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Research on Prediction of Rating of Rockburst Based on BP Neural Network

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Abstract: With the development of economic construction, underground space development continues to move towards the deep. "More, long, big, deep," will be the general trend of the development of underground engineering in the 21st century. Rock burst is a kind of sudden geological disasters with a higher frequency in deep tunnel construction. Rock burst prediction has very important significance for the construction of underground engineering in highland stress area. This paper described the mechanism of rockburst. The researchers systematically analyzed relevant factors of rockburst. In this paper, the principle and application of Back-Propagation (BP) neural network were introduced, and to improve the algorithm of neural network, the NNT prediction model was set up. The author have taken the seven parameters including (as input values): Index of brittleness, Ratio of Strength stress, Ratio of maximum stress to minimum stress, Depth of engineering, Completeness of rockmass, Structural strength, Depth of pit for rock burst. The results of rockburst also proved the prediction model has high accuracy and stability, indicating that the model has a good prospect in the rock burst forecasting.

Keywords: Deep rock engineering, neural network, prediction, rockburst.

1. INTRODUCTION

With the underground space development at home and abroad, and continue to move towards the deep space. Such as mountain long tunnel, the tunnel through the Alps up to 2500 m depth; hydropower projects over a thousand meters in depth, such as a maximum depth of 2600 meters in Jinping hydropower station and so on. China has entered a period of large-scale development projects and underground tunnels, with the acceleration of the process of China's western development, roads, utilities and mining and other fields will build more long tunnel project. "More, long, big, deep," will be the general trend of China's development in the 21st century tunnel project [1, 2].

At this stage, China's rock engineering has large-scale, high degree of difficulty, whether it is mining engineering, or hydropower engineering and traffic engineering, a lot of engineering to develop into the deep underground space, many of these projects have encountered rock burst phenomenon. All of these underground space construction and design, have encountered a number of common engineering problems: We must solve the deformation, damage and rock burst of deep rock under high stress conditions and other engineering problems [3].

There has the extremely complex relationship between rock burst and its influencing factors, a mathematical model of this highly complex nonlinear relationship was difficult to determine the expression, which requires the establishment of a number of kinds of factors can be considered high prediction accuracy of rock burst forecasting methods. Artificial neural network is a large number of neurons in some way connected to each other, it implements the human brain through the structure and mechanism of certain functions of the human brain simulation, the topology of neurons, with any precision approach, and any the ability of continuous functions, we can achieve the ability of various engineering information during dynamic information processing [4].

Hu Defu (2011) designed and determined the structure and parameters of the BP artificial neural network model, the use of genetic algorithm to optimize BP neural network threshold, so that accurate prediction is more accurate [5].

XUE Yangshuo, SUN Zhiguo, YU Quanyou (2013), in their study, considered the complicated geological conditions in Pangzhuang Coal Mine, and applied the BP neural network to take the dynamic prediction of rock burst in 75215 airway floor. The results show that the prediction data are consistent with the results of field observation [6].

Amoussou Coffi Adoko, Candan Gokceoglu, Li Wu, *et al*. (2013) in their research was intended to predict rock burst intensity based on fuzzy inference system (FIS) and adaptive neuro-fuzzy inference systems (ANFIS), and field measurements data, which has a total of 174 rock burst events. These results show that the models can be used for the rock burst prediction, and this may help to reduce the casualties sourced from the rock bursts [7].

Long-jun DONG, Xi-bing LI, Kang PENG. (2013) analyzed some main control factors of rock burst, such as the values of in-situ stresses, tensile strength of rock, the elastic energy index of rock, and uniaxial compressive strength. And Selected 46 sets of rock burst samples for training and

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test which come from underground rock projects in domestic and abroad. To compare the results of artificial neural network (ANN) method to random forest method. The results show that using the index I and RF model can accurately classify rock burst grade [8].

This study was based on conditions of rock burst, to select index of brittleness, Ratio of Strength stress, Ratio of maximum stress to minimum stress, Depth of engineering, Completeness of rockmass, Structural strength, Depth of pit for rock burst. To use neural networks to establish a BP neural network model to predict the rating of rock burst based on rock burst instance such as Jinping tunnel and underground engineering.

2. LEARNING ALGORITHM OF BP NEURAL NETWORK

2.1. Define the Variables of Neural Network

In the BP neural network with three layers, if neuron number of nodes of the input layer is *M*, neurons nodes of the hidden layer is *I*, neurons nodes of the output layer is *J* [9, 10].

