Measurement of Rock Deformation Parameters - Estimation of Stacked Fusion Model of Young's Modulus

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Abstract: Rock Young's modulus is an essential parameter for formation stress characterization and oil and gas reservoir evaluation work and plays an important role in oil drilling-related engineering type work. Aiming at the problems of doubtful confidence in Young's modulus measurements, time-consuming computation, and high measurement cost in oil drilling, this paper proposed Young's modulus estimation method based on the Stacking fusion model. The method first processed the downhole vibration data to obtain its time-domain feature data and then used the time-domain feature data as the input to the fusion model while used the rock Young's modulus data as the model output. The model learner used consists of three base learners, ANN, XGBoost, and CatBoost, with MLR as the model meta-learner. The mapping relationship between the time-domain features and Young's modulus was established by this method, and the prediction and estimation of Young's modulus parameters of the rock were finally realized. The results showed that the average absolute error (MAE) of the fused Stacking model was 0.2502 and the goodness-of-fit (R²) was 0.9691. Compared with other single models, the fused model based on Stacking had the advantage of being able to combine each single model, which provided a new method for estimation and prediction of Young's modulus of rocks.

1. Introduction

In the field of geotechnical design and construction, the engineering properties of rocks play a crucial role in exploring, planning and optimizing the use of the Earth's resources[1,2]. These properties include strength and deformation characteristics, which provide the necessary preconditions for ensuring engineering stability and reliability. One of the most important elastic constants is the elongation stress-strain ratio, or Young's modulus (E), which can usually be measured by the Unconfined Compression Test (UCT). This test has been standardized by the International Society for Rock Mechanics (ISRM2007). Direct measurement of this property in the laboratory is both complex and time-consuming, requiring not only the availability of high-precision core sampling samples, but also good equipment instrumentation and specialized personnel[3,4].

Therefore, the use of indirect measurement methods, such as empirical correlation and artificial intelligence (AI), can provide fast and reliable estimates of rock engineering properties. These methods have the advantages of low cost, short time to get results and less preparation of experimental samples. The aim of this study is to utilize machine learning algorithms in AI techniques to predict rock elastic properties based on nondestructive test data, providing a more efficient and faster alternative to traditional laboratory measurement methods. There have been many published related machine learning methods for predicting Young's modulus (E). For example, Elkatatny et al. proposed real-time prediction of dynamic Young's modulus through ANN by using drilling pressure, mechanical drilling speed, and torque data as inputs to a prediction model[5]. Manouchehrian et al. proposed a prediction model based on ANN and multivariate statistics to predict uniaxial compressive strength (UCS) using rock texture information as an input and obtained R² was 0.93, which indicated that the ANN was more powerful than the statistical model for predicting UCS[6]. Koopialipoor et al. proposed a Stacking prediction model based on multi-model fusion, which predicted Young's modulus of rocks using four metrics as model inputs, namely porosity, point load strength, Schmidt's hammer, and p-wave velocity, and the R² obtained was 0.8258, which was much higher than that of Stack-KNN, Stack-RF in terms of prediction accuracy, Stack-MLP models[7]. Currently, few studies had considered the use of downhole vibration data for prediction or estimation of rock Young's modulus, and the use of vibration data for estimation of rock Young's modulus makes sense due to the low latency and easy accessibility of vibration data.
In recent years, some studies have combined multiple single models with certain strategies to constitute an integrated model to improve the model’s problem solving ability. The research results show that the integrated learning model based on multiple single learners can often obtain superior generalization ability and robustness than a single learner, and can select a set of optimal sub-learners to improve the effectiveness of the learning system under the premise of ensuring the performance of the integrated model system.

Most of the current research is to establish a single model to quantitatively analyze the rock engineering properties. In this study, we try to establish a Stacking heterogeneous integrated model from the time-domain features of vibration data to the Young's modulus of rock based on ANN, XGBoost, CatBoost, etc., and we expect to obtain the prediction effect superior to each single model, to predict Young's modulus of rock quickly and conveniently, and to provide a new machine learning method for Young's modulus measurement and estimation of rock.

