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Study on Mechanic Parameters Selection of Rock Slope Based on BP Neural Network Displacement Back Analysis

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Abstract: *Natural rock mass is a complex three-phase composition, and its internal structure, physical characteristics such as fragmentation and water content have significant temporal and spatial variability. The method of assigning the mechanical parameters of rock mass according to the code ignores this important feature. In order to obtain the mechanical parameters of natural rock mass more accurately, based on a rock slope in NO.2 section of Ganxian-Xingguo expressway, a method for calculating mechanical parameters based on displacement back analysis of BP neural network was proposed on the basis of traditional code assignment. The back analysis model was optimized by neuron weight, inertia correction and algorithm step control, and then the mechanical parameters of the whole slope were back analyzed. Fatherly, the finite element numerical simulation software ANSYS was used to establish the grid model of the slope to judge the whole stability of the slope. The field monitoring was used to verify the calculation results. Facts and figures showed that the mechanic parameters gotten from the back analysis is more reliable than those in the code. The study can provide reference for mechanic parameters assignment of the rock slope.*

Keywords: *Rock mass, Mechanical parameters, Assignment, Back analysis, BP neural network*

1. Introduction

After continuous geological tectonic movement and weathering, the internal physical properties of natural rock mass are complex and changeable, and real practice shows there are often differences between the surface and the internal characteristics. For the strata with complex geological conditions and intense regional tectonic movement, the real structure and physical characteristics inside the rock mass have significant temporal and spatial variability. For a long time, how to assign mechanical parameters of natural rock mass and evaluate the stability of rock mass is an important content.

At present, the method of assigning the mechanical parameters of rock mass according to the specifications has the advantages of simplicity and rapidity, and has become the conventional method of assigning the mechanical parameters of rock mass at present. However, this method ignores the variability of internal physical characteristics of rock mass, considers that the physical characteristics of rock mass are static, and ignores the differences between the surface and the internal side. In addition, there is mutual compression between different areas in the real rock mass, that is, there is displacement and force transmission, but the code ignores this important feature.

In response to this problem, relevant scholars and technical personnel proposed a back calculation method of rock mechanical parameters based on actual displacement and stress, namely, back analysis. The basic idea of back analysis is to obtain the actual displacement and stress values of rock mass firstly, and then use mathematical models to back calculate the mechanical parameters, so as to avoid the blindness, experience and subjectivity of parameter assignment. In recent years, it has been widely used. For example, based on the vault subsidence and surrounding convergence value of an excavation working face of Guiyunshan tunnel on Xunwu-Quannan expressway, Wu *et al*. [1] used BMP90 displacement back analysis program to calculate the elastic modulus and lateral pressure coefficient of surrounding rock. Wang *et al*. [2] back analyzed the displacement sensitivity index of the tunnel by combining the displacement analytical solution with the differential evolution intelligent algorithm, and verified the uniqueness of the sensitivity and the five indexes under the given vertical ground stress.

Huang *et al*. [3] used elastic-plastic back analysis to calculate the deformation modulus of surrounding rock based on a tunnel of Lijiang-Dali expressway in Yunnan, and verified it through positive analysis. Caudal *et al*. [4] used remote sensing and numerical simulation to predict the landslide of chrysotile asbestos slope in Canada. The stress back analysis program was used to calculate the deep stress of large rock blocks and to simulate the three-dimensional displacement. Huang *et al*. [5] established a numerical back analysis model based on genetic algorithm and time-varying model to predict the long-term settlement of high fill slope, and calculated the lateral pressure coefficient of slope based on the measured data of a high fill slope at Chengde Airport. Na *et al*. [6] obtained the natural density and moisture content of carbonaceous shale surrounding rock of Jiangluling tunnel by indoor remodeling and direct shear compression test, and calculated the elastic modulus of surrounding rock by means of numerical back analysis. Undoubtedly, the above research has a positive effect on improving the theory and method of back analysis.

However, physical properties such as water abundance of natural rock mass have significant spatial variability. For rock mass with large scale and complex geological conditions, blind classification ignores the spatial variability of physical properties, which is unreasonable, and it is difficult to guarantee the reliability of the obtained mechanical parameters [7]. In addition, the above studies mostly focus on algorithm optimization and single-parameter back calculation, ignoring the interaction between multiple parameters. For example, although the algorithm was analyzed in References [3], [4], [5] and [6], only the single parameter was calculated. Although the parameters were expanded from one to two in Reference [1], the model was not significantly improved and optimized. Reference [2] not only realized the optimization and improvement of the algorithm, but also realized the back analysis of multiple parameters, while only the one-to-one mapping relationship between sensitivity and parameters was considered, without considering the interaction between parameters, which obviously did not meet the actual conditions of rock mass, and thus would limit the further promotion and application of the study.

