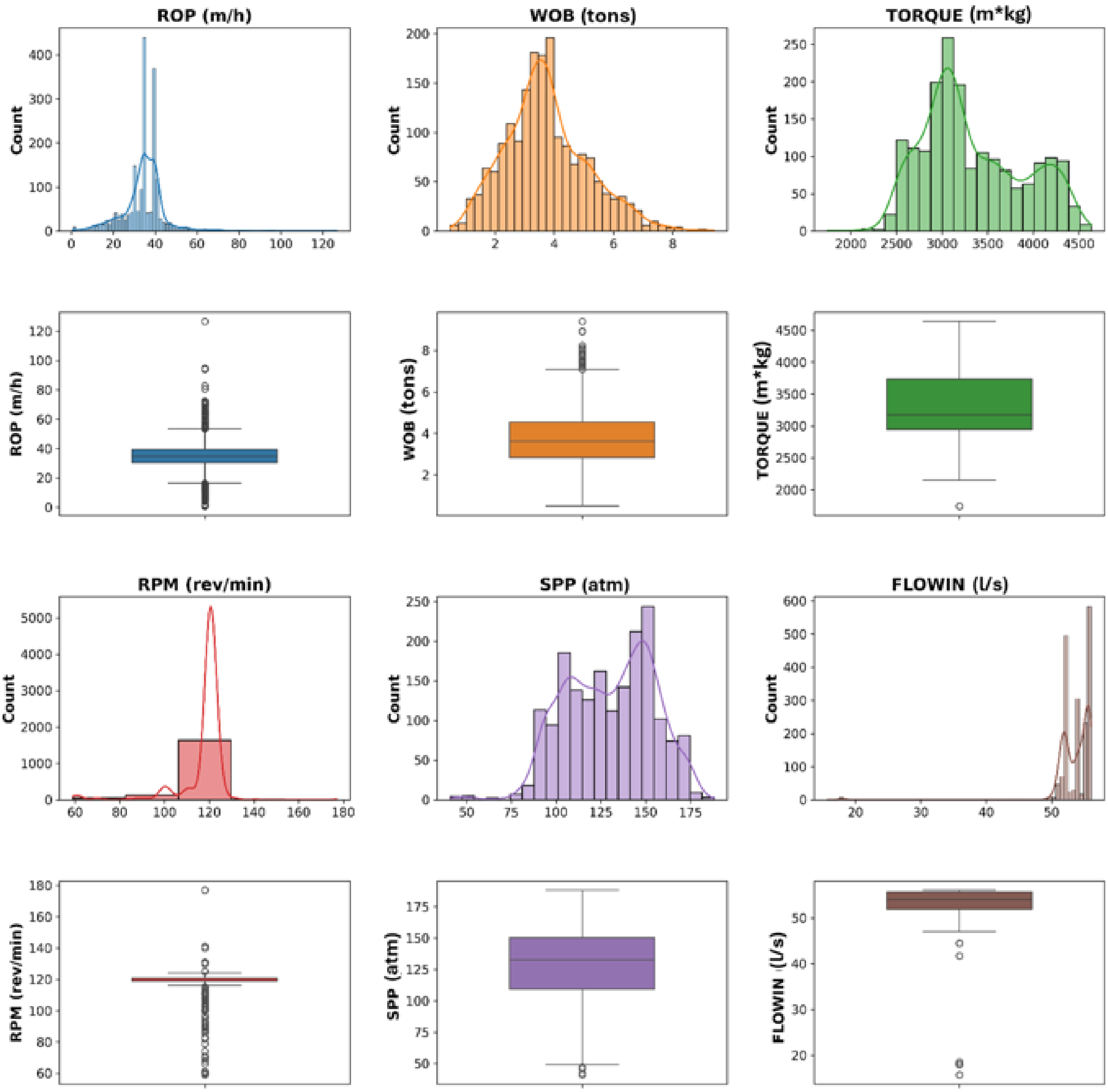

Figure 2. Frequency distribution histograms and box plots of the raw dataset.

bell-shaped curves, which is favorable for machine learning applications. The box plots display four key statistics: minimum, first quartile (Q1), median, third quartile (Q3), and maximum values. The interquartile range (IQR) represents the middle 50% of data, with whiskers extending to extreme values beyond outliers. Rate of Penetration (ROP) and Rotary Speed (RPM) show significant outliers that may affect prediction accuracy.