2. Estimation of Young's Modulus of Rock Based on Stacking Fusion Model

2.1. Stacking Fusion Model Estimation Process

Drill column vibration is an unavoidable and destructive load in drilling operations, which can trigger a variety of deleterious effects such as downhole fatigue failure, damage to wellbore assemblies and downhole tools, and may even lead to serious drilling accidents. Therefore, it is important to accurately measure drill column vibration. In practice, measuring downhole vibration data usually relies on accelerometers embedded near the drill bit. However, in downhole environments, factors such as high temperatures, high pressures, and corrosion place extreme demands on the reliability and durability of the sensors, making real sensor data acquisition more difficult. In order to overcome these difficulties, numerical algorithms utilizing the finite element method have become an effective means of simulating real sensors for data acquisition in recent years. With such simulation algorithms, vibration data similar to real sensors can be generated in a computer environment for analysis and modeling. During drilling operations, changes in Young's modulus of the rock lead to changes in the vibration parameters of the drilling tools, i.e., there is a relationship between the vibration data and the physical property structure of the formation[8]. Therefore, by processing and modeling the vibration data for analysis, the estimated measurement of rock modulus can be realized.

Traditional machine learning and regression analysis research efforts have played an important role in influencing the estimation of Young's modulus, but the analytical approach using a single model focuses too much on the hyper-parameter optimization of the model, which makes the robustness and generalization of the model constrained, and the optimization efforts are less effective[1]. Common integration strategies include voting, Boosting, Bagging, and Stacking. Voting is mainly used for classification problems, and the weak learners integrated in Boosting and Bagging are generally of the same type, i.e., isomorphic integration models. Stacking is a heterogeneous learner ensemble method, which combines different types of weak learners to improve the accuracy of model prediction. Stacking is a heterogeneous learner ensemble method, which utilizes different types of weak learners to combine them so that they can complement each other’s strengths and advantages in order to improve the accuracy of model prediction. Therefore, in this paper, the Stacking-based model fusion was used to estimate the Young's modulus of rock, and the process was shown in Figure 1. First, the established rock-drill column system was analyzed for dynamic response by inputting different values of rock Young's modulus using finite element analysis software; The vibration data obtained from the dynamic response analysis was preprocessed, including operations such as data normalization, to form the original sample set; The processed dataset was subjected to time domain feature extraction to obtain feature vectors for Stacking fusion model training. Subsequently, the feature vectors were fed into the Stacking fusion model for learning to obtain the trained Stacking fusion model. Finally, the evaluation of the Stacking fusion model was completed based on the test set samples.

![Figure 1. Stacking fusion model for rock Young's modulus estimation method flow](image-url)
2.2. Preprocessing and feature vector generation

In this paper, Young's modulus of the rock was used as an input to the simulation model of the downhole rock-drilling system, and the vibration acceleration data extracted from the power response analysis was used to simulate the sampling results of the real sensors. The vibration time series data generated and obtained from the dynamic response analysis under different rock Young's moduli can be used as the initial data set for subsequent training and testing of the rock Young's modulus estimation model.

The dynamic load tangential and axial forces of the rock-drill column system[9,10]analyzed by the dynamic response can be expressed by the following equations:

\[ F_x = \frac{2\tau_f}{f+1} \cdot \frac{S' \cos \phi}{1 - \sin(\phi - 0.75\theta + 22.5)} + \frac{3\pi^3\rho \rho R^3}{8} \]  \( (1) \)

and

\[ F_y = (\sigma_f + \frac{E}{c\eta})S \]  \( (2) \)

Where, \( F_x \) and \( F_y \) represent the system tangential force and axial force respectively; \( f \) is the stress distribution coefficient; \( \tau_f \) is the rock shear strength; \( \theta \) is the cutting front angle; \( \phi \) is the shear angle; \( n \) is the rotational speed; \( v \) is the drilling speed; \( \rho \) is the density of the rock; \( R \) is the radius of the cutting teeth of the drill bit; \( \sigma_f \) is the compressive strength of the rock; \( E \) is the elastic modulus of the rock; \( \eta \) is the coefficient of the viscosity of the indentation; and \( S \) is the area of the indentation.

By analyzing the dynamic load force state of the drilling column system in the formation, the finite element analysis model of the rock-drill column system was established, and the dynamic response analysis of transverse vibration and axial vibration was carried out by using D’Alembert’s principle, and the analytical model is expressed as the following equation:

\[ \{M\}\{\ddot{x}\} + \{C\}\{\dot{x}\} + \{K_s\}\{x\} = \{F_x\} \]  \( (3) \)

and

\[ \{M\}\{\ddot{y}\} + \{C\}\{\dot{y}\} + \{K_s\}\{y\} = \{F_y\} - \{F_x\} - \{\tau_f\} \]  \( (4) \)

Where, \( \{M\} \), \( \{C\} \), \( \{K_s\} \), and \( \{\tau_f\} \) are the overall system mass matrix, damping matrix, elastic stiffness matrix, and geometric stiffness matrix, respectively; \( \ddot{x}, \dot{x}, \) and \( x \) are the transverse vibration acceleration, velocity, and displacement of the rock-drill column system, while \( \ddot{y}, \dot{y}, y \) are the axial vibration acceleration, velocity, and displacement of the rock-drill column system, respectively; and \( F_x, F_y \) are the propulsive force and the drilling tool's own gravity, respectively.