Based on a rock slope of Ganxian-Xingguo expressway in Jiangxi province, this study proposes a method for anti-calculating the mechanical parameters of the slope by using the BP neural network back analysis. On this basis, ANSYS finite element numerical simulation software is used to analyze the stability of the slope, so as to provide relevant reference for the design and construction.

The rest of this paper is arranged as follows. Section 2 introduces the general conditions of the slope, and puts forward the research scheme. Section 3 establishes the neural network model and optimizes the algorithm, and gives the network training scheme. In section 4, the finite element numerical simulation analysis model is established and the sliding displacement of the slope element is calculated. Besides, the simulation calculation value of the sliding displacement is verified by the field monitoring measurement. Finally, the paper summarizes the achievements and contributions of the research in conclusions.

2. Project Introduction and Study Scheme

2.1. Project Introduction

This expressway crosses the mountain by open-cut method, thus forming high and steep rock slopes on both sides. The maximum height of this slope is more than 20 meters, and the mountain is NE-trending, and the route is basically orthogonal to the mountain range. The bedrock on the mountain surface is exposed well, with less vegetation and less Quaternary overburden.

The structural plane of the slope is obvious, which is mainly steep, but there are some gently inclined structural planes. There are structural planes along and gently inclined on both sides of the slope, which is unfavorable to the slope. For the left side slope, the structure of 290∠40 is unfavorable to the slope stability, which may cause the slope instability. Slope instability and local rock mass collapse may occur when large-scale blasting, excavation or not supporting in time after excavation are adopted. Therefore, it is urgent to predict the stability of slope so as to provide relevant reference information for design and construction.

2.2. Study Scheme

According to the constitutive relationship of rock mass, the deformation and displacement of block are the equilibrium results between elastic resistance and effect, and the resistance of rock mass is

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directly affected by its own shear strength index, Poisson's ratio and other parameters [8], [9]. In addition, due to the influence of environmental factors (water, structural plane, filler, etc.), the mechanical parameters of rock mass are not independent, and there are also mutual influences between them. In other words, when a mechanical parameter changes, it will change other mechanical parameters and generate increments in turn. On the other hand, due to the block contact and extrusion, there is a transfer of displacement and stress between each other, the motion state of adjacent rock blocks will cause disturbance to the surrounding rock blocks. Therefore, there is not only the transfer of displacement and stress between rock blocks, but also the interaction between mechanical parameters in essence, that is, the influence of fault tolerance [10]-[12]. This effect is highly similar to the node connection and weight transfer in the BP neural network, and it can always obtain the optimal analytical solution within the error control range after iterative operation, which provides a direction for the iterative operation of the mechanical parameters of the rock block unit by using the neural network and the calculation of the complete slope mechanical parameters accordingly.

Therefore, a improved BP neural network was introduced to back calculate the mechanical parameters of the complete slope. Then, the obtained mechanical parameters were applied to the finite element numerical simulation to analyze the stability of the slope. Finally, the field monitoring measurement was used to verify the simulation results. Figure 1 shows the study scheme.