We used the Interquartile Range (IQR) method for outlier detection and removal. For each parameter, we calculated Q1 and Q3, then removed data points outside the range [Q1 - 1.5×IQR, Q3+1.5×IQR]. This approach removes anomalous values while keeping most representative data.

The processed data shows improved structure and interpretability (Figure 3). This preprocessing enhances model training and reduces prediction errors from noisy data.

2.4. Feature Selection Analysis

Machine learning model performance depends heavily on input data quality. Noise and irrelevant features reduce prediction accuracy. While six

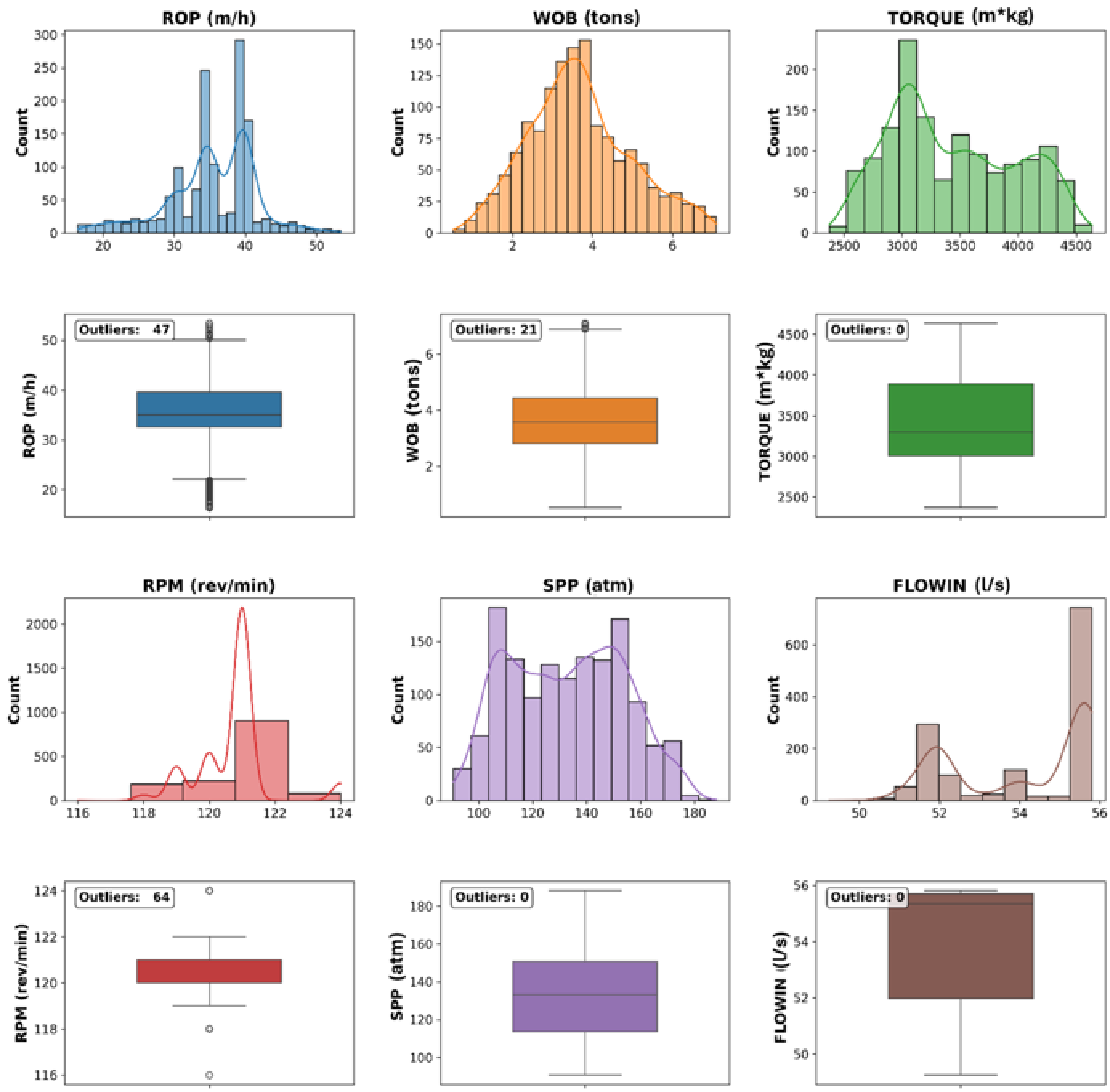

Figure 3. Frequency distribution histograms and box plots of the dataset after outlier removal.

drilling parameters characterize formations well, selecting optimal features must balance prediction ability with computational needs.

