DEFORMATION PREDICTION METHOD OF SOFT ROCK IN DEEP SHAFT BY MACHINE LEARNING

by

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Predicting the unsupported deformation behavior of a shaft is crucial for evaluating the stability of the rock mass, selecting an appropriate support scheme. Random forest, XGBoost, LightGBM, and K-nearest neighbors regression models were trained for database, and their accuracy was evaluated. It aimed to examine the effects of various parameters on shaft deformation, including the maximum tangential stress of the surrounding rock, elastic modulus, Poisson's ratio, cohesion, internal friction angle, and rock mass compressive strength. The results indicate that the coefficient of determination for random forest model is outperformed the other models. The importance of the characteristic parameters, in order, is cohesion, rock mass compressive strength, elastic modulus, rock compressive strength, internal friction angle, Poisson's ratio, and maximum tangential stress of the surrounding rock.

Key words*: deformation, prediction method, soft rock, deep shaft, machine learning*

Introduction

With the deepening of underground engineering construction, shaft projects under soft rock conditions are increasingly facing challenges in deformation control [1]. During the excavation of the shaft, varying degrees of deformation often occur, posing a significant threat to both the shaft's structural integrity and the safety of personnel [2, 3]. Therefore, the assessment and prediction of surrounding rock stability are crucial. Currently, the main methods for predicting shaft deformation in mining areas include data analysis-based machine learning methods, mechanics-based theoretical analysis methods, and empirical parameter-based model prediction methods. Spesivtsev *et al*. [4] proposed a machine learning-based approach by constructing and training an ANN, utilizing a dataset generated from a full-scale transient shaft flow numerical simulator, to develop a predictive model for multi-phase shaft flow in order to forecast the key parameter of bottom hole pressure. Wu *et al*. [5] introduced a hybrid prediction framework based on RF-RFE and BO-NGBoost, aiming to accurately predict tunnel deformation induced by adjacent foundation pit construction. Xu *et al*. [6] proposed an analytical solution for the vertical additional forces in the shaft, providing a basis for subsequent shaft wall

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deformation predictions. Han *et al*. [7] established a dynamic prediction model for the shaft using the probabilistic integral method and the Knothe time function. Tang *et al*. [8] applied a support vector machine model to establish a deformation-time relationship model for shaft deformation and disaster prediction. Khan *et al*. [9] utilized mechanical analysis and numerical simulation methods to achieve rapid analysis of shaft failure and incorporated neural networks to establish a neural network prediction system for shaft collapse. Yuan *et al*. [10] innovatively combined machine learning technology with traditional physical models, developing a grey-Markov model by integrating the grey prediction model and the Markov model to predict surface subsidence in mining areas. Bai *et al*. [11] developed a real-time updating model based on fuzzy multi-attribute decision-making, integrating expert evaluations and data analysis to provide a new method for assessing the risk of large deformations in soft rock. Feng *et al*. [12] conducted a deep investigation into the deformation mechanisms of surrounding rock during SBM tunneling through numerical simulations and proposed an innovative analysis model, which incorporates additional vertical stress to consider the extrusion effect of SBM, thereby providing a more accurate calculation of the radial deformation of the shaft's surrounding rock.

This study constructs a shaft deformation prediction model for soft rock based on four machine learning algorithms: random forest, XGBoost, LightGBM, and *K*-nearest neighbors regression. On this basis, the deformation risk of the shaft is evaluated, and the prediction results are compared with measured values, validating the reliability of the shaft prediction model. This provides accurate and reliable shaft deformation forecast information, offering significant reference value for shaft repair, remediation, and safety management.