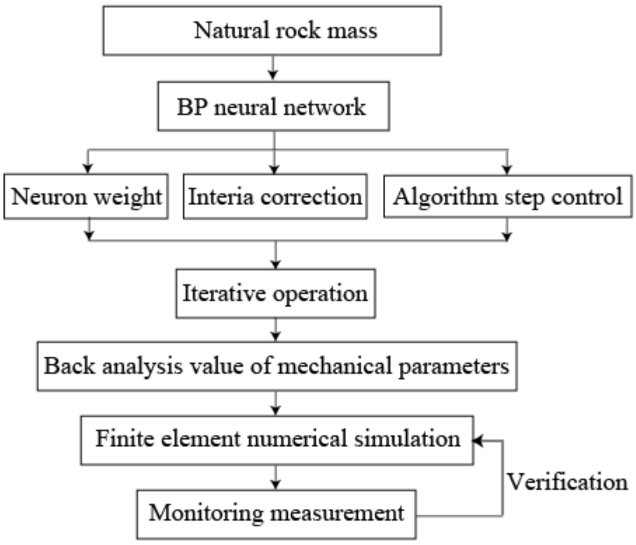

Figure 1: Study scheme

3. Displacement Back Analysis of BP Neural Network

The displacement and stress of rock mass are essentially the equilibrium results of resistance and effect. The resistance and effect are affected by internal and external environmental factors at the same time, and show certain mechanical properties in the microscopic . The complete rock mass is composed of micro-unit rock blocks and structural planes. A single rock block itself has corresponding mechanical properties and forms mutual restraint and coordinated deformation through the contact surface. Finally, it shows the displacement and stress properties macroscopically and can be described by certain mechanical parameters. In order to obtain macroscopic mechanical parameters, the widely used rock mechanics test method like plate load test (PLT) and hydraulic fracturing technique are available, but the timeliness is poor, time-consuming and laborious, which cannot meet the emergency needs.

BP neural network belongs to the error signal back propagation artificial neural network. It has good nonlinear dynamic identification and adaptive ability under the condition of uncertain parameter mapping relationship, and can establish a good corresponding relationship after weight control. The relationship between mechanical parameters and deformation of real rock mass units is often uncertain, and the interaction between units is also unclear.

According to the large deformation consolidation and nonlinear theory, in this complex situation, it is an attemptable research direction to obtain the parameter value through some parameter error correction and adaptive operation. A large number of previous studies have confirmed that BP neural network has the above error control and adaptive function, which is an optional tool for back analysis of mechanical parameters of rock mass units. In this regard, the BP neural network was selected to implement the displacement back analysis of the slope so as to obtain the mechanical parameters of the complete slope.

3.1. Model Establishment

The neural network consists of three layers, namely, the parameter input layer, the intermediate hidden layer and the output layer. The middle hidden layer is the core of the whole neural network, which is composed of many neurons. Neurons are essentially intermediate variables obtained after the weight operation, and they interact with each other through the weight. Assuming that u_j (j=1,2,...n) is the input signal of neuron j, the influence weight between neuron j and neuron i is τ_{ji}, and f_j is the control error of neuron, the output signal u_x (x=1,2,...n) obtained by weight operation and error control can be expressed by Eq.1.

$$u_x = \sum_{j=1}^{n} u_j \tau_{ji} - f_j \tag{1}$$

u_x is the input signal of neuron x, which will continue to be transmitted downward until the final output is generated after the calculation of the next layer of influence weight and control error. Thus, each neuron will receive an input signal, and then generate a new signal after the weight and error control operation, and continue to circulate to the next hidden layer. If the error does not meet the requirements, then the neuron signal will be transmitted reversely to the input layer neurons and distributed to other neurons at the same time until it meets the error requirements.

It should be noted that the neurons in the middle layer are arranged in a single parallel neural bundle, so any neurons in the upper layer will be transmitted to all neurons in the next layer after operation, but the neurons in the same layer do not affect each other. Through the weight and error control, the middle hidden layer has good fault tolerance and adaptability, but if the number of hidden layers is too large, it will lead to slow convergence and unstable operation, so the number of hidden layers is not the more the better. Studies have shown that the number of hidden layers composed of single-row nerve bundles in parallel should be set based on the basic principle of preventing local minimum. Usually, the number of three-layer hidden layers is sufficient to complete complex operations. Therefore, this paper uses three-layer hidden layers.

The mechanical parameters of rock mass will be gradually transferred and inverted in the hidden layer through weight and error control. The nerve bundles in the hidden layer represent different mechanical parameters, and the neurons represent different parameter values. In order to better provide reference for the subsequent finite element numerical simulation and avoid the shortcomings of the back analysis of single mechanical parameters, five parameters that are most relevant to the mechanical behavior of rock mass were selected for back analysis in this paper, namely, shear modulus G, elastic modulus E, Poisson’s ratio μ, cohesion force c and internal friction angle φ. It can be seen from the above analysis that different neurons also affect each other, so it is necessary to determine the functional relationship between different mechanical parameters.

