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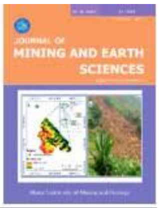

Prediction of Poisson's ratio for hydraulic fracturing operations in the Oligocene formations in the Bach Ho field

Tu Van Truong [1,*], Vinh The Nguyen [1] , Long Khac Nguyen [1], Thinh Van Nguyen [1], Hung Tien Nguyen [1], Tai Trong Nguyen [2], Thinh Duc Kieu [3]

[1] *Hanoi University of Mining and Geology, Hanoi, Vietnam*
[2] *Zarubezhneft E&P Vietnam, HoChiMinh City, Vietnam*
[3] *Thuy Loi University, Hanoi, Vietnam*

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ABSTRACT

In rock geomechanics analysis, Poisson's ratio is one of the critical factors that affect mechanical properties of rocks and soils, wellbore stability, in situ stress, drilling efficiency, and hydraulic fracturing design. There are two conventional methods for measuring Poisson's ratio, they are called acoustic wave method and compression testing of core sample. In the first, the Poisson's ratio is determined based on well-log data known as dynamic values. Conversion formulas need to be established for different geological conditions to obtain reliable computational results. However, the determination of each suitable conversion formula is time and money-consuming, as well as the process, is relatively complicated. The latter method must be performed in the laboratory with high accuracy equipment and requires the availability of core samples obtained through the coring process with high expenditure. To overcome the limitations of these two methods, the authors used the Artificial Intelligence technique to establish correlations between the value of Poisson's ratio and drilling parameters (e.g., weight on bit, flow rate, torque, annulus velocity, pressure losses) in the Oligocene formation of the Bach Ho field. Two machine learning algorithms including Random Forest (RF) and Decision Tree (DT) were applied in this study. On the other hand, the offset data from Well A and Well B penetrated through the Oligocene formation of the Bach Ho field were used to build, train, and verify the accuracy of the artificial intelligence simulations. Both wells have similarities in lithological characteristics and composition. The results indicated that the Artificial Intelligence models are highly accurate in predicting the value of Poisson's ratio, with correlation coefficient results for the RF model and the DT model being at 0.79 and 0.76 respectively.

*Corresponding author.
E-mail address: truongvantu@humg.edu.vn
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1. Introduction

Hydraulic fracturing is a highly effective methodology for the improvement of the production rate of oil and gas wells as well as enhancing the formation capacity for injection wells. In this method, injection fluid is pumped into a reservoir formation at high pressure to induce additional fractures. Subsequently, sand/propant is pumped into the reservoir to keep the fractures open to maintain the permeability and sustain the conductivity after the fracturing process is completed. In the hydraulic fracturing design simulation for fractures, the key input data including Young's modulus and Poisson's ratio, are related to the mechanical properties of rock formation (Tu et al., 2017).

For the fracture simulations, Young's module, Poisson's ratio, and other geomechanical parameters of formations are typically determined by core compression tests and the interpretation from well-log data. However, there are some limitations to the application of these methods. The values obtained from well log data interpetation shall be indicated as "Dynamic", thus they are not suitable for wellbore stability analysis. To obtain reliable calculation in the wellbore stability analysis, it is necessary to convert “Dynamic” to “Static” values in the geological condition respectively. References suggest that the Dynamic Poisson's ratio is higher than the Static Poisson's, and the relationship between them is not clear, especially for low-deformative rock formations. The differences between these values are explained by the influence of porosity, size and orientation of fractures. Finding an appropriate conversion formula requires significant time, cost, and relative complexity (Abdallah et al., 2014; Lal, 1999). Core compression tests in the laboratory offer a high accuracy but they require available core samples, additional equipment, and sometimes the need for supplementary core measurement results, which consume time and sampling costs (Müller et al., 2019).

Researchers face the challenge of establishing a causal relationship between Poisson's ratio and drilling parameters. Some authors, including Elkatatny (2021), Mutalova et al. (2020), and Siddig et al. (2021), have applied Artificial Intelligence (AI) to derive geomechanical parameters such as Young's modulus, Poisson's ratio, bulk modulus, shear modulus, and minimum horizontal stress-from well log data or drilling parameters. These AI-driven approaches offer a more efficient, cost-effective, and rapid means of predicting fracture development and enhancing fracturing efficiency. Building on this, studies by Abdulraheem et al. (2019) and Ahmed et al. (2021) demonstrated the high accuracy of AI models like artificial neural networks (ANNs) and adaptive neuro-fuzzy inference systems (ANFIS) in predicting Poisson’s ratio from well-log data. Siddig et al. (2021) further explored real-time prediction using drilling parameters and machine learning, achieving strong correlations with minimal error. Additionally, Müller et al. (2019) provided an efficient laboratory method for determining Poisson’s ratio, validated against traditional techniques. These diverse methodologies highlight AI's potential in overcoming traditional limitations, particularly in correlating Poisson's ratio with various influencing parameters, including real-time drilling data.