Construction of soft rock deformation prediction model based on machine learning

The deformation of soft rock shafts is influenced by various factors, including the intrinsic properties of the rock and external environmental conditions, as well as loading scenarios. The intrinsic characteristics affecting shaft deformation include the elastic modulus, Poisson's ratio, cohesion, internal friction angle, and rock compressive strength. The maximum tangential stress of the surrounding rock and the compressive strength of the rock mass are considered external characteristics. To investigate the intrinsic and extrinsic factors influencing the deformation of soft rock deep shafts, multiple numerical simulations were conducted using FLAC 3-D to explore the system's response under different parameter combinations. However, compared to actual values, the results of numerical simulations often overlook non-linear phenomena, complex boundary conditions, and human factors involved in data acquisition. To enhance the realism and quality of the dataset, noise was added during the processing phase. Utilizing the new dataset, four models were selected for training and accuracy evaluation: random forest, extreme gradient boosting, optical gradient enhancement mechanism, and K-nearest neighbors regression. The optimal algorithm was then chosen for predicting the deformation of the soft rock deep shaft. The flowchart illustrating this process is shown in fig. 1.

Data preprocessing

The dataset is derived from numerical simulation results based on geological data from a coal mine in Northwest China. By varying the intrinsic characteristics of the model, ten distinct numerical models have been created to simulate the external characteristics and deformation of the shaft. To account for uncertainties in real data-such as the influence of the external environment and human measurement errors-noise is introduced to enhance the robustness of

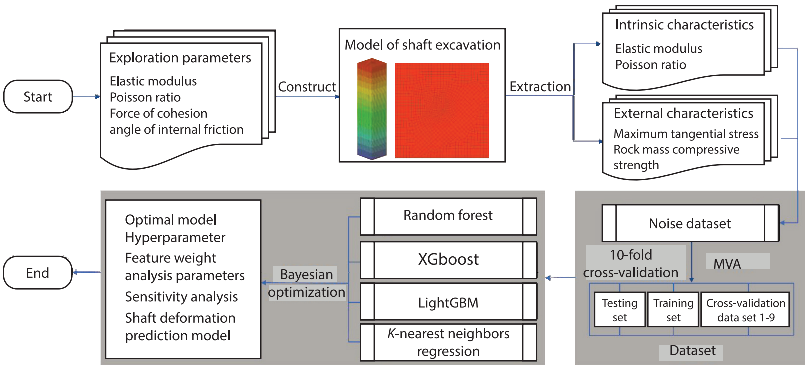

Figure 1. Floe chart

the simulation results and reduce the model's sensitivity to uncertainty. Since characteristic values are typically obtained through sensors, multiplicative noise is employed to either amplify or diminish the numerical simulation results, thereby generating a noise dataset, as illustrated in eqs. (1) and (2). For instance, the noise before and after processing for the elastic modulus is depicted in fig. 2.

$$x' = x(1+\eta), \ \ \eta \sim N(0, 0.15) \tag{1}$$

where x' is noise dataset, x – original dataset, and η – noise figure.

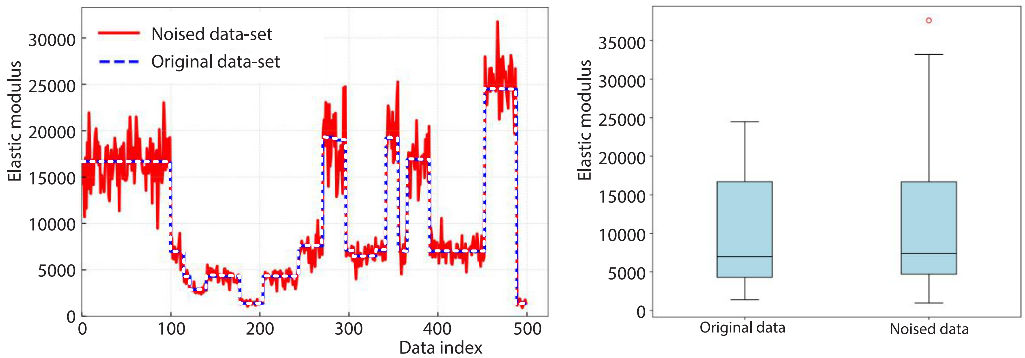

Figure 2. Original dataset and noisy dataset

In order to improve numerical stability, accuracy and convergence speed, the noisy dataset is normalized by mean variance, thereby reducing the influence of outliers and improving the generalization ability of the model, eliminating the influence of dimension. The normalization equation:

$$x'' = \frac{x' - \mu}{\sigma} \tag{2}$$

where x'' is the homogenous dataset, μ – the mean, and σ – the standard deviation.