After the above dynamic response analysis, the vibration time series data could be obtained. Considering that the magnitude difference between it and Young's modulus of the rock was too large, in order to reduce the influence of data differentiation and improve the robustness and stability of the model, the data were preprocessed before the model was trained, i.e., the data were normalized to the interval of \([0, 1]\). The normalization used in this paper was the min/max normalization, which is given by the following equation:

\[ X' = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \]  \( (5) \)

Where \( X' \) is the normalized data; \( x \) is the original data; and \( x_{\text{max}} \) and \( x_{\text{min}} \) are the maximum and minimum values of each column of data, respectively.

After the data normalization was completed, the feature vectors for the Stacking fusion model training were obtained using the time domain feature extraction method.

2.3. Stacking Fusion Model

The core idea of the Stacking fusion model as a stacking integration approach is to improve the overall model prediction performance by stacking multiple base models, combining and retraining their prediction results to form a more powerful meta-model[11]. In the traditional Stacking fusion modeling framework, a high-fit training model is usually chosen to act as the base learner for the purpose of efficiently extracting the nonlinearly varying features of the original data. Due to the different training processes of each base learner, the trained fusion model is prone to overfitting problems. In order to improve the overfitting problem and enhance the prediction accuracy and prediction performance, this paper introduced a novel Stacking fusion model framework based on feature combination[12,13], as shown in Figure 2.

![Figure 2. Schematic of Stacking fusion model training](image-url)
In this framework, firstly different base learners were trained using the training set and the prediction results of each base learner were obtained. Secondly, the obtained prediction results were merged and organized into a new feature set of the form \((N, K)\) (\(N\) represents the number of samples and \(K\) represents the number of base learners). The original features in the training set were also selected and trained as inputs to the meta-learner together with the new set of features obtained from the prediction of each base-learner to obtain the final estimation results. The reason for introducing primitive features as part of the input to the meta-learner was to improve the overall prediction of the model by using the primitive features to constrain the whole prediction process on the one hand, and on the other hand, to effectively suppress the risk of overfitting due to the selection of a better-fitting base-learner.

Stacking’s base learner was as follows:
1) ANN: Artificial Neural Network (ANN) is a network structure that is connected by a series of neurons, consists of multiple layers, and is capable of information transfer[14]. It usually consists of three layers: input layer, hidden layer, and output layer, in which the input layer receives external input data, the hidden layer performs weighted summation and activation function according to the input signals, and finally the output layer produces prediction and classification results, which is well adapted to high-dimensional nonlinear problems and has good generalization performance.

2) XGBoost: Extreme Gradient Boosting Tree (XGBoost) is an improved and extended algorithm based on GBDT[15], essentially additive modeling. It combines a weak learner (decision tree or regression tree) into a strong learner, and through continuous iterative training the decision tree fits the residuals of the previous prediction, and ultimately makes the residuals between the predicted value and the actual value gradually reduce, so as to obtain a better prediction model.

3) CatBoost: As an upgraded version of the GBDT algorithm, CatBoost, compared to the traditional GBDT algorithm[16], introduces symmetric tree structure, regularization, adaptive learning rate, and other mechanisms, by using repeatable and incremental training methods, training and combining multiple weak classifiers, and ultimately constructing a strong classifier model with high robustness and strong generalization ability, which is suitable for a variety of classification and regression problems.

2.4. Test set update and model evaluation

In order to evaluate the performance of each base learner on unknown data and to provide a more representative test set for training the meta-learner, the original test set was fed into each base learner that had been trained to make predictions, and then the resulting predictions were averaged to form a new test set. Provided sample data for subsequent model evaluation and rock Young's modulus estimation.

After the model training was completed, the model performance and prediction accuracy were evaluated using three commonly used regression evaluation metrics: mean square error (MSE), mean absolute error (MAE), and goodness-of-fit (R2), and the MSE and MAE and R2 were calculated as follows:

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2
\]

and

\[
MAE = \frac{1}{m} \sum_{i=1}^{m} |X_i - \hat{X}_i|
\]

and

\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}
\]

The smaller MSE and MAE represent the better predictive performance of the model. The value of R2 ranges from [0,1], and the closer R2 is to 1, the better it represents the fit of the model. Let the Young's modulus \(E\) of the samples in the test set be \(y\), the Young's modulus obtained by the prediction model be \(\hat{y}\), and the mean value of Young's modulus of the samples in the test set be \(\bar{y}\).