Set the m^{th} neuron of input layer as x_m, set the i^{th} neuron of hidden layer as k_i, set the j^{th} neuron of output layer as y_j.

The connection weight values from x_m to k_i is w_{mi}, the connection weight values from k_i to y_j is w_{mi}.

The transfer function of hidden layer is Sigmoid function, Sigmoid function is divided into two categories: Log-Sigmoid function

$f(x)=\dfrac{1}{1+e^{-x}}$; Tan-Sigmoid function, $f(x)=\dfrac{e^x-e^{-x}}{e^x+e^{-x}}$.

The transfer function of the output layer is a linear function Pure=$kx+b$.

The length of Input vector of the network model is *M*, and finally, to output a vector with the length of *J*.

Apply *u* and *v* to represent the input and output of each layer respectively, such as: The variable u_I^1 represents the input *I* of hidden layer in the first neuron.

Actual output of the neural network is:

$$Y(n)=[v_J^1,v_J^2,\cdots,v_J^J]$$

Desired output of neural network is:

$$d(n)=[d_1,d_2,\cdots,d_J]$$

Where, *n* is the iterations.

The error signal of the n^{th} iteration can be defined as:

$$e_j(n)=d_j(n)-Y_j(n)$$

The error energy function can be defined as:

$$e(n)=\frac{1}{2}\sum_{j=1}^{J}e_j^2(n)$$

2.2. Forward Propagation Information of Input Layer and the Hidden Layer

The input information is the input signal of the input layer of the neural network:

$$v_M^m(n)=x(n);$$

The input of i^{th} hidden layer neuron is equal to the sum of the weighted value $v_M^m(n)$:

$$u_I^i(n)=\sum_{m=1}^{M}w_{mi}(n)v_M^m(n)$$

If $f(\cdot)$ is Sigmoid function, the output value of the ith hidden layer neuron is:

$$v_I^i(n)=f\left(u_I^i(n)\right)$$

The input of the j^{th} output layer neuron is equal to the sum of the weighted value $v_I^i(n)$:

$$u_J^j(n)=\sum_{i=1}^{I}w_{ij}(n)v_I^i(n)$$

The output of the jth neuron of output layer is:

$$v_J^j(n)=g\left(u_J^j(n)\right)$$

The error of the jth neuron of the output layer is:

$$e_j(n)=d_j(n)-v_J^j(n)$$

The sum of the errors of the neural network is:

$$e(n)=\frac{1}{2}\sum_{j=1}^{J}e_j^2(n)$$

2.3. Back-propagation Signal of Output Error of Neural Network

In the phase to adjust the connection weights, from the output layer to the hidden layer and from the hidden layer to the input layer, and the output error signal to spread along the network converse, and make adjustments.

The connection weight between the output layer to the hidden layer is w_{ij}.

According to the steepest descent method, it must calculate the gradient

$\dfrac{\partial e(n)}{\partial w_{ij}(n)}$ of error w_{ij},

further adjusted connection weight along the reverse direction:

$$\Delta w_{ij}(n)=-\eta\frac{\partial e(n)}{\partial w_{ij}(n)}$$

$$w_{ij}(n+1)=\Delta w_{ij}(n)+w_{ij}(n)$$

To solve partial derivative of the gradient, to attain:

$$\frac{\partial e(n)}{\partial w_{ij}(n)} = \frac{\partial e(n)}{\partial e_j(n)} \cdot \frac{\partial e_j(n)}{\partial v_J^j(n)} \cdot \frac{\partial v_J^j(n)}{\partial u_J^j(n)} \cdot \frac{\partial u_J^j(n)}{\partial w_{ij}(n)}$$

Because $e(n)$ is a quadratic function of $e_j(n)$, Its differential function is a linear function:

$$\frac{\partial e(n)}{\partial e_j(n)} = e_j(n)$$

$$\frac{\partial e_j(n)}{\partial v_J^j(n)} = -1$$

The derivative of transfer function of the output layer is:

$$\frac{\partial v_J^j(n)}{\partial u_J^j(n)} = g' u_J^j(n)$$

$$\frac{\partial u_J^j(n)}{\partial w_{ij}(n)} = v_I^j(n)$$

Then, the value of the gradient is:

$$\frac{\partial e(n)}{\partial w_{ij}(n)} = -e_j(n) g'\left(u_J^j(n)\right) v_I^i(n)$$

