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Evaluation on Stability of Stope Structure Based on Nonlinear Dynamics of Coupling Artificial Neural Network

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Abstract: The nonlinear dynamical behaviors of artificial neural network (ANN) and their application to science and engineering were summarized. The mechanism of two kinds of dynamical processes, i.e. weight dynamics and activation dynamics in neural networks, and the stability of computing in structural analysis and design were stated briefly. It was successfully applied to nonlinear neural network to evaluate the stability of underground stope structure in a gold mine. With the application of BP network, it is proven that the neuro-computing is a practical and advanced tool for solving large-scale underground rock engineering problems.

Key words: coupling neural network; nonlinear dynamics; structural stability; stope parameters

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1 Introduction

Recently, application of the coupling ANN (artificial neural network) greatly developed in rock engineering, including slopes, open-pit mines, quarries, shafts, tunnels, caverns, underground mines, metro-systems, dams and hydro-electric stations, and radioactive waste disposals. Many practical engineering problems, such as controlling,predicting, analyzing, decision-making of rock engineering, have been solved. Utilizing the coupling ANN calculation, the aim of structure analyzing problems can be achieved. All parameters of the network structure could be attained. According to the input of ANN system, the evaluation and prediction of the structural fault could be worked out when the dynamical learning process was over. M. F. Cai [1] even has succeeded in applying coupling ANN to the large scale calculation in geotechnical engineering.

It is important to optimize the stopes of structural parameters in situation in Xincheng gold mine. Firstly, rock is composite and confounded material. The stopes are complex system consisting of many nonlinear structural elements or sub-systems. Then the nonlinear dynamics of ANN can optimize and verify the stability of structure of stope. The research couples simulation of finite element method (FEM) and the weighted value dynamics. It adopts dynamically learning to actual data. It can identify and evaluate on the deep mining scheme in gold mine. Finally the system suggests preliminary structure parameters of the stope and ensures the reliability of the structural parameters.

2 The NN Elements

ANN is based on the simulation of physical element and function of the biological neural network. It consists of a large number of simple nodes. Each node is connected to other node(s) through a synaptic connection or a link. Information processing takes place through the interaction between the nodes. Each node is associated with an activation value that passes through an activation function $f(\cdot)$ to provide an actual output. Generally, the function of the input-output of the neuro-cell model is expressed in equation (1) and (2):

$$I_i=\sum_{j=1}^{n} w_{ji}x_j-\theta_i \quad (1)$$

$$y_i=f(I_i) \quad (2)$$

where θ_i is the threshold value, w_{ji} stands for the connective weighting value from cell j to cell i, $f(\cdot)$ is the output connecting function which is a nonlinear function of sigmoid type. These simple neuro-cells can be built into different analysis structure of ANN by different models. With the correspondences between the minimum point of the ANN energy function and the stable and equilibrium point of the system, the answer of the minimum point of the function can be got. The

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interconnection ANN can be applied to solve all kinds of optimization problems. Composing of input layer, under cover layers and output layer, a BP network was adopted, and the neuro-cells in every layer only accept the output from the upper layer. The task of BP calculations is learning and adjusting the connective weight coefficient of the network, so that the giving in-output relations could be got. By resorting to the fact that original network collects the specimen, the trained network can also get appropriate output. This quality is called capability of generalization. It must be pointed out that the more times of training can not always get the right corresponding relation of input and output. Whether or not the quality of network can be measured it depends on its capability of generalization.

2.1 Principles of the neural calculation

In general, ANN consists of a number of layers and nodes in each layer.The general model assumes complete interconnections among all the nodes, and resolves the cases of the un-connected nodes (i, j) by setting the weights = 0. The activation function and the activation values to be used in the network are often restricted in range [0,1]. If the input value is discrete, it can be taken only two values—0 or 1. The number of activation functions can be used to define the propagation law in the network. In the processing of the rock underground engineering structure analysis, BP network is directly used to realize the nonlinear mapping relation $f: x \to y$ of input parameter $x \in \mathbf{R}^n$ and output parameter $y \in \mathbf{R}$ in the structure system. Firstly, the network is trained by the results that were got from the traditional mechanical analysis or experimental approach, after adjusting the connective weight value, then, the structure can be analyzed by the trained network. In fact, it is an interpolative and extrapolative method that uses a multi-layers network. Its mechanical analysis or experimental approach adopts the traditional method. The approach of the network is actually a best fitting process of the scattered spatial point $\{x, y\}$ based on basic function. Because of the better mapping capacity of input and output, the extensive adaptability and simple calculation of the forward network, and no need of constructing any system mathematical model, it is widely applied in structure engineering.

