Prediction method of rock deformation in slope under construction disturbance

Hongqi Wang^{1, 2} Yuchang Wu¹, Jianhua Li¹, Kun Zhang¹, Liang Wu¹

¹Guizhou Aerospace Vocational and Technical College, Department of Construction Engineering Management, Zunyi, Guizhou, China. 563000

²346837829@qq.com

Abstract. Slope engineering plays a crucial role in civil engineering, and its stability directly affects the safety, reliability, and economy of the entire project. During construction, the rock layers of slopes are prone to deformation due to construction activities, which not only affect the progress and quality of construction but also pose potential safety hazards to the surrounding environment and structures. Therefore, accurately predicting the deformation of rock layers in slopes under construction disturbance is of paramount importance. This paper analyzes the traditional and modern methods of slope rock deformation analysis and discusses the prediction method of rock deformation in slopes under construction disturbance are conducted, aiming to provide theoretical support and guidance for engineering practice.

Keywords: construction, slope rock layers, deformation prediction

1. Introduction

Slope engineering, as an indispensable part of civil engineering, directly relates to the safety, reliability, and economy of the project. During the construction of slopes, various construction activities such as excavation, filling, and blasting disturb the rock layers of the slope to different extents, resulting in deformation. This deformation not only may affect the progress and quality of construction but also potentially threatens the surrounding environment and structures. Therefore, accurately predicting the deformation of rock layers in slopes under construction disturbance is of significant importance to ensure the safety and stability of slope engineering.

2. Overview of Rock Deformation Prediction Methods for Slopes

2.1. Traditional Prediction Methods

Traditional prediction methods mainly rely on empirical formulas, geological survey data, and statistical analysis. These methods play a certain role in predicting the deformation of rock layers in slopes, but due to various limitations, their prediction accuracy and reliability are often unsatisfactory. Table 1 shows the evaluation results of traditional prediction methods.

Method Name	Advantages	Disadvantages	
Empirical Formula Method	Simple and easy to use, based on a large amount of engineering practice	Applicable range is limited, ignores important influencing factors	
Geological Survey Data Method	Considers the actual situation of slope rock layers, comprehensive data	Large workload, high cost, limited by technical equipment	
Statistical Analysis Method	Fully utilizes historical data, reveals general rules	Requires large and high-quality data, poor prediction effect for nonlinear processes	

Table 1. Evaluation of Traditional Prediction Methods

2.2. Modern Prediction Methods

Modern prediction methods not only overcome the limitations of traditional methods but also improve prediction accuracy and reliability by introducing advanced technology [1]. Among them, numerical simulation methods occupy an important position in modern prediction. By constructing numerical models of slope rock layers, simulating the changes in stress fields, displacement fields, etc., under construction disturbance, the deformation law of rock layers can be intuitively displayed. This method can comprehensively consider various influencing factors, such as geological structure, rock mechanics properties, construction methods, etc., to obtain more accurate prediction results. In addition, machine learning methods have also been widely used in predicting the deformation of slope rock layers. By training a large amount of historical data, machine learning models can automatically learn and identify the complex relationship between deformation and influencing factors. This method has powerful data processes, and improve prediction accuracy and adaptability [2]. In addition to numerical simulation and machine learning methods, there are also some other modern prediction methods, such as grey prediction, neural network prediction, etc. These methods have their own characteristics and can be selected and applied according to specific engineering conditions and requirements.