Constructing machine learning models

To enhance the model's ability to generalize and accurately evaluate its performance, 80% of the dataset is designated as the training set. In comparison, the remaining 20% is reserved for hyperparameter tuning and model evaluation. The dataset is divided into 10 equal parts using 10-fold cross-validation. In each iteration, one part serves as the validation set, and the other nine parts are utilized as the training sets. This process is repeated nine times, with a different part selected as the validation set each time. The average performance across all folds is then calculated to maximize the use of the dataset and minimize the bias introduced by a single partition.

Bayesian optimization is employed to construct a Gaussian process that approximates the objective function. The Gaussian process model assumes that the objective function values corresponding to all input points follow a joint Gaussian distribution, as shown in eq. (3). New sampling points are selected based on existing data and Bayesian inference, aiming to minimize the number of evaluations while identifying the optimal solution for the objective function. Table 1 presents the range of hyperparameters selected for four machine learning algorithms:

$$f_* \mid \mathbf{X}, \mathbf{f}, \mathbf{x}_* \sim N(\mu_*, \sigma_*^2) \tag{3}$$

where $f_*|\mathbf{X}, \mathbf{f}, \mathbf{x}_*$ is the conditional and $N(\mu_*, \sigma_*^2)$ – the normal distribution.

Table 1. Search range of selected hyperparameters

Model	Hyperparameters	Range
Random forest	n_estimators	[5, 100]
	max_depth	[1, 30]
	min_samples_split	[2, 12]
	max_features	[0.1, 0.4]
	min_samples_leaf	[1, 10]
XGBoost/ LightGBM	n_estimators	[50, 500]
	learning_rate	[0.01, 0.5]
	max_depth	[3, 10]
	min_child_weight/ min_child_samples	[1, 10]
	colsample_bytree	[0.5, 1]
	subsample	[0.5, 1]
	reg_alpha	[0.01, 10]
	reg_lambda	[0.01, 10]
K-nearest neighbors regression	n_neighbors	[1, 30]
	weights	["uniform","distance"]
	metric	["euclidean","manhattan", "minkowski"]
	algorithm	["ball_tree","kd_tree","brute"]

Evaluating the learning effectiveness of a machine learning model is a crucial step in ensuring that the model can effectively address problems and make accurate predictions. Consequently, the RMSE, MAE, and coefficient of determination, R^2, are employed to assess the model's learning performance, as illustrated:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{5}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{6}$$

where y_i is the true value, $\bar{y}$ – the average of the true values, and $\hat{y}_i$ – the predicted value distribution of the predicted point.

Results and discussion

Hyperparameter tuning plays a crucial role in optimizing the performance of machine learning models. Table 2 shows the performance evaluation of predicting wellbore deformation values using a noisy dataset following Bayesian optimization.

Table 2. Performance evaluation

Date	Evaluation indicators	Random forest	XGBoost	LightGBM	*K*-nearest neighbors regression
Testing datset	RMSE	0.0012	0.0016	0.0019	0.0013
	MAE	0.0006	0.0009	0.0012	0.0007
	R^2	0.9862	0.9785	0.9680	0.9843
Training datset	RMSE	0.0006	0.0015	2.0188	0.0014
	MAE	0.0003	0.0007	0.0007	0.0006
	R^2	0.9953	0.9820	0.9795	0.9810
10-fold cross-validation datset	RMSE	0.0015	0.0018	0.0022	0.0018
	MAE	0.0007	0.0009	0.0013	0.0008
	R^2	0.9775	0.9666	0.9470	0.9662