Correction amount for the connection weight is:

$$\Delta w_{ij}(n) = \eta e_j(n) g'\left(u_J^j(n)\right) v_I^i(n)$$

To define local gradient δ_J^j is:

$$\delta_J^j = -\frac{\partial e(n)}{\partial u_J^j(n)} = -\frac{\partial e(n)}{\partial e_j(n)} \cdot \frac{\partial e_j(n)}{\partial v_J^j(n)} \cdot \frac{\partial v_J^j(n)}{\partial u_J^j(n)} = e_j(n) g'\left(u_J^j(n)\right)$$

Therefore, the amount of correction connection weights can be expressed as:

$$\Delta w_{ij}(n) = \eta \delta_J^j v_I^i(n)$$

Local gradient may be required to characterize the incremental connection weights.

The increment is equal to the product of the error message of neuron and derivative of transfer function.

In general, the transfer function of the output layer is a linear function, its derivative is 1:

$$g'\left(u_J^j(n)\right) = 1$$

from the above equation, to attain:

$$\Delta w_{ij}(n) = \eta e_j(n) v_I^i(n)$$

Forward propagation of error information, to adjust connection weights w_{mi} between the input layer and hidden layer, to attain:

$$\Delta w_{mi}(n) = \eta \delta_I^i v_M^m(n)$$

$v_M^m(n)$ is the output of input neurons, then

$$v_M^m(n) = x^m(n)$$

δ_I^i is local gradient, which can be defined:

$$\delta_I^i = -\frac{\partial e(n)}{\partial u_I^i(n)} = -\frac{\partial e(n)}{\partial v_I^i(n)} \cdot \frac{\partial v_I^i(n)}{\partial u_I^i(n)} = -\frac{\partial e(n)}{\partial v_I^i(n)} f'\left(u_I^i(n)\right)$$

$f(g)$ is a type of sigmoid transfer function.

Firstly, apply reverse error information in calculation, to obtain local gradient of output layer nodes; finally, to solve the partial derivative of the error output value of hidden layer:

$$\frac{\partial e(n)}{\partial v_I^i(n)} = \sum_{j=1}^{J} \delta_J^j w_{ij}$$

To attain:

$$\delta_I^i = f'\left(u_I^i(n)\right) \sum_{j=1}^{J} \delta_J^j w_{ij}$$

Thus, the error correction of neural network is complete in one round.

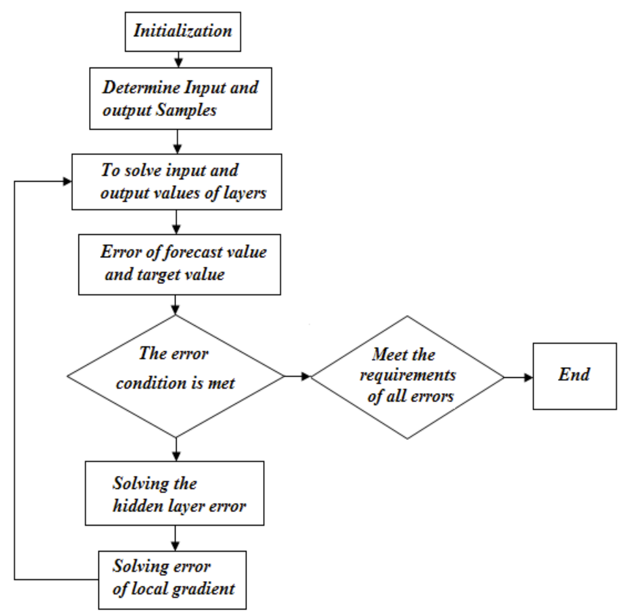

Fig. (1). The flow diagram to solve neural networks.

The flow diagram to solve neural networks is shown as Fig. (**1**).

3. MECHANISM OF ROCK BURST

Rock burst is a special underground engineering phenomenon, with the surrounding rock suddenly, violently catapult to excavate space, throw, spray characteristics. Its mechanism and disaster forecasting has become necessary to address the academic strength of rock key scientific issues and technical problems. From the strength, stiffness, stability, energy, fracture, injury, and fractal theory of mutation breeding and mechanism of rock burst was studied, forming a rock burst strength theory, energy theory, theory and rock burst tendency rigidity theory. Because of the physical and mechanical properties of the rock itself, the complexity and geotechanical conditions and predisposing factors, factors affecting the construction of rock, making the mechanism of rock burst is extremely complex. Research of rock burst mechanism remained mostly qualitative interpretation stage.