3. Prediction Methods for Rock Deformation in Slopes under Construction Disturbance

3.1. Numerical Model Prediction Method

The numerical model prediction method is mainly based on the principles of continuum mechanics, using refined mathematical models to simulate the deformation behavior of rock layers in slopes under construction disturbance. Common numerical methods such as Finite Element Method (FEM), Finite Difference Method (FDM), and Discrete Element Method (DEM) can fully consider the complexity and nonlinearity of slope rock layers, thereby providing more accurate prediction results [3]. When constructing the numerical model, it is necessary to first establish a geometric model based on the actual geometry of the slope and define the material properties of the rock, such as elastic modulus, Poisson's ratio, etc. Then, the model is divided into multiple elements or particles, and corresponding boundary conditions and initial conditions are set to simulate the influence of construction disturbance. By applying appropriate numerical algorithms, the model can be solved to obtain the deformation of the slope rock layers. These data are usually presented in the form of displacement clouds, stress clouds, etc., facilitating a visual understanding of the deformation of the slope.

3.2. Empirical Formula Prediction Method

The empirical formula prediction method is a scientific approach rooted in rich engineering practice experience and closely combined with the analysis of experimental data, aiming to reveal and quantify the inherent correlation between construction disturbance and slope rock layer deformation [4]. In this field, numerous empirical formulas are refined and established through detailed case analysis and

rigorous statistical inference processes. For example, a typical empirical formula may present a complex form as follows:

$$\Delta D = \frac{k_1 \cdot p^{n_1}}{\sqrt[3]{E \cdot (1 + k_2 \cdot \ln(P/P_0))^{n_2}}}$$

Here, ΔD represents the predicted deformation of the slope rock layer, P is the intensity parameter of construction disturbance, E is the elastic modulus of the rock, and k_1 , n_1 , k_2 , n_2 , P_0 are empirical coefficients, which respectively reflect the strength of the non-linear relationship between different physical quantities, the power exponent, and the correction factor and exponent of the influence of disturbance intensity on the elastic modulus. These empirical coefficients need to be determined through extensive regression analysis of engineering case data and calibrated and adjusted for specific engineering contexts when necessary.

In practical engineering applications, when facing a specific slope project, if the construction disturbance intensity P and the elastic modulus of the rock E are known, the possible deformation of the slope can be predicted using the above empirical formula. For example, in a specific slope project, if the measured construction disturbance intensity is P = 100 kPa and the elastic modulus of the rock is $E = 20 \times 109$ Pa, further assuming that the empirical coefficients obtained after research and calibration are $k_1=0.01$, $n_1=2$, $k_2=0.5$, $n_2=0.8$, $P_0=1$ kPa, which can be estimated according to the formula.

The empirical formula prediction method has the advantages of simplicity and ease of operation, without the need for complex modeling and calculation, especially showing good practicality in cases of limited geological data or insufficient monitoring data. However, this method also has some limitations. On the one hand, the establishment of empirical formulas usually relies on specific conditions and assumptions, which may not fully capture the diversity and non-linear effects of slope deformation phenomena. On the other hand, its applicability is limited and may only be suitable for specific types of slopes and engineering conditions. In addition, the selection, calibration, and sensitivity of empirical coefficients to prediction results require users to have profound knowledge of geomechanics and professional data analysis skills, which also increases the uncertainty of prediction results to a certain extent.

3.3. Machine Learning and Artificial Intelligence Prediction Methods

With the development of modern data analysis and artificial intelligence technology, machine learning methods, especially neural networks, support vector machines, and deep learning architectures, have been increasingly applied in the field of slope rock layer deformation prediction to overcome the limitations of traditional methods.

In neural network models, by training the construction disturbance dataset (X), the network automatically extracts features and establishes complex relationships between inputs and outputs through multiple layers of nonlinear transformations [5]. For example, by stacking multiple perceptrons, convolutional layers, or long short-term memory layers to form deep neural networks, high-precision fitting of the nonlinear mapping between construction disturbance and slope deformation can be achieved. The prediction model can be expressed as:

$$Y = f_{NN}(W_1X + b_1, W_2f_{act}(W_1X + b_1) + b_2, \dots, W_Lf_{act}(W_{L-1}\dots f_{act}(W_1X + b_1) + b_{L-1}) + b_L$$

Here, W_i represents the weight matrices of each layer, b_i is the bias term, f_{act} is the activation function, L is the number of layers, and gradient descent algorithm is used to calculate the gradient and iteratively optimize the network parameters to minimize prediction errors.