Building on these advancements, this study aims to compare the performance of two models: Random Forest (RF) and Decision Tree (DT). By evaluating their accuracy and efficiency in predicting the Poisson coefficient, this study seeks to determine which model offers superior performance and robustness for this application.

2. Data Description and Analysis

2.1. Data Description

In this study, data was collected from drilling operations in the Bach Ho field, offshore Vietnam. The drilling parameters and related Poisson's ratio values while drilling a 8 ½” hole section shall be utilized. Meanwhile, the lithological composition of the Oligocene formation (from upper to lower) consists of shalestone and sandstone as given in Figure 1. Well A contributed a total of 714 data points used for building the study model. Among those data points, there are 70% of the data are used for the training set and the rest is used for model verification. On the other hand, 196 data

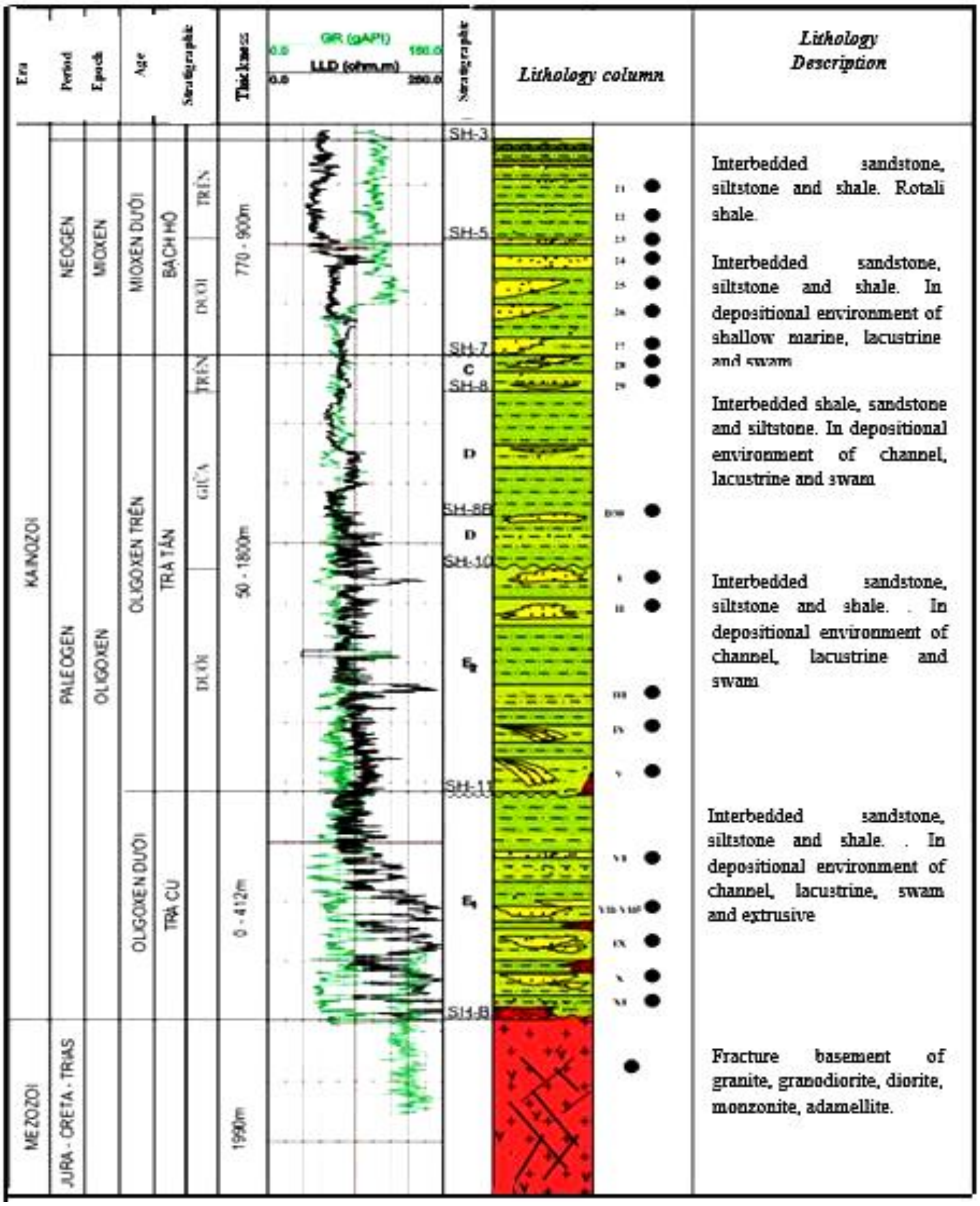


Figure1. Lithology column for Well A.