Excavation of rock high in situ stress in ah room, rock stress suddenly released, broken and thrown rocks dynamic phenomenon. Rock burst pressure and impact the earth is a destructive phenomenon, the fundamental cause of stress is causing it to happen. On its mechanism of rock burst occurred can be divided into three categories, called the strain type of rock burst, and the other called the stereotype of rock burst, there is a class structure hybrid strain and rockburst. Based rock categories to consider, can be divided into uniform and non-uniform rockburst categories.

At present, people from the strength, stiffness, energy, stability, fracture, damage, and other aspects of fractal and mutation analysis of rock dynamics, put forward various criterion. Domestic and foreign scholars have studied the dynamics of rock underground engineering prediction method, summarized the research status of rock dynamics to predict [11,12].

Rock burst is one kind geological disaster of underground engineering in high-stress areas; it is the most intense kind of damage type of a variety of destabilization of rock around underground space. The damage form of rock burst can be divided into two types: splitting failure and shear failure.

Neural network has a strong self-learning ability of nonlinear dynamics and parallel distributed processing. Therefore, the neural network is a powerful theoretical tool for rock mechanics and engineering problem solving.

According to the mechanism of rock burst occurrence, it can be divided into: the strain-type rock burst, the stereotype of rock burst, the strain and construct hybrid rock burst [13].

Rock excavation project will produce unloading. From the energy point of view, unloading is the process of deformation energy converted into kinetic energy, this transformation is one part of the excavation caused, another part of cavern roof damage caused. The kinetic energy of rock burst is equal to a difference of the total deformation energy and destruction energy [14].

Qi Qingxin, Li Hongyan, proposed three-factor theory of rock burst: the first factor is the impact of rock tendencies, the second factor is the geological structure, and the third is the stress factor [15].

Shang Yanjun, summed up the 24 rock burst engineering example at home and abroad, and proposed several discriminant function of the strength of the boundaries of rock burst, for strong rock burst: $\sigma_\theta / \sigma_c = 0.5084 K_v^{-0.6417}$, ($R^2$=0.9344); for moderate rock burst: $\sigma_\theta / \sigma_c = 0.0454 K_v^{-2.0028}$, ($R^2$=0.9777); for the faint of rock burst: $\sigma_\theta / \sigma_c = 0.0939 K_v^{0.940}$, ($R^2$=0.8651), where σ_θ / σ_c is the ratio of shear stress σ_θ and uniaxial compressive strength σ_c; K_v is the coefficient for rock integrity [15].

According to Hou Faliang formula, in considering only the weight of the overlying rock rockburst case the minimum depth, critical depth that rock burst generated [16]:

$$H_{cr} = \frac{0.318 R_b (1-\mu)}{\gamma(3-4\mu)}$$
$$= \frac{0.318 \times 65000(1-0.29)}{26(3-4\times 0.29)}$$

where:

R_b—Saturated uniaxial compressive strength (MPa), 65MPa;

μ—Poisson's ratio, 0.29;

γ—Bulk density, 26 kN /m^3;

The above data into the above equation, and seek H_{cr}=306.8m.

(1) Index of brittleness (R_c/R_t)

Brittle rock high stress areas with a large elastic strain energy, prone to rock burst. In general, you can use the brittleness index $n_b=R_c/R_t$ expressed. The smaller the ratio, the greater the likelihood of rockburst, rockburst intensity level is higher. Therefore, the higher the degree of brittle rock, the greater the depth and range of rockburst damage.

(2) Ratio of Strength stress (σ_c/σ_1)

The ratio of the uniaxial compressive strength of rock and the maximum principal stress is called stress intensity ratio (σ_c/σ_1), the intensity of the rock mass initial stress field, the basic physical and mechanical properties of the rock, the rock to withstand compressive stress ability, both indicators can be compared to rock burst through the intensity of the stress levels of discrimination [14].

(3) Ratio of maximum stress to minimum stress (σ_1/σ_3)

Tectonic stress and self-generated stress depth is the key factor affecting the rock burst, the rock of the initial maximum principal stress and the ratio of the minimum principal stress (σ_1/σ_3) may reflect changes in the weight distribution of the stress field after rock excavation law, in the vicinity of the excavation face, the higher the concentration of secondary stress field, the more prone to rock burst.