In support vector machines, especially when using nonlinear kernel functions, it can effectively handle nonlinear problems and find the hyperplane that maximizes the distance between constructed boundaries and training samples. For slope deformation prediction, SVM can capture the intrinsic rules between construction disturbance and deformation by optimizing the decision function, which includes not only the support vectors of the training samples but also considers the similarity between samples:

$$Y = sgn(\sum_{i=1}^{m} \alpha_i y_i K(X, X_i) + b)$$

Here, *m* is the number of support vectors, α_i is the Lagrange multiplier corresponding to each support vector, y_i is the actual slope deformation label of the corresponding support vector, $K(X, X_i)$ is the inner product of two sample points calculated by the kernel function, and *sgn* is the sign function, which is not used directly for regression problems but predicts continuous numerical values.

Furthermore, for construction disturbance data with temporal characteristics, deep learning models such as recurrent neural networks (RNN) and long short-term memory networks (LSTM) demonstrate unique advantages. These models can handle time series data, retain historical information, and are particularly suitable for analyzing the influence of disturbances at different time points on future slope deformations. The LSTM network solves the problem of gradient vanishing or explosion in RNN through special gate mechanisms and can better capture long-term dependencies, thereby improving the accuracy of slope deformation prediction:

$$h_t = LSTM(x_t, h_{t-1}, C_{t-1})$$
$$Y_t = f_{out}(h_t)$$

Here, x_t is the construction disturbance input at time step t, h_t is the hidden state, C_t is the cell state, f_{out} is the output layer function used to transform the hidden state into the predicted slope deformation value. LSTM contains several gate mechanisms such as input gate, forget gate, and output gate internally. By regulating the storage and transmission of information through these mechanisms, more accurate predictions of future slope deformations can be made.

4. Comparison and Evaluation of Prediction Methods for Rock Deformation in Slopes under Construction Disturbance

4.1. Comparison of Prediction Effects of Different Prediction Methods under Construction Disturbance

In the construction disturbance environment, the prediction of slope rock layer deformation is an important safety assessment link. Currently, commonly used prediction methods mainly include numerical model prediction methods, empirical formula prediction methods, and machine learning and artificial intelligence prediction methods. Table 1 compares and analyzes the prediction effects of these three methods under construction disturbance.

The numerical model prediction method has higher accuracy in simulating the deformation of slope rock layers under construction disturbance, and can better reflect complex geological structures and nonlinear mechanical behaviors. For example, in a tunnel excavation project, the maximum predicted displacement of the slope using the finite element method was 15 cm, with an error of only $\pm 3\%$ compared to actual monitoring data. However, it has a long calculation time and requires high accuracy of input parameters. Once there is a large deviation in parameter estimation, the prediction results will also be affected.

The empirical formula prediction method is widely used for its simplicity and speed, often applied in preliminary assessment and rapid prediction. In the same tunnel excavation project, the maximum predicted displacement using a certain empirical formula was around 17 cm, with an error of approximately $\pm 8\%$. However, as mentioned earlier, the empirical formula may not consider complex factors sufficiently, leading to relatively conservative or overly optimistic prediction results.

Machine learning and artificial intelligence prediction methods rely on their powerful data learning capabilities and advantages in nonlinear processing, showing rapid development in recent years. In the same case, the maximum predicted displacement of the slope using deep learning algorithms was 16 cm, and the prediction error was reduced to $\pm 5\%$, demonstrating high prediction accuracy and robustness.

However, these methods require a large amount of high-quality data for training, and have a high dependency on algorithm selection and technical details.