points from Well B were used for model validation. In addition to Poisson's ratio as the output, each data point contains drilling parameters used as input parameters. The drilling parameters listed below were measured in the field and used to build a predictive model:

- Weight on bit (WOB);
- Torque on bit (TQR);
- Standpipe pressure (SPP);
- Rotary speed (RPM);
- Flow rate (FLOWIN);
- Rate of penetration (ROP).

2.2. Data Analysis

Before running the data through machine learning algorithms, the datasets were preprocessed to remove noise and outliers using the Z-score method (Tripathy et al., 2013), analyzing the data based on the correlation between two variables. Statistical analysis of the dataset used for model construction is presented in Table 1.

The selection of input data for training and testing process is an important step that determines the accuracy of the model. The correlation coefficients between the Poisson's ratio and different drilling parameters are presented in Figure 2. From Figure 2a, it can be observed that the correlation coefficients between the drilling parameters and Poisson's ratio are all below 0.5. Therefore, applying artificial intelligence models will offer better results than linear regression methods as they can approximate more complex relationships.

In Figure 2b, a relatively strong correlation is shown between the Poisson's ratio and some drilling parameters such as standpipe pressure (SPP), torque on bit (TQR), weight on bit (WOB), and rate of penetration (ROP). Lower correlation coefficients for other parameters do not necessarily imply the absence of a relationship between these inputs and the Poisson's ratio. It indicates that a linear equation does not adequately describe the relationship between the inputs and the output. These analyses highlight the importance of the parameters. Specifically, it is shown that achieving 95% importance requires 6 parameters. This indicates that the selected dataset is highly reliable and that the chosen features are crucial for ensuring model accuracy.

3. Methodology

In prediction stage of the Poisson's ratio from drilling parameters, the authors utilise an algorithm flowchart as given in Figure 3. The input data consists of drilling parameters and actual Poisson's ratio from two wells, A and B. Data from well A was split into a train set (70%) and a test set (30%) for the model training process. Data from well B was used as an independent test set to validate the accuracy of the trained model.

Random Forest and Decision Tree Algorithms

With the aim of building the relationship between Poisson's Ratio and drilling parameters, two machine learning algorithms, DT and RF, were used separately. Both algorithms could perform

Table 1. Input database.

	ROP	WOB	RPM	TQR	SPP	FLOWIN	POISSON
Count	714	714	714	714	714	714	714.000
Mean	17.44	8.27	117.47	1575.95	195.26	37.78	0.316
Std	9.99	1.90	20.96	204.29	24.18	9.30	0.029
Min	0.78	2.33	40.00	1037.60	143.32	22.06	0.200
25%	11.86	7.07	116.00	1534.15	184.28	34.77	0.301
50%	17.35	8.41	121.00	1593.30	202.85	38.05	0.320
75%	21.07	9.20	122.00	1669.88	212.06	38.10	0.337
Max	45.40	13.87	161.00	2185.30	224.00	54.64	0.392

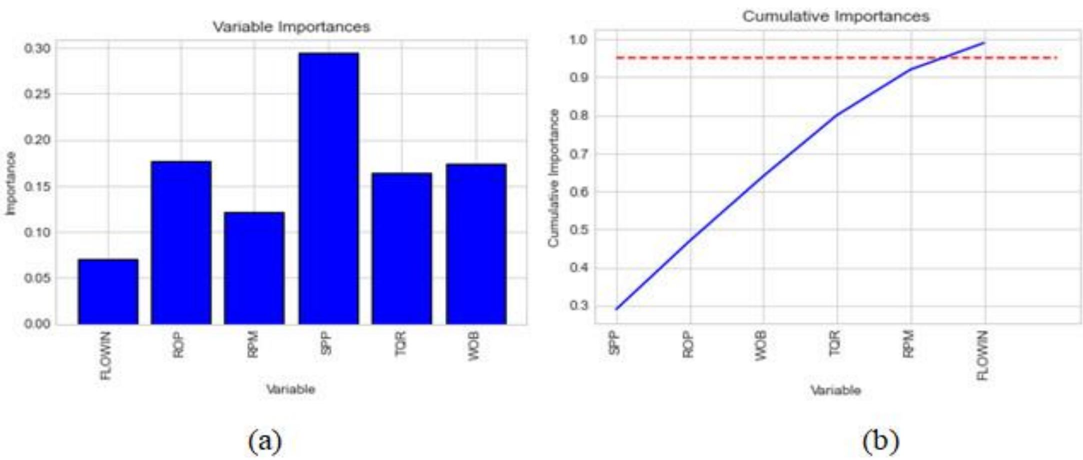


Figure 2. The correlation between predicted coefficient and the parameters used for prediction stage.