(4) Depth of engineering, h

Generally, the greater the depth of rock, earth stress is, the more prone to rock burst. Stress, stress to the general this level, above the critical depth, the stress in the horizontal direction greater than the vertical direction is the maximum principal stress; depth below the critical stress, the stress in the vertical direction is larger than the horizontal direction, the vertical stress is the greatest principal stress.

(5) Completeness of rockmass, K_r

The rock joints, cracks the less developed, more complete rock, so brittle rock similar elastomer, capable of storing large amounts of elastic strain energy, rock by excavation unloading, the rock will break after catapult and projectile out. Therefore, the integrity of the rock mass is an important factor in rock blasting and rock burst pit depth rating impact.

(6) Structural strength, S_s

Causes of rock burst depends on excavation and construction of ground stress field conditions and specific rock underground chambers of the triggering factors supporting

Table 1. Training samples of neural network for rock burst.

R_c/R_t	σ_c/σ_1	σ_1/σ_3	h	K_r	S_s	h_{rb}	Rating of Rock burst
16.299	1.433	1.414	1700	2	2	1.0	2
33.366	2.083	1.536	2445	2	0	0.8	2
33.366	2.083	1.536	2445	2	1	0.4	1
33.366	2.070	1.541	2450	1	1	0.7	2
27.439	1.667	1.459	2370	1	1	0.3	1
16.292	1.447	1.426	1680	2	1	1.5	3
33.366	2.457	1.337	2055	1	3	0.8	2
24.899	1.706	1.490	2400	2	3	1.0	2
33.088	1.631	1.582	2490	2	2	0.3	1
27.439	1.996	1.317	1910	1	3	2.4	3
27.439	1.686	1.449	2360	2	1	0.8	2
33.088	1.600	1.440	2540	2	1	0.8	2
33.366	2.273	1.384	2270	3	1	0.8	2
33.088	1.669	1.562	2470	2	2	0.4	1
27.439	2.033	1.318	1930	2	2	0.8	2
33.088	1.645	1.470	2380	2	2	0.3	1
27.439	1.754	1.439	2350	1	2	1.5	3
33.366	2.331	1.347	2097	2	2	1.5	3
27.439	1.761	1.512	2422	1	3	0.3	1
33.366	2.451	1.317	1920	1	3	1.0	3
33.366	2.294	1.349	2109	2	3	0.8	2
33.088	1.645	1.470	2380	1	1	0.9	2
33.366	2.597	1.329	2024	1	1	1.5	3
27.439	2.141	1.322	1985	2	3	0.8	2
33.366	2.049	1.449	2360	1	1	2.0	3
33.088	1.934	1.345	2090	2	3	0.3	1
33.366	2.213	1.419	2330	1	0	0.3	1
33.088	1.957	1.343	2080	2	1	0.3	1
33.366	2.024	1.459	2370	1	0	0.6	2
27.439	2.053	1.319	1940	2	2	2.5	3
33.366	2.000	1.470	2380	1	2	0.3	1
27.439	1.988	1.320	1890	2	2	0.7	2

R_c/R_t: Index of brittleness; σ_c/σ_1: Ratio of Strength stress; σ_1/σ_3: Ratio of maximum stress to minimum stress;
h: Depth of engineering; K_r: Completeness of Rockmass; S_s: Structural strength; h_{rb}: Depth of Pit for rock burst.
Rating of Rock burst.

Test samples of Neural network for rock burst was shown in Table **2.**

Table 2. Test samples of neural network for rock burst.

R_c/R_t	σ_c/σ_1	σ_1/σ_3	h	K_r	S_s	h_{rb}	Rating of Rock burst
33.366	2.049	1.449	2360	1	2	0.4	1
27.439	1.980	1.316	1900	1	3	1.0	3
33.366	2.024	1.459	2370	1	1	1.0	2
33.366	2.331	1.346	2095	1	2	1.5	3
33.088	1.650	1.572	2480	3	2	0.4	1
27.439	1.667	1.459	2370	2	2	0.8	2

R_c/R_t: Index of brittleness; σ_c/σ_1: Ratio of Strength stress; σ_1/σ_3: Ratio of maximum stress to minimum stress; h: Depth of engineering; K_r: Completeness of Rockmass; S_s: Structural strength; h_{rb}: Depth of Pit for rock burst.
Rating of Rock burst.

different manner to achieve the supporting strength is an important factor affecting rock burst level [14].