Correlation analysis (Figure 4) shows moderate to weak correlations (0.05÷0.29) between individual drilling parameters and dynamic Young's modulus. This indicates that single-parameter prediction would be insufficient. The relatively low correlations between parameters suggest that multiple features provide complementary information without redundancy. Therefore, all six parameters serve as independent inputs. This configuration balances prediction accuracy with model simplicity, preventing overfitting while preserving formation characterization quality.

3. Methodology

This study develops machine learning models for real-time dynamic Young's modulus prediction during drilling operations at the CT oil field, offshore Vietnam. We use drilling parameters as input features, with dynamic Young's modulus values from density logs and sonic velocities as reference targets.

Direct dynamic Young's modulus measurements are not available during drilling, so we used well logging data to create reference values for model training and validation.

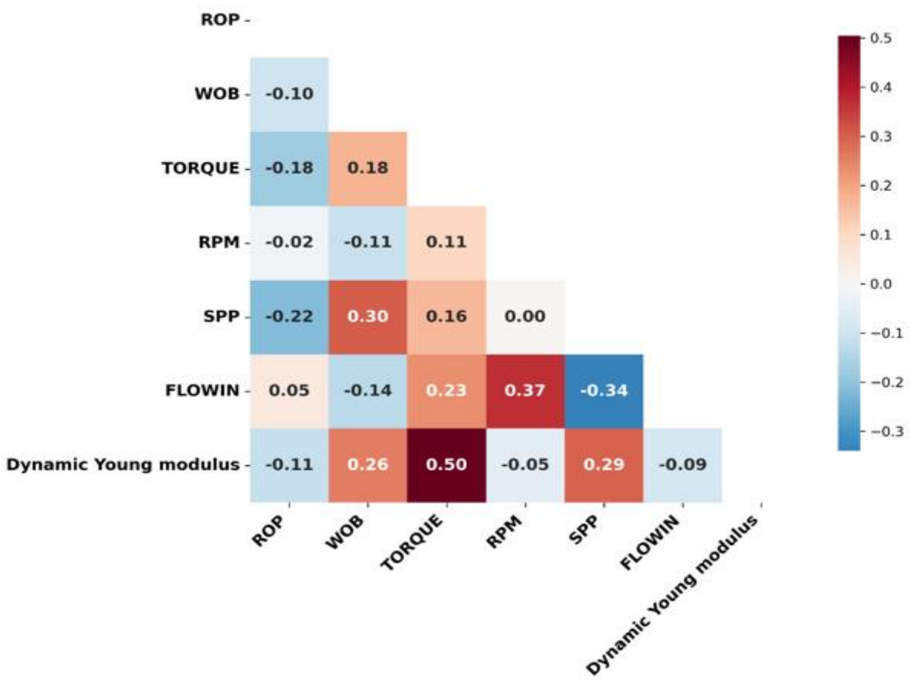

Figure 4. Heatmap of correlation coefficients between parameters in the dataset.

Dynamic Young's modulus can be calculated from well logging data using petrophysical relationships that combine sonic velocity and density measurements. This approach uses the correlation between elastic wave velocities and rock mechanical properties, based on elasticity theory (Zoback, 2007). The standard formula for determining dynamic Young's modulus from well logs is:

$$E_{dyn} = \rho \times Vs^2 \times (3Vp^2 - 4Vs^2) / (Vp^2 - Vs^2) \quad (1)$$

Where: E_{dyn}- Dynamic Young's modulus (GPa); ρ - bulk density from density log (g/cm^3); Vp - compressional wave velocity from sonic log (m/s); Vs - shear wave velocity from sonic log (m/s).