The smaller the RMSE and MAE, and the closer the R^2 is to 1, the more accurate the model's predictions become. As shown in tab. 2, the R^2 for the four machine learning models exceed 0.94, indicating excellent predictive performance. Among these models, the random forest (RF) algorithm stands out as the most exceptional. In the testing set, $R^2 = 0.9862$, $RMSE = 0.0012$, and $MAE = 0.0006$. In the training set, $R^2 = 0.9953$, $RMSE = 0.0006$, and $MAE = 0.0003$. In the 10-fold cross-validation, $R^2 = 0.9775$, $RMSE = 0.0015$, and $MAE = 0.0007$. This data indicates that the performance evaluations of the training set, testing set, and cross-validation set are consistent, suggesting that the model is not overfitting. The hyperparameter values for the RF model were n_estimators = 16.57, max_depth = 19.61, min_samples_split = 2.38, max_features = 0.26, and min_samples_leaf = 1.07. The prediction results are shown in fig. 3.

Combined with fig. 4, it is evident that the various parameters influencing wellbore deformation can be ranked in order of importance cohesion, rock compressive strength, elastic modulus, internal friction angle, Poisson's ratio, and the maximum tangential stress of the surrounding rocks. Cohesion and rock compressive strength are critical factors affecting deformation behavior, as they significantly contribute to the structural integrity of the rock mass. The higher these values, the greater the external load the rock can withstand, resulting in reduced plastic deformation. Additionally, the elastic modulus, internal friction angle, and Poisson's ratio are also important factors that influence deformation behavior and enhance the overall stability of the structure. Although the maximum tangential stress of the surrounding rock has a minimal effect on wellbore deformation, it remains a crucial consideration during stability assessments to prevent structural failure caused by local stress concentrations.

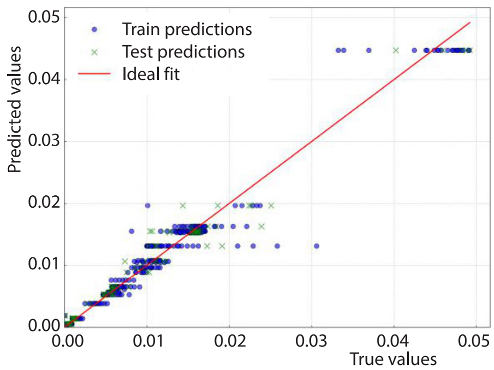

Figure 3. True value and predicted value

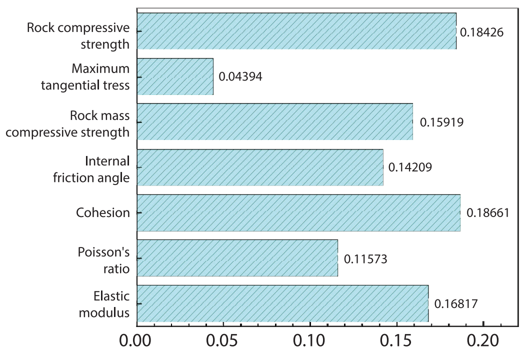

Figure 4. Importance analysis of feature parameters

Conclusion

An algorithmic model for predicting soft rock wellbore deformation was developed using a machine learning framework, achieving a determination coefficient of up to 0.9775. This model is designed to forecast unsupported wellbore deformation in deep vertical shafts. The key factors were analyzed and ranked: cohesion, rock mass compressive strength, elastic modulus, rock compressive strength, internal friction angle, Poisson's ratio, and the maximum tangential stress of surrounding rocks.

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Nomenclature

$f_*|\mathbf{X}, \mathbf{F}, \mathbf{x}_*$ – the conditional
$N(\mu_*, \sigma_*^1)$ – normal distribution
y_i – true value
$\bar{y}$ – the average of the true values

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