The preliminary geological survey shows that there was no high ground stress area along the highway, and the slope was a bedding slope, and the friction of the structural plane was mainly plane friction. Therefore, the shear stress and normal stress of the structural plane obey the Mohr-Coulomb strength criterion, and according to the AMONTON law, the shear stress and normal stress of the slope unit obey the relationship described in Eq.2.

$$\tau = 0.85\sigma \tag{2}$$

Where τ called shear stress and σ called normal stress. Both units are MPa. In addition, G, E and μ obey the relationship described in Eq.3. The unit of G and E is Pa and μ is dimensionless.

$$G = \frac{E}{2(1+\mu)} \tag{3}$$

Based on the above analysis, the neural network of the slope rock mass was set to five single-row parallel three-layer hidden layer structures, as shown in Figure 2.

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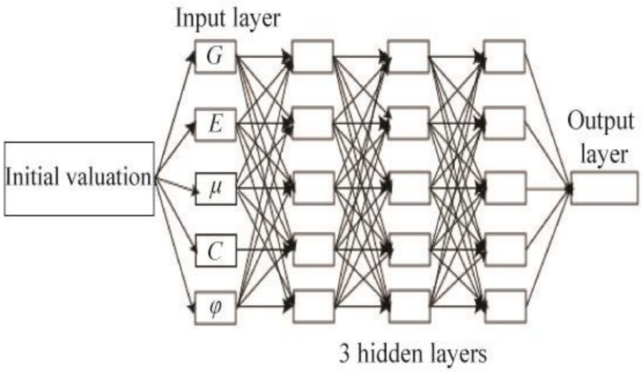

Figure 2: Model structure

3.2. Algorithm Improvement and Network Training

The neural network has good operational stability, but under the condition of multi-parameter iterative operation, the convergence speed is slow and it is easy to fall into local minimum. The established network has five operation parameters, belonging to the multi-parameter operation environment. Therefore, it is necessary to modify and improve the conventional algorithm to ensure the stability and convergence of the solution.

1) Momentum Inertia Correction

Momentum inertia correction refers to the continuation of the error correction value in the operation of the upper layer to the next layer for iterative operation until the last layer, thus forming the inertia continuation of error control. The significant advantage of momentum inertia correction is that it can circularly distribute the difference between the input value and the target value to each layer of neurons, which can well prevent falling into local extremum. Compared with single-layer neuron correction, it can significantly accelerate the iteration speed and convergence effect.

The mechanical inversion parameters of the above slope reach five, belonging to the complex calculation of multiple factors. To improve the operation speed, the momentum inertia correction was used to improve the algorithm, and the function relationship is shown in Eq.4.

$$\omega_i^{'} = \omega_i + \eta\omega_{i-1}(i-1) \tag{4}$$

Where ω_i called the initial correction obtained when *i* operations are completed, η called the inertia coefficient, ω_{i-1} called the correction obtained when (*i*−1) operations are completed, and $\omega_i^{'}$ is the correction value of ω_i. Because the correction of the upper layer does not need all transfer, so η should not be greater than 1.0. According to the convergence stability, this paper takes values between 0.5 and 0.9.

2) Step Length Optimization

The iterative operation of BP neural network is essentially a down-sampling operation, and the convergence efficiency is low when the number of inversion parameters is large. In addition to the above momentum error, the step length is another important factor affecting the convergence efficiency. The step length of BP neural network is divided into two categories, namely, fixed step and adaptive step. When the fixed step length is adopted, the convergence speed is slow. Figure 3 shows the convergence speed curve of the neural network model of the slope when the fixed step length was 0.95. It can be seen that it gradually converges when the iteration times reach 200.

Obviously, under the condition of fixed step length, the timeliness requirement cannot be met, and there were network training and finite element numerical simulation analyses in the follow-up. If the convergence efficiency cannot be improved, the follow-up process was likely to be delayed. For this reason, the adaptive step length was used, and its function expression can be shown as follows.

$$s = \frac{(h_i - h_{i-1})}{E_i - E_{i-1}} E_i \tag{5}$$

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Where s represents the adaptive step length between 0-1, h_i and E_i represent the learning factors and errors, which are dimensionless. Figure 4 shows the iterative curve after using adaptive step length. It can be seen that it has stabilized after 30 iterations, which greatly improves the computational efficiency.