These log-derived dynamic Young's modulus values provide reference targets for training machine learning models to predict the same parameter from real-time drilling data.

3.1. Machine Learning Algorithms

After calculating dynamic Young's modulus from well logging data using equation (1), we proceeded to develop machine learning models for dynamic Young's modulus prediction using drilling data as input. The objective is to build high-accuracy prediction models that can directly forecast dynamic Young's modulus during drilling operations without requiring well log data, thereby saving time and costs, improving operational efficiency, and reducing drilling incidents.

Algorithm selection considers dataset characteristics, computational requirements, and prediction accuracy. ANNs are optimal for large datasets requiring maximum accuracy, RF provides robust performance with interpretability for heterogeneous data, while SVM offers precision for moderate-sized datasets with complex feature relationships (Abiodun & Sangki, 2021). The methodology evaluates all three approaches to identify the most suitable algorithm for CT oil field conditions.

Artificial Neural Networks (ANN)

ANNs utilize interconnected nodes organized in layers to process information through non-linear activation functions, learning complex input-output relationships via backpropagation and gradient optimization (Krenker et al., 2011). For Young's modulus prediction, ANNs excel at modeling non-linear relationships between acoustic velocities, density, weight on bit (WOB), and rate of penetration (ROP) with rock stiffness. ANNs demonstrate superior performance in geomechanical applications, with studies achieving prediction errors below 10% when trained on sonic log data, outperforming traditional empirical correlations (Abiodun & Sangki, 2021). The algorithm integrates multiple drilling parameters including torque and mud pressure to enhance accuracy. However, ANNs require substantial computational resources and large datasets, potentially limiting practical deployment in resource-constrained environments.

Random Forest (RF)

RF employs ensemble learning by aggregating multiple decision trees trained on random data and feature subsets using bootstrap aggregating to reduce overfitting (Fawagreh et al., 2014). This approach effectively handles multidimensional, noisy datasets combining acoustic velocities, porosity, and drilling parameters (ROP, RPM). RF provides variable importance quantification, facilitating formation characterization and feature selection. Research demonstrates correlation coefficients above 0.9 for Young's modulus prediction from drilling data, particularly in heterogeneous formations (Abiodun & Sangki, 2021). RF offers implementation simplicity and reduced parameter sensitivity compared to deep learning approaches, though it may underperform in capturing complex non-linear relationships. The algorithm provides reliable predictions with diverse input types, making it practical for geomechanical applications.

Support Vector Machine (SVM)

SVM utilizes optimal hyperplane concepts and kernel functions to map data in high-dimensional space, maximizing class margins or employing kernel transformations (e.g., Gaussian RBF) for non-linear relationships (Abiodun & Sangki, 2021). For Young's modulus prediction, SVM maps parameters including shear wave velocity, density, WOB, and ROP to rock stiffness values. SVM demonstrates particular effectiveness with small-to-medium datasets, handling low-correlation features and delivering accurate predictions despite noise. The algorithm exhibits strong generalization capability, minimizing errors in complex geological settings. However, SVM faces scalability challenges with large datasets and requires careful kernel selection, potentially constraining application scope.

3.2. Model Development and Optimization

Each algorithm required hyperparameter tuning to improve dynamic Young's modulus prediction accuracy.

ANN optimization used RandomSearch-Tuner with Keras library to adjust:

- Hidden layer structure and neuron numbers;
- Learning rate and activation functions;
- Network depth for capturing non-linear relationships.

SVM optimization focused on;

- Kernel selection and regularization parameters;
- Parameter tuning for specific kernels;
- Cross-validation to balance complexity and generalization.

RF optimization applied RandomizedSearchCV with scikit-learn to adjust:

- Number of trees and maximum depth;
- Minimum samples per split and leaf;
- Parameters for ensemble robustness.

Model Validation

Cross-validation divided training data into N subsets, using N-1 subsets for model training and one subset for evaluation. This validation subset stayed separate from the final test dataset. After finding optimal hyperparameters (Table 2), we retrained final models on the complete training dataset.

Table 2. Optimum set of parameters for models.