(7) Depth of pit for rock burst h_{rb}

Rockburst pit depth by nature brittle rock or plastic, and is closely related to the degree of development joints, gravity stress field, tectonic stress field, and underground engineering depth, size and construction parameters [14].

4. TO ESTABLISH BP NEURAL NETWORK MODEL

Prediction of rating of rockburst is the use of measured data for complex non-linear model. The process is: To use artificial neural network to establish the non- linear relationship between the Rating of Rock burst and the seven factors. R_c/R_t: Index of brittleness; σ_c/σ_1: Ratio of Strength stress; σ_1/σ_3: Ratio of maximum stressto minimum stress; h: Depth of engineering; K_r: Completeness of Rockmass; S_s: Structural strength; h_{rb}: Depth of Pit for rock burst.

The output of the neural network is the Rating of Rock burst.

The diagram of neural network prediction model for rating of rockburst was shown in Fig. (**2**).

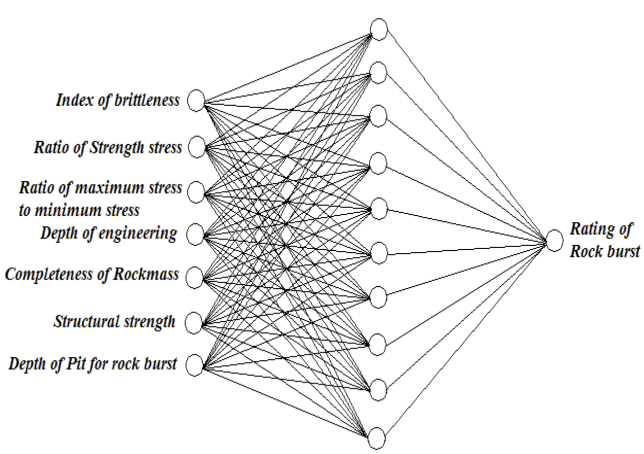

Fig. (2). Diagram of neural network prediction model for predicts rating of rockburst.

To determine nodes of hidden layer

For neural network models, the hidden layer nodes take great influence on the performance of neural networks.

The more hidden layer nodes is, it may make the better performance of neural network model, but it may lead to training time is too long.

Currently, there is no ideal analytical formula can be used to determine the number of nodes in the hidden layer of the neural network, the usual empirical methods are:

(1) $\sum_{i=0}^{n} C_M^i > k$, k is number of samples, M is the number of hidden layer neurons, n is the number of input layer neurons. If, $i > M$, then determine $C_M^i = 0$.

(2) $M = \sqrt{n+m} + a$, m and n are respectively represent the number of neurons of the input layer and output layer, $a \in [0,10]$, a=const.

(3) $M = \log_2^n$, n is the number of neurons of the input layer.

When the network layer is determined by the above method, to increase the nodes of neurons in the hidden layer can improve the training accuracy. Generally, the more of the nodes of the hidden layer, the more the network could approximate fitting the nonlinear curve, but too much of the hidden layer neurons will reduce the convergence rate.

In theory, it has been proven that the BPNN can approximate to any differentiable function at any precision, when the 3-layer back propagation network with the input layer nodes (m) and with a $2m + 1$ hidden layer nodes.

In this paper, the prediction model has seven input variables, hidden layer neuron number is set to 15. To select one of the 32 sets of data as a training network of learning samples from collected data. The training sample data were shown in Table **1**.

CONCLUSION

(1) In this paper, considering the variety of qualitative and quantitative factors surrounding rock rockburst, using

seven parameters as indicators such as the establishment of BP artificial neural network forecasting model of rock burst. Domestic Jinping underground works as a sample of rock burst instance, through study, training, so that the trained network to better reflect the degree of the mapping between rock burst and the impact of various factors, making the pre-side rock burst rating more reasonable. Examples show, BP neural network model to predict the results used in this paper is consistent with the actual situation, to illustrate the effectiveness of this model.

(2) The process rock burst is very complex, the mechanism of rock burst is not yet clear that this would require a sample database, and steadily improved database. Learn more samples, the impact of factors to be considered more fully, characteristics of the network the more memory, the accuracy of pre-side network continues to increase.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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