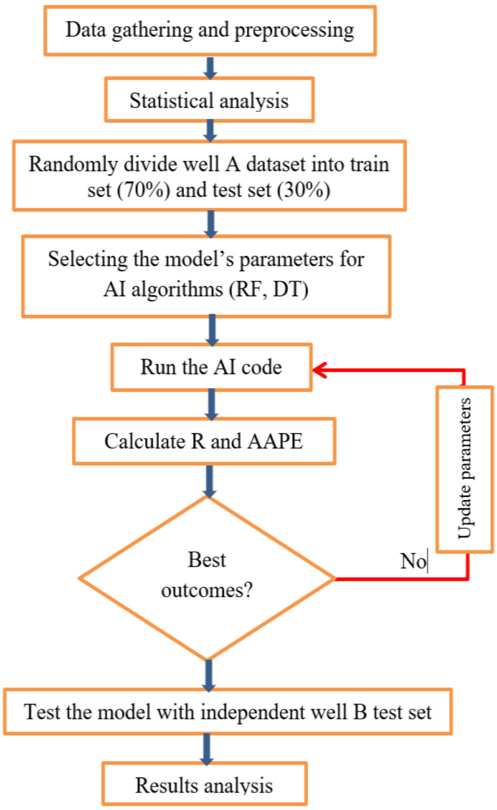


Figure 3. Flow chart for generation of AI model.

classification and regression tasks, but for this paper, only regression was employed and discussed.

Decision Tree

The training data for DT Regression is represented as (x, y) = (x_1, x_2, ..., x_k, y), where: y is the target variable (Poisson coefficient) and x_1, x_2,..., x_k are independent variables of drilling parameters.

The process of building a regression DT involves two steps (James et al., 2017):

a. Prediction space, which is the set of values for x_1, x_2, ..., x_k, is divided into J distinct and non-overlapping regions, R_1, R_2, ..., R_J.
b. For all of the observed variables in the region Rj, the same prediction is made, which is the average value of the target variable for training observations in Rj.

To build optimal regions R_1, R_2, ..., R_J, the prediction space is divided into multidimensional boxes that minimize the residual sum of squares (RSS):

$$RSS = \sum_{j=1}^{J} \sum_{i \in R_j} (y_i - \hat{y}_{R_j})^2 \tag{1}$$

Where $\hat{y}_{(Rj)}$ - is the average value of the target variable in the j^{th} box.

Random Forest

RF is an ensemble learning algorithm proposed by Breiman in 2001 (Breiman, 2001). It constructs a large number of random decision trees on bootstrapped training samples and aggregates their predictions by averaging the results (James et al., 2017). It has become a major data mining tool for both regression and classification problems. Recently, the consistency of RF has been proven by Scornet in 2015 (Scornet et al., 2015). Compared to other machine learning algorithms like neural networks, RF can achieve relatively high prediction performance with only a few adjustable parameters (Genuer et al., 2017).

There are several open-source implementations of DT and RF algorithms, among which scikit-learn (Pedregosa et al., 2011; https://scikit-learn.org/) is a widely machine learning library chosen for these studies, with the parameter sets described in the next section.

Selection of Parameter Sets for RF and DT Algorithms

The selection of parameters for both the RF and DT algorithms is described in step 3 of the algorithm flowchart in Figure 3. The parameters for both algorithms are presented in Table 2 and Table 3, respectively (https://scikit-learn.org/).