Model	Hyper parameters
ANN	'learning_rate_init': 0.001, 'hidden_layer_sizes': (100), 'alpha': 0.01, 'activation': 'relu'
SVM	'kernel': 'rbf', 'gamma': 'scale', 'C': 10
RF	'n_estimators': 250, 'min_samples_split': 8, 'min_samples_leaf': 4, 'max_features': log2, 'max_depth': 20,

This optimization approach improves model performance and reliability for real-time geomechanical predictions during drilling.

4. Results and discussion

All three machine learning algorithms predicted dynamic Young's modulus well, achieving high correlation coefficients and low error rates (Figure 5). Performance evaluation on training and test datasets shows different strengths for each algorithm in geomechanical prediction.

RF achieved training R^2 of 0.925 and test R^2 of 0.86, with RMSE values of 0.126 (training) and 0.159 (testing) (Figure 6). This ensemble method showed good generalization with a reasonable gap between training and test performance.

Support Vector Machine had lower performance with training R^2 of 0.896 and test R^2 of 0.820. RMSE values were higher at 0.149 (training) and 0.181 (testing), showing less accurate predictions.

ANN performed best overall with training R^2 of 0.933 and test R^2 of 0.879 with RMSE values of 0.12 (training) and 0.148 (testing). The neural network handled complex relationships between drilling parameters and dynamic Young's modulus while maintaining good performance on new data. The small difference between training and test results makes this algorithm suitable for real-time drilling applications.

The results show that both neural networks and ensemble methods work well for predicting dynamic Young's modulus from drilling parameters in complex geological formations. Finally, the optimal selected ANN model uses six drilling

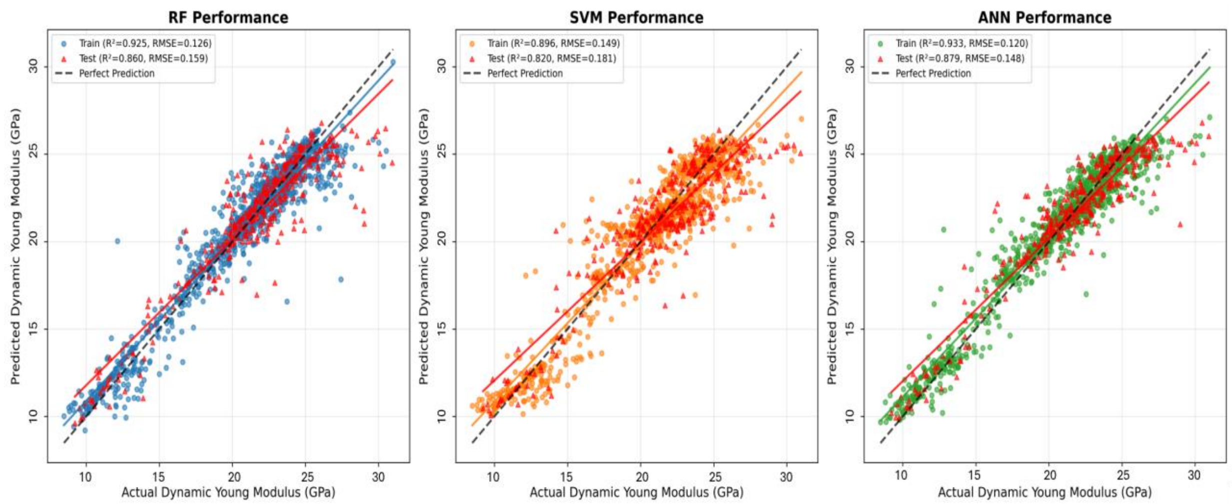

Figure 5. Prediction results of dynamic Young's modulus from drilling data using the RF, SVM and ANN models.