3. Application of Stacking Fusion Model to Young's Modulus Of Rocks

3.1. Data set preparation

Due to the limited access to the real data of downhole vibration, in order to obtain enough training data to verify the accuracy and credibility of this method, this paper adopted the simulation model of the drilling column system drilling into the rock in the literature[9], and obtained the downhole vibration data of the drilling column system drilling into the rock by using the finite element simulation model, and the triaxial vibration data under the different settings of Young's modulus \(E\) are shown in Figure 3.
Analyzing Figure 3, it was found that: (1) the length of time that the drill bit drills into the rock are 5 seconds, and when the drill bit touches the rock, the triaxial acceleration data begins to change, and then produces a larger value of the vibration change; (2) the differences in vibration data when drilling into rock with different Young’s moduli are obvious; (3) the overall triaxial vibration data show irregular amplitude changes as the rock body undergoes shear disintegration when drilling into rock.

In order to better realize the training and prediction of the subsequent network model, the original vibration data obtained from the simulation should be subjected to time domain feature extraction[17], obtained time-domain characteristics of XYZ axes: mean, peak, RMS, kurtosis factor (lp), impulse factor (cf), and the time-domain features of XYZ axes with rock Young’s modulus (output) were used as the sample set for subsequent fusion model training and estimation.

3.2. Fusion model training

The estimation of Young's modulus of rock based on vibration data is a regression problem, and the Stacking strategy was used for fusion estimation, Figure 4 shows the block diagram of the Stacking fusion model training.
In the model training, firstly, for the entire historical dataset of time-domain features of vibration data (3081 entries), 90% of the data (2716 entries) were selected as the training set for training, and the remaining 10% of the data (365 entries) were used as the test set for verifying the performance of the model and the accuracy of the prediction. Secondly, the 10-fold cross-validation method was used to re-divide the divided training set, which was randomly divided into train1 to train10 with a total of 10 sets of sample sets (271 entries) to complete the division of the dataset.

In the base learner training of the first layer prediction model, taking the XGBoost model as an example, 9 of the 10 sample sets after division were selected sequentially as the training set, and the remaining 1 was used as the test set. Then used the 10-fold cross-validation method to train the model, and after the training was completed, made predictions on the 10-fold test set, and got the prediction result \( y_i, (i = 1, 2, \ldots, 10) \). After 10 predictions, got \( Y = \{y_1, y_2, \ldots, y_{10}\} \) as the prediction result of the XGBoost model. In this way, the training of ANN and CatBoost models was completed by the same training process and all the prediction results of the first layer prediction model and the new test set after estimation averaging of the original test set were obtained.

In the second layer of the prediction model, the prediction results of all base learners of the first layer of the prediction model were used as new features and were combined with the corresponding time-domain features and rock Young’s modulus of the samples of the original training set (2716 entries) to generate a new training set. The second layer prediction model was based on the new training set, and the meta learner (MLR) was trained to complete the training of the whole Stacking fusion model. The values of some key parameters taken during the training process were shown in Table 1.

### Table 1. Key parameters of the model section

<table>
<thead>
<tr>
<th>Base learner</th>
<th>Key parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>XGBoost</td>
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<td></td>
<td>max_depth</td>
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</tr>
<tr>
<td></td>
<td>Learning rate</td>
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<td>gamma</td>
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<td></td>
<td>min_child_weight</td>
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<td>ANN</td>
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<tr>
<td>CatBoost</td>
<td>One hot max size</td>
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</tr>
<tr>
<td></td>
<td>l2 leaf reg</td>
<td>1</td>
</tr>
</tbody>
</table>

#### 3.3. Analysis of rock Young’s modulus estimation

In order to verify the reliability of the estimation results of the Stacking fusion model, the model performance of the Stacking fusion model and the other three single models were analyzed using evaluation metrics such as MSE, MAE, and R2.