Model Performance:

To evaluate all model experiments, five statistical metrics were employed: the correlation coefficient (R), the average absolute percentage error (AAPE), the mean absolute error (MAE), the coefficient of determination (R^2), and the root mean square error (RMSE). These metrics were calculated using the following equations:

$$R = \frac{\left[N \sum_{i=1}^{N} (\mu_{given\,i} \times \mu_{Predicted\,i})\right] - \left[\sum_{i=1}^{N} (\mu_{given\,i} \times \mu_{Pre}\right.}{\sqrt{\left[N \sum_{i=1}^{N} (\mu_{given\,i})^2 - \left(\sum_{i=1}^{N} \mu_{given\,i}\right)^2\right]\left[N \sum_{i=1}^{N} (\mu_{Predicted\,i})^2 - (\sum\right.}} \tag{2}$$

$$APE = \frac{\sum_{i=1}^{N} \frac{\mu_{given\,i} - \mu_{Predicted\,i}}{\mu_{given\,i}} \times 100\%}{N} \tag{3}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |\mu_{given\,i} - \mu_{Predicted\,i}| \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(\mu_{given\,i} - \mu_{Predicted\,i})^2}{\sum_{i=1}^{N}(\mu_{given\,i} - \bar{\mu}_{given\,i})} \quad (5)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mu_{given\,i} - \mu_{Predicted\,i})^2} \quad (6)$$

Where: μ_{given} - The actual Poisson coefficient based on the geological literature; $\bar{\mu}_{given}$ - The mean (average) of all actual values; μ_{given} - across the dataset; $\mu_{Predicted}$ - The predicted Poisson coefficient; N - Total number of data points.

For each RF and DT model, an optimal set of parameters was used. The Grid Search algorithm was employed to identify the best model by examining all possible values or names for each parameter. This approach is detailed in Section 3, Methodology. After conducting iterations of the algorithm flow depicted in Figure 3 and using the parameters listed in Tables 2 and 3, the best-performing parameter set was selected for each model. For the RF model, the optimal parameters were: 'n_estimators': 400, 'min_samples_split': 3, 'min_samples_leaf': 2, 'max_features': 'sqrt', 'max_depth': 20, 'bootstrap': False. For the DT model, the selected parameters were: 'min_samples_split': 5, 'min_samples_leaf': 1, 'max_features': 'auto', 'max_depth': 10. Performance metrics for these parameter sets have been included in the revised tables to facilitate the identification of the optimal configurations.

Table 2. Optimum set of parameters for the RF model.

Parameter	Value
n_estimators	400
max_features	sqrt
max_depth	20
min_samples_split	3
min_samples_leaf	2
bootstrap	False

Table 3. Optimum set of parameters for the DT model.

Parameter	Value
max_features	auto
max_depth	10
min_samples_split	5
min_samples_leaf	1

3. Results and Discussions

The performance of the predictive models was evaluated using five statistical metrics to show their accuracy and reliability. The key results are summarized in Table 4.

Table 4. Summary results of evaluation metrics.

Dataset	Metrics	DT	RF
Train set	R	1	0.97
	AAPE	2.0x10^-16 (≈0)	1.03
	R2	1.00	0.98
	RMSE	6.1x10^-16 (≈0)	0.41
	MAE	6.8x10^-17 (≈0)	0.28
Test set	R	0.71	0.74
	AAPE	2.73	2.82
	R2	0.69	0.74
	RMSE	1.66	1.53
	MAE	1.15	1.12
Indepenent test set	R	0.76	0.79
	AAPE	2.95	2.97
	R2	0.67	0.68
	RMSE	1.30	1.27
	MAE	0.93	0.98

3.1. Random Forest Model

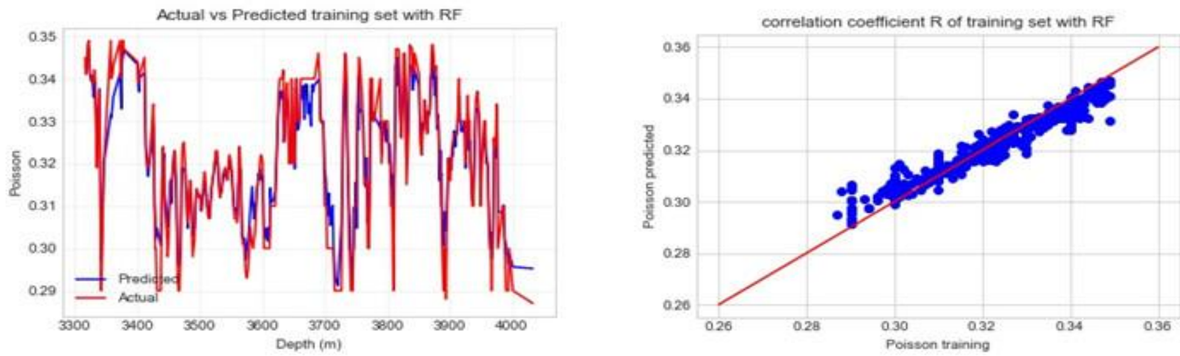
Training the RF Model using Well A dataset

The RF model has learned to predict the Poisson's Ratio based on the following parameters: Weight on Bit (WOB), Torque on Bit (TQR), Standpipe Pressure (SPP), Rotary Speed (revolutions per minute) (RPM), Rate of Penetration (ROP), and Pump rate In (FLOWIN). The model was trained and tested on 714 data points from Well A. Figures 4a and 5a illustrate the close proximity between the actual (red curve) and predicted (blue curve) Poisson coefficients with respect to depth for the training and testing datasets. The Average Absolute Percentage Error (AAPE) values for these datasets are 1.03% and 2.82%, respectively.