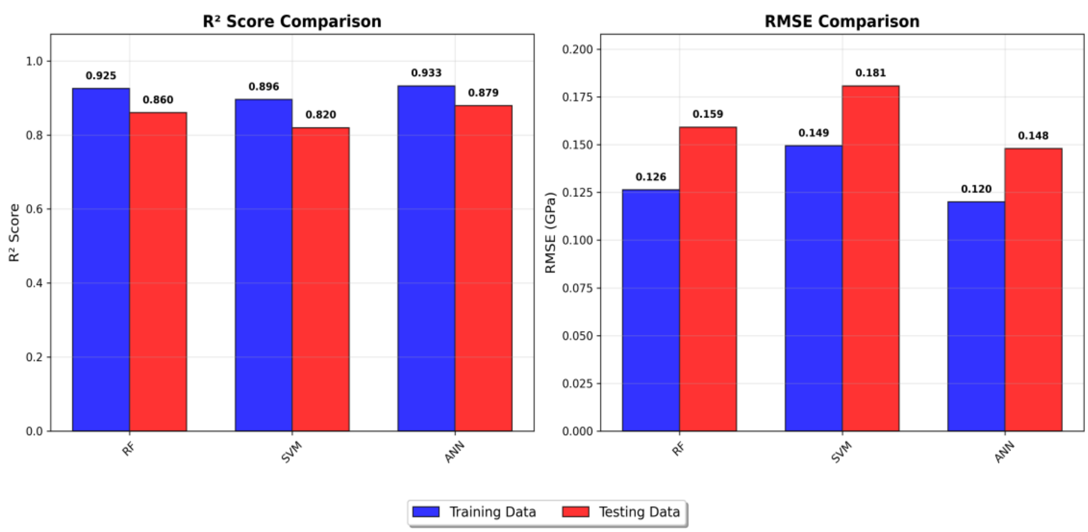

Figure 6. Performance comparison of models.

parameters as input features with the following setup:

- *Architecture:* Single hidden layer with 100 neurons
- *Activation function:* ReLU for capturing non-linear relationships
- *Training parameters:* Maximum 1000 iterations
- *Regularization:* L2 regularization (strength = 0.01) to prevent overfitting
- *Output layer:* Linear activation for continuous regression output

This architecture processes drilling parameters (ROP, RPM, WOB, SPP, FLOWIN, TORQUE) through the wide hidden layer for feature extraction. ReLU activation provides sparsity and computational efficiency for geomechanical applications.

Blind Test Validation: We evaluated model generalization using Well C from the CT oil field. This well's drilling data was kept separate from training and validation datasets to provide an independent test of model performance. Well C penetrates similar geological formations to the training wells but represents a different structural location within the field. The blind test provides an unbiased assessment of model performance under real conditions, which is particularly important in heterogeneous geological environments with interbedded sandstone-shale sequences and varying formation properties.

The ANN model performed well on blind test validation, achieving a high correlation coefficient and low RMSE when comparing actual dynamic Young's modulus values derived from well logs against predicted values from the ANN model. The correlation coefficient of 0.912 indicates strong agreement between actual and predicted values, while the RMSE of 0.134 represents the average prediction error, demonstrating good accuracy for practical drilling applications. The high correlation coefficient indicates the model captures complex, non-linear relationships between drilling parameters and rock stiffness when applied to new, unseen data (Figure 7).

Beyond the high correlation and low error rates, the model predictions track dynamic Young's modulus variations with depth, reflecting the natural geological trends observed in the CT oil field.