2.2 The material constitutive model based on ANN

Principles of finite element analysis based on all inter-linked ANN have been achieved in estimating. According to the principle of the artificial nerve cell, the nerve cell of freedom can be got. The stiffness matrix of finite elements in computational mechanics can be described by the weighted value of the nerve cells, and the external structure load can be made as the external input of the nerve cell. Therefore, all kinds of neural computational element can be constructed corresponding to different finite elements. After being coupled, the ANN can be constructed to solve the nonlinear rock dynamics and mechanics problem. The material constitutive model based on ANN is proposed. This kind of model can not only re-show the training result but also predict other test result approximately, moreover, learn the ANN and make it more perfect by using testing data. The material constitutive model based on the self-adapting ANN can be shown in equation (3).

$$\Delta\sigma = \Delta\sigma_{NN}(\Delta\varepsilon, \sigma_j, \varepsilon_j) \tag{3}$$

Because the testing data of the material are in the form of network structure, the constitutive model is described by self-adapting network. Its training process is shown in **figure 1**.

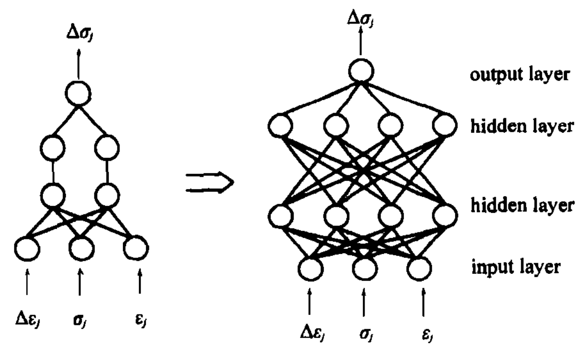

Figure 1 Analysis structure of the training process of network

3 FEM Analysis of Mining Structure Parameter

3.1 Computing program and model

The excavation of an underground opening results in a damage zone in the rock mass within the intimate approximation of the opening. In many numerical modeling of underground openings the damage zone is not captured by the simulation, in particular in works where the rock is modeled as an equivalent continuum. Presumably, the failure criterion to comply with the failure regulations in rock is generally fed with large strength values. It represents the intact rock but not the rock mass.

Mohr-Coulomb failure criterion has been used vastly to describe the shear failure of rock (see reference [5]). The Hoke and Brown failure criterion [6] has also been used extensively in recent years in studying the brittle failure of rock mass. However, these criteria are incapable of capturing the onset of brittle failure perfectly, nor estimating the minimum depth.

Hoek and Brown [5] empirical failure criterion, usually expressed in the following form:

$$\sigma_1 = \sigma_3 + \sqrt{m\sigma_c\sigma_3 + s\sigma_c^2} \tag{4}$$

where σ_1 and σ_3 are the major and the minor principal stresses at failure, σ_c is the uniaxial compressive strength of the intact rock and the empirical constants, m and s are related in a general sense to the angle of internal friction ϕ and the rock mass cohesive strength C.

For both the Mohr-Coulomb and the Hoek and Brown failure criteria, it is implicitly assumed that the cohesive (C or s) and the frictional (ϕ or m) strength component are mobilized simultaneously.

It was postulated that around underground openings, the brittle failure process is dominated by a loss of the intrinsic cohesion of the rock mass. The frictional strength component can be ignored. For the boundary of an opening, $\sigma_3 = 0$, equation (4) reduces to

$$\sigma_1 = \sqrt{s\sigma_c^2} \tag{5}$$

3D-σ large scale nonlinear program was used for the FEM analysis. The failure criterion outlined was used in the mechanical computations in order to estimate the depth of the excavation damage. The computing geometry model is shown in **figure 2** whose length (x direction) is 760 m, witdth (z direction) is 300 m and height (y direction) is 360 m. The model includes 7 000 elements and 26 000 nodes. The orebody is to be mined from +30 m level to −330 m level.

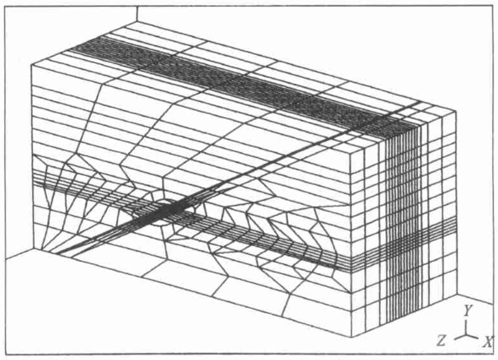

Figure 2 Mesh of FEM model

3.2 Mechanical parameters of material

Based on the test results of mechanical parameters of intact rock and weakness, and investigation of joint condition in rock mass, the mechanical parameters of rock mass are defined in **table 1.** During the calculation of the mechanical parameters of rock mass, empirical reduction factors were used.

Table 1 The parameters of material mechanics

Rock	E / MPa	ν	γ / kN·m^{-3}	C / MPa	ϕ / (°)	σ_t / MPa
Upper	8 500	0.23	26.9	4.17	52	7.50
Lower	9 300	0.22	26.4	5.33	53	7.60
Ore-body	10 000	0.21	28.1	5.40	54	8.16
Fault	1 000	0.29	21.2	0.80	32	0.52
Filling	1 200	0.28	20.2	0.35	40	0.50

Note: E—modulus of elasticity; ν—Poisson ratio; γ—bulk weight; C—cohesion; ϕ—friction angle; σ_t—uniaxial tensile strength; filling means filling material used for enhancing the strength of rock mass.