This is also evident in Figures 4b and 5b, which demonstrate the compatibility between the predicted and actual Poisson coefficients, with correlation coefficients (R) of 0.972 and 0.742, respectively.

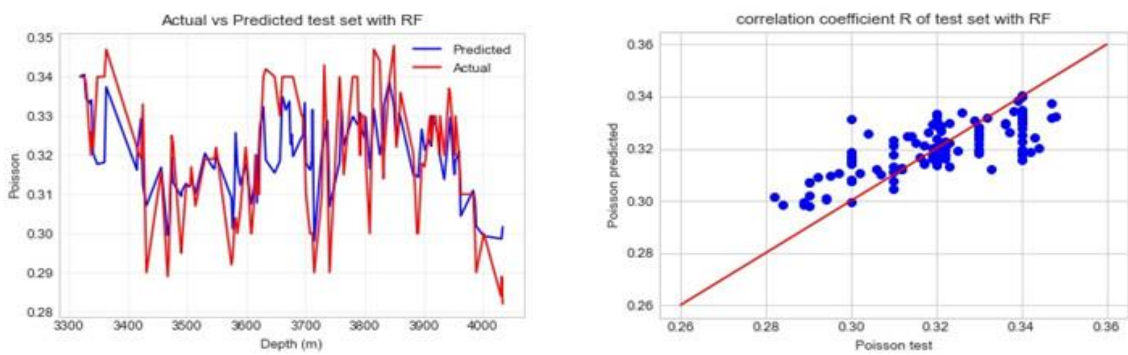
Validating the trained RF model using an independent test set of Well B

The RF model created by using data from Well A was evaluated by using 196 data points from Well B. Figures 6a and 6b demonstrate the accuracy of the model's predictions, with a very low Average Absolute Percentage Error (AAPE) of only 2.97% and a relatively high correlation coefficient (R) of 0.79. These results confirm the capability of utilizing the developed empirical correlations based on drilling parameters to enable the prediction of the Poisson coefficient, as demonstrated in this study. The model demonstrates high correlation coefficients and low errors for the training, testing, and validation datasets. This is due to the RF algorithm, which



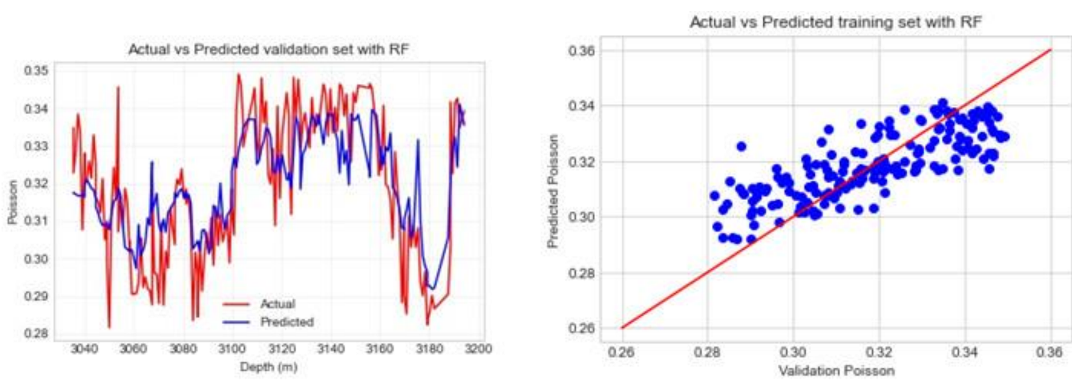
(a) (b)

Figure 4. Actual and RF predicted Poisson's ratio for training phase.



(a) (b)

Figure 5. Actual and RF predicted Poisson's Ratio for testing phase.



(a) (b)

Figure 6. Actual and RF predicted Poisson's Ratio for trained model using independent test set.

constructs an ensemble of decision trees. Each tree is built using a bootstrap sample (random sampling with replacement), and at each node, the best split is determined by randomly selecting a subset of features. The generalization error of the RF model depends on the accuracy of each individual tree and the interactions among the trees. The RF algorithm achieves high accuracy compared to current supervised learning algorithms by maintaining low bias (error unrelated to the training data) and using randomness to ensure low correlation between the trees.