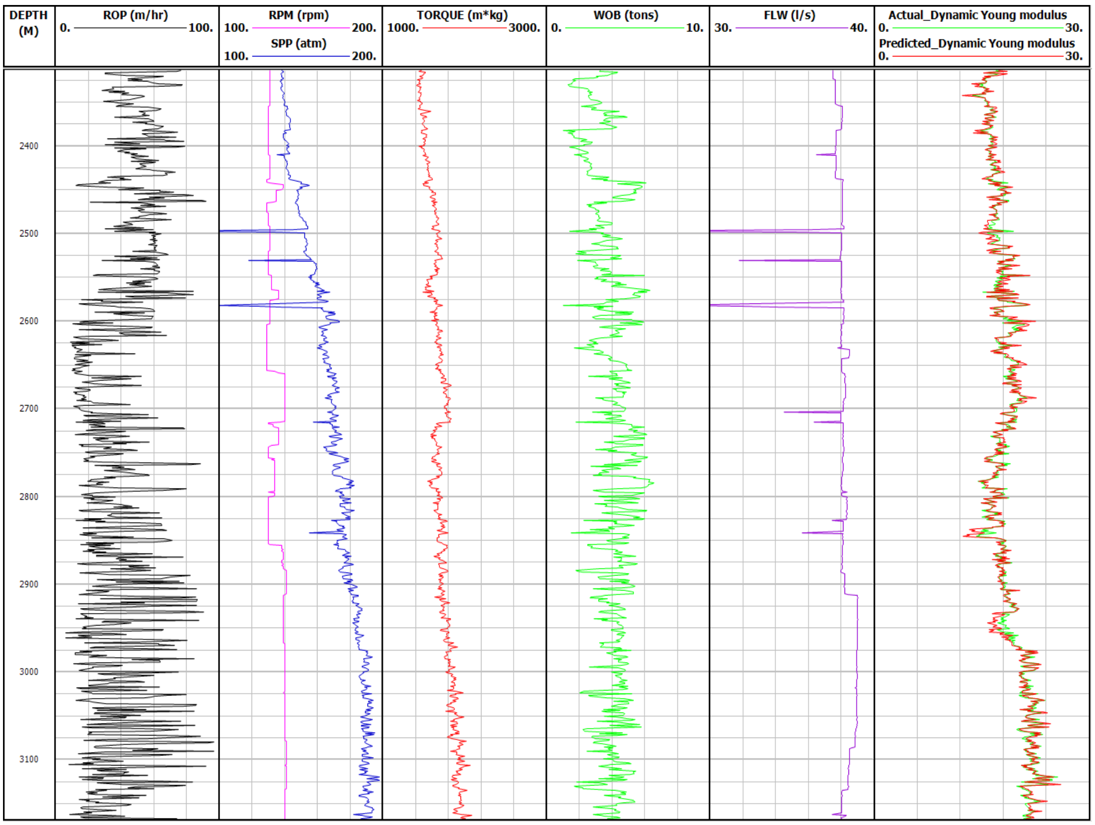

Figure 7. Comparison of the predicted dynamic Young's modulus curve from the model with the actual curve for Well C in the CT field

This depth-dependent trend matching is important for practical applications, as it ensures the predictions follow physically meaningful patterns that drilling engineers can use for operational decisions. The consistent performance across different wells confirms the model's suitability for field-wide application. The ability to reproduce both absolute values and geological trends provides confidence in the model's practical utility for real-time drilling operations.

5. Conclusions and recommendations

This study shows that machine learning can predict dynamic Young's modulus directly from drilling parameters at the CT oil field, offshore Vietnam. We developed and validated three algorithms-Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forests (RF)-using 1,061 samples from wells A and B. Six drilling parameters were used: ROP, RPM, WOB, SPP, FLOWIN and TORQUE.

All three algorithms achieved good performance, with the ANN model performing best. It achieved a correlation coefficient of 0.912 and RMSE of 0.134 GPa on blind test validation using Well C. Despite moderate correlations (0.05÷0.29) between individual parameters and Young's modulus, the multi-parameter approach allows the model to capture complex relationships between drilling parameters and rock stiffness. Blind testing on an independent well showed strong generalization capability, important for practical use in varied geological environments.

The validated approach shows that machine learning, particularly ANN models, can predict dynamic Young's modulus from drilling parameters. This offers a practical alternative to traditional methods. The approach provides several operational benefits: reduced costs by eliminating expensive well logging and core testing, real-time predictions during drilling operations, immediate geomechanical characterization for better decision-making, and continuous formation evaluation along well trajectories. Integrating drilling data into geomechanical workflows improves wellbore stability design and risk management in challenging geological settings.

The successful blind test validation indicates the model is ready for operational deployment. This has important implications for oil and gas operations: optimized drilling strategies through formation characterization, improved risk management via better prediction of formation behavior, and enhanced reservoir characterization through continuous mechanical property profiling. These capabilities represent an important advance in drilling technology and formation evaluation.

This study establishes a solid foundation for drilling-based dynamic Young's modulus prediction. Future research should address: geographic expansion to different geological settings beyond CT oil field, incorporating additional drilling variables such as mud properties and environmental conditions, model improvement through advanced architectures, multi-field validation for transferability assessment, and integration with other geomechanical models for comprehensive formation characterization.

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Contributions of authors

Duong Hong Vu - methodology, writing, review and editing; Hung Tien Nguyen - writing, review and editing; Thach Thiet Vu - supervision.

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