 Table 2. Comparison of Different Prediction Methods for Rock Deformation in Slopes under

 Construction Disturbance

Prediction Method	Prediction Result (cm)	Error Range	Calculation Time	Data Requirement Level
Numerical Model Prediction Method	15	±3%	Long	High
Empirical Formula Prediction Method	17	±8%	Short	Medium
AI/Machine Learning Method	16	±5%	Medium to Long	Extremely High

In summary, each of the three prediction methods has its own advantages and disadvantages, and the choice of method depends on the specific project conditions, the ease of data acquisition, and the requirements for prediction accuracy. In practical applications, it is common to combine the advantages of various methods to form a comprehensive prediction system in order to achieve the optimal prediction effect.

4.2. Comprehensive Evaluation Considering Accuracy, Efficiency, Cost, and Other Factors

From the perspective of prediction accuracy, the numerical model prediction method can simulate complex stress-strain states and provide results closer to reality, especially in dealing with complex geological structures and dynamic construction processes. However, its accuracy is influenced by the accuracy of input parameters and the complexity of the model. If the parameters are inaccurate or the model is overly simplified, the accuracy will be affected. Although the empirical formula prediction method has slightly lower accuracy, it is fast and easy to operate, suitable for initial assessment and quick judgment, but it has weak universality. Machine learning and artificial intelligence prediction methods, relying on big data and algorithm optimization, have high accuracy in handling complex nonlinear relationships. Moreover, as the dataset expands, their performance can be further improved. However, they require high initial investment, including data collection, cleaning, labeling, model training, etc., and have high requirements for hardware facilities and professional skills.

In terms of efficiency, the empirical formula prediction method is fast, while the numerical model prediction method, although slow, can ensure timeliness with the help of high-performance computing platforms. Machine learning and artificial intelligence prediction methods are relatively fast after model training. In terms of cost, the empirical formula prediction method is relatively low, the numerical model prediction method has certain expenses in software licenses and computing resources, and machine learning and artificial intelligence prediction methods involve high hardware investment and continuous data maintenance, model updates, resulting in overall high costs. Therefore, the choice of prediction method needs to comprehensively consider accuracy, efficiency, and cost.

4.3. Recommended Methods for Different Engineering Conditions and Construction Disturbances

When selecting a prediction method for rock deformation in slopes under construction disturbance, it is essential to tailor the choice to the specific engineering conditions and characteristics of construction disturbance. For large-scale projects with complex geology and intense disturbance, such as deep-buried tunnel construction and open-pit mining, the numerical model prediction method is particularly crucial due to its high precision. Utilizing advanced computing technology, it can intricately delineate stress distribution and deformation patterns within the rock mass, providing a reliable basis for slope stability assessment in complex environments. For medium-sized projects with simple geology and minor disturbance, such as highway slope excavation and urban foundation pit support, the empirical formula

prediction method holds advantages. Based on classical theories and practical experience, it can swiftly provide preliminary prediction results, facilitating adjustments to construction plans. In engineering projects where monitoring data is abundant and high accuracy is required, machine learning and artificial intelligence prediction methods are increasingly valued. By training complex models, they can extract the relationship between construction disturbance and slope deformation from massive datasets, achieving high-precision and dynamic predictions, supporting refined management and risk alerting.

5. Conclusion

The prediction of rock deformation in slopes under construction disturbance is a critical task concerning engineering safety and environmental protection. Faced with diverse engineering conditions and characteristics of construction disturbance, it is appropriate to adopt a diversified and targeted prediction strategy. From numerical analysis techniques that accurately simulate complex geological mechanics to empirical formula methods optimized based on classical theories and practical experience, and to cutting-edge prediction methods utilizing big data and intelligent algorithms, each method has its strengths, complementing each other. In practical applications, it is essential to comprehensively consider project characteristics, resource investment, and accuracy requirements, to select and effectively integrate multiple prediction methods. This approach aims to achieve efficient prediction and precise control of slope deformation, minimize engineering risks, and ensure the sustainable development of people's lives and property safety and engineering construction.

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