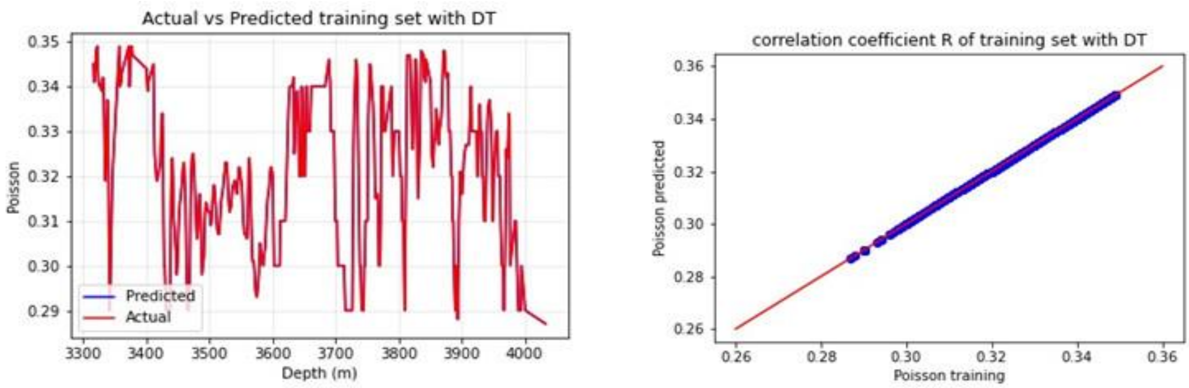
3.2. The Decision Tree Model

Training the DT Model using Well A dataset

The DT was trained and tested on 714 data points from Well A. The DT model also achieved high accuracy, as shown in Figures 7a and 8a, with Average Absolute Percentage Error (AAPE) values of 0% and 2.73%, respectively, and correlation coefficients (R) of 1 and 0.71 (Figures 7b and 8b). The DT model exhibited overfitting for the training data, as indicated by an AAPE of 0% and an R value of 1 in Figure 7. This is an example of an overfitting phenomenon, where the model cannot accurately predict the test data despite performing well on the training dataset. This occurs because the model memorizes the training data too well and becomes dependent on it, which prevents it from generalizing the rules to work with unseen data (validation), a common issue with DT algorithms. However, it still demonstrated high accuracy on the test and independent test sets, as shown in Figures 8 and 9.

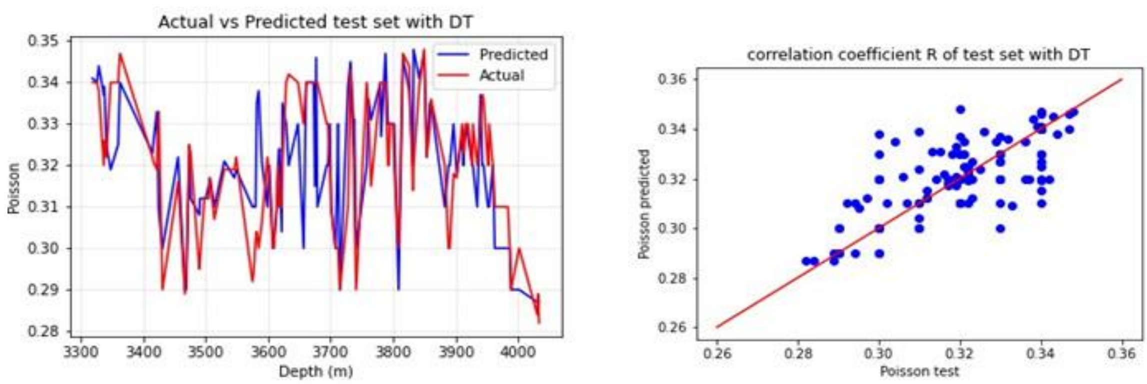
Validating the trained DT model using an independent test set of Well B.

Figures 9a and 9b illustrate the correlation between the predicted Poisson coefficients and the actual Poisson coefficients of the validation dataset. Figure 9b clearly shows that the predicted curve (blue) of the Poisson value has very similar trends



(a) (b)

Figure 7. Actual and DT predicted Poisson's Ratio for training phase.



(a) (b)

Figure 8. Actual and DT predicted Poisson's Ratio for testing phase.