As can be seen from Table 2, the Stacking fusion model and the remaining three single models showed a better estimation of Young’s modulus. Among them, The three evaluation metrics MSE, MAE, and R2 for ANN and XGBoost are 0.6896, 0.6718, and 0.7881 and 0.4299, 0.4896, and 0.8611, respectively. CatBoost outperformed the other 2 base learner models in three evaluation metrics, with MSE, MAE, and R2 reaching 0.3287, 0.4845, and 0.8886, respectively. The Stacking fusion model had a more obvious improvement in prediction performance compared to the optimal single model CatBoost. Taking the goodness-of-fit R2 as an example, the R2 of the Stacking fusion model reached 0.9691, which was improved by 0.0805 compared with the single model CatBoost, and the model’s fitting effect reached a better one. It could be seen that the Stacking fusion model had higher reliability and better model performance than the three single models, and the estimation results of Young’s modulus of rock were more accurate. The results showed that the Stacking fusion model constructed by this method could not only effectively integrate the advantages of each single model, but also discarded the poor estimation part of the single model so that the overall fusion model could be improved in terms of stability and estimation accuracy.

### Table 2 Single Model vs. Stacking Fusion Model

<table>
<thead>
<tr>
<th>Model</th>
<th>MSE</th>
<th>MAE</th>
<th>R2</th>
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<tr>
<td>Single-base learner model</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>ANN</td>
<td>0.6896</td>
<td>0.6718</td>
<td>0.7881</td>
</tr>
<tr>
<td>XGBoost</td>
<td>0.4299</td>
<td>0.4896</td>
<td>0.8611</td>
</tr>
<tr>
<td>CatBoost</td>
<td>0.3287</td>
<td>0.4845</td>
<td>0.8886</td>
</tr>
<tr>
<td>Fusion model</td>
<td>0.0835</td>
<td>0.2502</td>
<td>0.9691</td>
</tr>
</tbody>
</table>

To further validate the prediction performance of rock Young’s modulus under the Stacking fusion model, the learning performance of the fusion model and the single model were compared and analyzed with the above-divided test set (365 sets). The estimation results of each single model and fusion model are shown in Figure 5(a)–(d), where the horizontal coordinate is the real value of Young’s modulus in the simulation model of the drill bit drilling into the rock, and the vertical coordinate is the estimated value of Young’s modulus in each base learner, and the black solid line is the contour line, and the closer the red data point is to the contour line in the figure.
represents the better fitting goodness of the model. The error space formed by the blue dotted line indicates that the deviation between the predicted value and the true value obtained by each model is less than ±25%, and it can be clearly seen from the figure that the predicted value obtained by the Stacking fusion model is basically within the error space, and the deviation of only five samples is greater than ±25%, indicating that the prediction effect of the Stacking fusion model is excellent. Thus, the above fitting goodness-of-fit graph showed that the proposed Stacking fusion model in this paper had the best fit on the test set, followed by CatBoost and XGBoost, and finally ANN.

As could be seen by the line graphs of the estimation results of Young's modulus of rocks for each model in Figure 5, plots(e)~(h), the estimation of the Stacking fusion model was closer to the real value than the other single models, and the magnitude of the variation of the error is the smallest. The above results showed that the Stacking fusion model could combine the advantages of each base learner model to show better performance than a single model, which improved the prediction ability to a certain extent, thus enabling better and more effective estimation of rock Young's modulus based on downhole vibration data.

The above research results can enrich the prediction methods of rock engineering properties, support the analysis of stratigraphic stress characteristics and the evaluation of oil and gas reservoirs and other subsequent work to plan accordingly, and can effectively improve the efficiency of the subsequent exploitation and exploration of the earth's resources.

Figure 5. Comparison of Stacking fusion model and single model estimation results Figure. Fig.(a)~(d) respectively show Goodness-of-fit of ANN, XGBoost, CatBoost and Stacking fusion models.Fig.(e)~(h) represent the plots of predicted versus true values for ANN, XGBoost, CatBoost and Stacking fusion, respectively.

4. Conclusions

Aiming at the problems of doubtful confidence in prediction results and difficulty in obtaining rock core samples in Young's modulus measurements, this paper proposed a method for estimating rock Young's modulus based on the Stacking fusion model. The method took the time-domain features of downhole vibration data as input and rock Young's modulus as output and finally constructs a rock Young's modulus estimation model with high estimation accuracy and excellent overfitting resistance by fusing multiple differentiated base learner models and introducing feature fusion. The experimental results showed that this method could effectively estimate Young's modulus of rock by the time-domain characteristics of vibration data, and the mean absolute error (MAE) of the model evaluation index reached 0.2502 and the goodness-of-fit (R2) reached 0.969. Compared with other single models, the Stacking fusion
model has higher estimation accuracy and better model performance, which can provide a new effective method for rock Young's modulus measurement.

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**References**