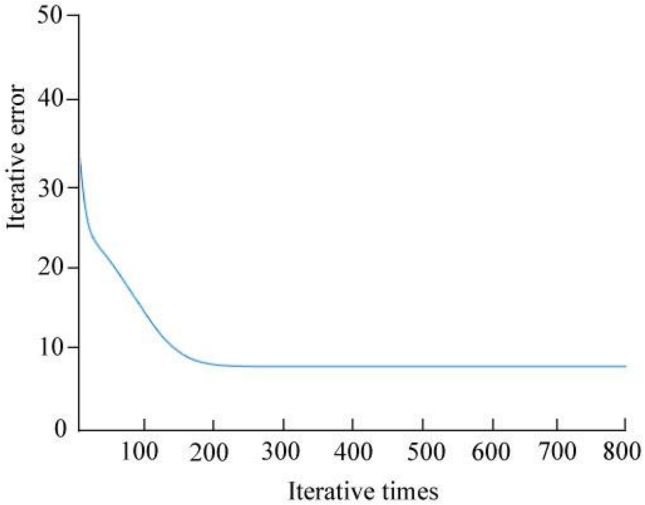

Figure 3: Convergence curve with fixed step length

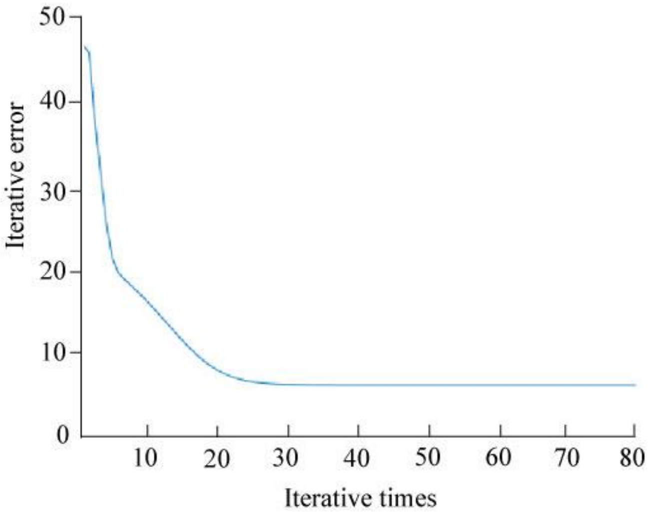

Figure 4: Convergence curve with adaptive step length

3) Network training

The neural network consists of many factors such as hidden layer, algorithm, weight, error and step length control and has obvious systematic features. The model established based on the above analysis is not necessarily able to achieve ideal operation accuracy, so it is necessary to train it to further optimize the relevant values such as weight, error coefficient and step length.

The traditional (0,1) grey-white training model can test the convergence of neural network, but it does not consider the deformation effect of rock mass itself, so it cannot be directly used to test the neural network established above. Different from the simple convergence test, in order to ensure the effectiveness and comparability of the training results, the stress release method was used to collect the mechanical parameters of rock mass in the construction stage and take them as the sample parameters. Finally, a total of 32 groups of sample parameters were obtained by statistics. At the beginning, the sample parameters were input into the neural network model one by one. Then, based on the difference between the output results and the sample, the convergence efficiency of the model, and the stability and generalization of the solution, typical indexes such as the weight, inertia coefficient and step length were constantly adjusted and optimized. Finally, the current initial mechanical parameters of the slope were input into the network model for iterative analysis, so as to obtain the final value and apply it to the finite element numerical simulation.

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4. Finite Element Numerical Simulation

Based on the above analysis, ANSYS was used to predict the stability and the mechanic parameters obtained according to the back analysis were adopted during the simulation process. Meanwhile, the displacement monitoring was used to verify the calculation results. Tab.1 shows the calculation and monitoring results for the whole slope. Obviously, the simulation displacements are close to the one of the monitoring. It shows the mechanic parameters gotten from the BP neural network is reliable and feasible.

Table 1:Displacement values

ID of rock block	Sliding displacement (mm)	
	Simulation results	Monitoring results
1	4.21	3.98
2	3.19	3.33
3	1.52	1.44
4	5.21	5.12
5	2.17	2.03
6	5.16	5.07
7	3.12	2.96
8	4.71	4.66
9	2.84	2.61
10	7.63	7.55

5. Conclusion

BP neural network displacement back analysis model has good mapping ability of mechanical behavior. On the basis of this method, more reliable mechanical parameters can be obtained. In addition, the effectiveness of mechanical parameters is an important prerequisite for ensuring the reliability of numerical simulation results. The calculation method of mechanical parameters based on artificial intelligence back analysis is feasible, which should be paid more attention in the future.

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