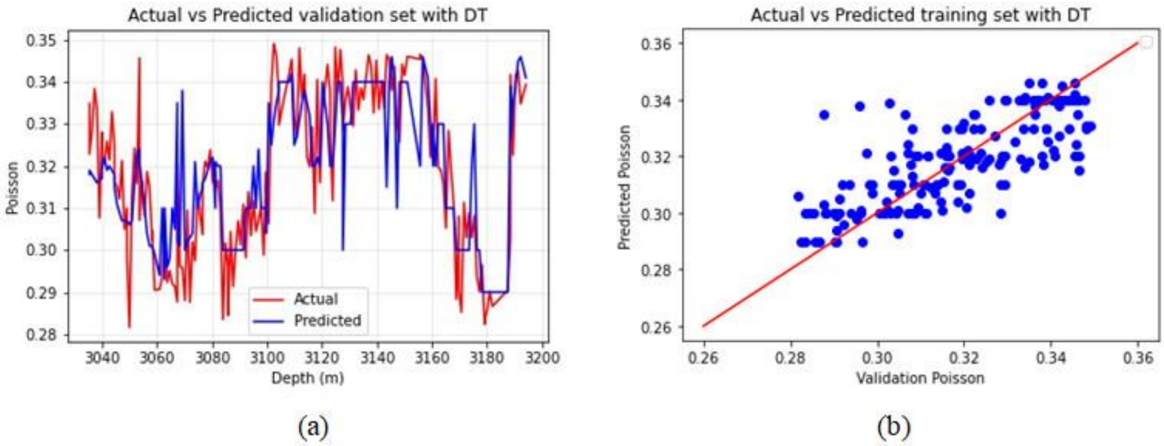


Figure 9. Actual and DT predicted Poisson's Ratio for trained model using independent test set

with the actual curve (red) values, especially at the depths from about 3040÷3060 m and from 3080÷3120 m. In addition, Figure 9b shows that all data points are very close to the diagonal line at 45 degrees, confirming the high predictive ability of the DT model with an estimated correlation coefficient (R) of 0.76 and an Average Absolute Percentage Error (AAPE) of 2.95%. This further supports the effectiveness of the DT model in accurately predicting the Poisson coefficient. The DT algorithm model for forecasting the Poisson coefficient on the validation dataset has a mean absolute percentage error (AAPE) of 2.95% and a correlation coefficient R of 0.76. It is observed that the validation set shows only an average correlation coefficient due to one of the common limitations of the DT algorithm: they often struggle with time-dependent data, which may prevent the construction of an optimal tree. Additionally, there is a risk of overfitting (creating trees that closely fit the training data or become overly complex) and a tendency to favor features with more values.

4. Conclusions and Recommendations

Poisson's ratio is usually determined by two traditional methods: sound wave method and core testing for compressive strength methodology. However, the databases for input data are not always available. The application of artificial intelligence for predicting Poisson's Ratio by using drilling parameters as discussed in this paper has shown promising results and potential use for estimating Poisson's Ratio. The following conclusions and recommendations can be drawn based on the presented findings:

- Compared to other conventional methods, using AI to build models for predicting the Poisson's Ratio from drilling parameters could establish a good correlation between the Poisson's Ratio and the relevant parameters. This method provides an effective prediction tool for hydraulic fracturing and various other applications in the oil & gas industry. It also saves cost, time, and overcomes the lack of available data, additional measuring equipment, and supplementary core sample measurements. Therefore, predicting the Poisson coefficient from drilling data using models built from AI offers practical benefits.

- Both machine learning algorithms RF and DT were investigated in this study and provided promising results. In comparisons between those two methods, the RF model demonstrated better prediction performance for the Poisson coefficient. The optimization of different parameters used in the algorithm has been presented, resulting in the best-performing model.

- The correlation ratio between the actual and predicted values ranged from 0.74÷0.79, with an AAPE consistently less than 3%. The RF is the best-performing model for predicting the Poisson coefficient and showed good performance with different datasets.

- The results presented in this study indicate a promising ability for the application of AI to predict the Poisson's Ratio from drilling data. However, it is recommended to work with other machine learning methods as well. Additionally, the use of drilling data in predicting other geomechanical properties can be further investigated by using similar approaches. It is noted that the data used in this study is from a specific area of the Bach Ho field in Vietnam, and to create a more diverse prediction model, testing with data from other basins should be considered.

- Overall, the application of artificial intelligence for predicting the Poisson's Ratio by using drilling data holds great potential use for improving efficiency and accuracy in the oil and gas industry. Further research and development in this field can lead to valuable insights and practical applications.

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Contributions of authors

Tu Van Truong – conceptualization, review & editing; Vinh The Nguyen, Long Khac Nguyen, Hung Tien Nguyen, Thinh Van Nguyen - writing - original draft, discussed research problems; Tai Trong Nguyen and Thinh Duc Kieu - prepared the pictures and database.

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