3.3 Analysis of coupling models

Based on the viewpoint of mechanics, the mining of rock failure process results in dynamic change of stress in the surrounding rock. So, the behavior regime in the surrounding rock is related with structure parameters of the stope, mining sequence, and time of supporting forms, etc. To make sure of optimizing the parameters of all these factors, respectively, 8 coupling models consisting of ANN and FEM structural parameters in the stope are adopted for simulation [2].

4 Coupling Analysis and Evaluating Structure Parameters

4.1 Couple computing analysis

In order to compare the stability status of mining structures and to study the effect of different mining orders, 8 models were analyzed [2]. This mainly considered intact rock stress, stability, strength and intensity, fault and weakness, filling condition, structural parameters, etc. The process of identifying the structure parameters is the learning process of the network. In the learning process, parameters (including learning rate, momentum constant) are added respectively to carry out the self-adapting evaluation. The output results of ANN are shown in **table 2.** The learning curves (a) scheme 7 and (b) scheme 8 of Sum-Squared Error (1 000 epoch) are shown in **figure 3.**

4.2 Analysis of result

Comparison of mining safety coefficient, stress concentration degree, SSE and coefficients and some key data are shown in table 2. Model 1 and Model 7 have the same safety coefficients. Model 4 and Model 7 have the equal stress concentration degree. The SSE of Mod-

Table 2 The output results of ANN (1 000 epochs)

Model	H / m	W / m	$\sigma_{c,f}$ / MPa	U_x / m	U_y / m	f	S	Output		
								SSE	EW/m	EH/m
1	3.3	8	5.75	0.05	0.050	0.50	1.00	0.007 9	0.86	2.8
2	4.0	8	—	0.05	0.052	0.50	0.40	0.009 5	0.87	3.4
3	3.3	10	4.33	0.05	0.070	0.50	0.30	0.002 7	0.79	2.6
4	4.0	10	—	0.05	0.072	0.40	0.47	0.129 7	1.00	4.0
5	4.5	8	—	0.05	0.058	0.52	0.50	0.007 8	0.87	3.9
6	4.5	10	—	0.05	0.061	0.50	0.43	0.129 9	1.00	4.7
7	5.0	8	5.73	0.05	0.045	0.30	1.00	0.000 8	1.00	5.0
8	5.0	10	—	0.05	0.060	0.70	0.50	0.129 9	1.00	5.0

Note: H—slice height; W—stope width; $\sigma_{c,f}$—uniaxial compressive strength of filling material; U_x—horizontal displacement; U_y—vertical displacement; f—stress concentration degree; S—safety coefficient; SSE—sum-squared errors; EW—expected weight; EH—expected height.

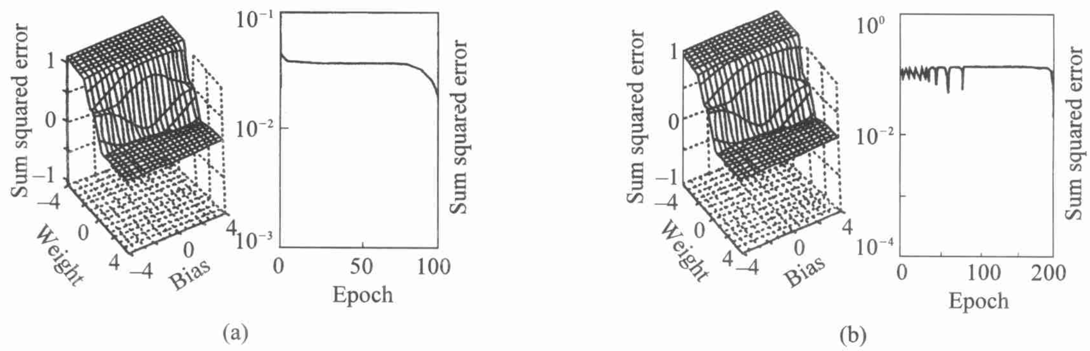

Figure 3 The learning curve (a) scheme 7 and (b) scheme 8 of Sum-Squared Error (1 000 epoch).

el 7 and Model 3 is smaller.

According to the measured in-situ stresses, geological and deposit conditions in the mine and taking consideration of the practical production conditions, 3D-σ FEM program has been adopted to calculate and analyze the structure parameters in the stope of eight models. Model 7 was finally selected, in which the slice height is 5.0 m, the stope width is 8.0 m. It was verified that the structure stability is feasible.

5 Conclusions

(1) Not only for the tentative stope, but also for the design of whole deep mining, and the method of coupled ANN theory are all useful and successful.

(2) In the structural-engineering field of underground rock mass, because the rock mass is a complex and confounded material, it is necessary to select the suitable analytical method to evalute the behavior of failed rock masses for building large structures.

(3) Stability evaluation increasingly emphasizes on non-linear and discontinuous model to reflect the mechanisms. This subject that concerns both non-linear rock mechanics principles and dynamics to mining and civil engineering projects should be a primary goal of future development.

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