Research Article

Prediction and Evaluation of Rockburst Based on Depth Neural Network

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The formation mechanism of rockburst is complex, and its prediction has always been a difficult problem in engineering. According to the tunnel engineering data, a three-dimensional discrete element numerical model is established to analyze the initial stress characteristics of the tunnel. A neural network model for rockburst prediction is established. Uniaxial compressive strength, uniaxial tensile strength, maximum principal stress, and rock elastic energy are selected as input parameters for rockburst prediction. The neural network model shows that the rockburst risk is closely related to the maximum principal stress. Based on the division of rockburst risk areas, according to different rockburst levels, the corresponding treatment methods are put forward to avoid the occurrence of rockburst disaster. Based on the field measured data and test data, combined with the existing rockburst situation, numerical simulation and neural network method are used to predict the rock burst classification, which is of great significance for the early and late construction safety of the tunnel.

1. Introduction

Deep tunnel rockburst has great harm, and the mechanism and law of rockburst formation have not been fully revealed, which leads to the difficulty of comprehensive, accurate, and complete rockburst prediction and prevention methods. The academic theories related to its formation mainly include strength theory, impact tendency theory, stiffness theory, energy theory, and three-criterion instability theory.

For example, in Feng et al.’s work [1], in the field of coal mining, based on the elastic thin plate theoretical model, the roof deformation deflection equation and surrounding rock deformation energy equation are derived. A method is proposed to reduce the risk of rockburst by quantitatively adjusting the strength of backfill. Li et al. [2] established an elastic-plastic brittle catastrophe rockburst model of rock with structural plane and studied the relationship between energy accumulation and dissipation in the process of dynamic fracture of coal and rock. In the work of Pan et al. [3], based on energy theory and damage mechanics, the quantitative functional relationship between joint density and energy density was derived. Then, the theoretical results are verified by numerical simulation and uniaxial compression test, and the influence of joint density on rockburst tendency of elastic brittle plastic rock mass is discussed. In the work of Pan et al. [4], based on energy theory and damage mechanics, the quantitative functional relationship between joint density and energy density is derived. In the work of Wang et al. [5], based on the instability theory and cusp catastrophe theory, the instability conditions of pillars under asymmetric mining conditions were determined. According to the complexity and uncertainty of rockburst prediction, Ran et al. [6] established a rockburst classification prediction model based on rough set normal cloud. Xue et al. [7] proposed a method of rockburst evaluation based on rough set theory and extension theory. Ma et al. [8] analyzed several main rockburst theories, including strength theory, energy theory, blasting responsibility theory, stiffness theory, and instability theory. Li et al. [9–11] used neural network inversion technology to analyze the in situ stress distribution characteristics and engineering failure phenomenon of rock mechanics engineering.

In terms of rockburst prediction method and rock mechanics research method, Ji et al. [12] studied the
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Yufengsi tunnel is located in

2.1. Geological Characteristics.

2.2. Rock Strength.

2. Engineering Geological Conditions

The in situ stress is an important factor affecting tunnel rockburst. With the increase of depth, the in situ stress increases, and the number, frequency, and intensity of rockburst increase. At the same time, the structure and strong denudation are easy to produce abnormal distribution and concentration of in situ stress. Therefore, it is very important to use numerical simulation and machine learning method for in situ stress inversion.

3. In Situ Stress Inversion

3.1. Model Establishment. Taking the tunnel as the central axis, rectangular areas with side lengths of 10889 m and 2500 m are selected, and the bottom surface of the model is taken to 1000 m below the tunnel axis. The establishment of the top surface is based on the contour plane map provided by the geological exploration data, which is imported into surfer software, and the high-precision terrain coordinate

contribution of multiple MS data (including MS original wave data and MS energy data) to rockburst by using the method of combining support vector machine (SVM) and genetic algorithm (GA). Zhou et al. [13] used the stress type rockburst criterion of Gaoligongshan tunnel to identify the high-risk area and low-risk area of rockburst. Then, acoustic emission (AE) method is used to predict the magnitude and location of rockburst danger area. Cai et al. [14] established the membership function in fuzzy model by using Gaussian shape and exponential distribution function in reliability theory. The core of performance measure in confusion matrix is used to determine the weight of each index [15–19]. Other experts have also provided relevant research on rockburst prediction by using rock fractal, indoor experiments and engineering practice [24–26].

As an effective means to study rock mechanics, numerical simulation has been widely used in various fields of rock mechanics. At the same time, relying on the effective analysis of the field data to obtain the relevant physical and mechanical model is also essential for the research [27–31].

In this paper, Yufengsi tunnel is taken as a typical engineering example. Firstly, according to the stratum lithology and rock mass in the study area, the in situ stress parameters and rock strength parameters are obtained through laboratory tests. Then, through numerical simulation, the in situ stress field is inverted, and the main control factors of rockburst are selected. Finally, through the neural network training model, the characteristics of the target rockburst are analyzed, and the preventive measures are put forward. The research can provide an important basis for the division of rockburst area and subsection control.

The principle of maximum membership degree (MMDP) is combined with variable fuzzy pattern recognition (VFPR) to obtain the comprehensive prediction results [20–23].

2.1. Geological Characteristics. Yufengsi tunnel is located in the south section of Yulong Snow Mountain in the Sanjiang orogenic belt, northwest of Lijiang, Yunnan Province. The tunnel site belongs to the high mountain area of tectonic denudation. The mountain system is nearly north-south. The main peak of Yulong Snow Mountain is 5596 m above sea level. The tunnel passes through the watershed between Lijiang basin and Jinsha River on the southwest side of Yulong Snow Mountain and runs to 310 km. The total length is about 10.9 km, and the maximum buried depth is more than 1000 m. It is a deep buried tunnel, as shown in Figure 1.

Due to the multistage tectonic process in geological history, the structural deformation in the field area is strong, folds and active faults are developed, and the tunnel passing area is mainly controlled by nearly north-south comb folds and faults. From the entrance of Lijiang basin tunnel to the exit of Renheguo tunnel, the line successively passes through Daju Lijiang fault zone, Wenhai fault zone, Wenhai anticline, Xuehuacun syncline, and other geological structures. The total length of the tunnel longitudinal section is about 10.96 km. According to the engineering rock mass classification standard (GB 50218-94), the surrounding rock quality can be divided into several levels, such as II, III, IV and V. Among them, class V surrounding rock is mainly distributed in the loose eluvium section near the tunnel entrance, and the loose eluvium section is about 150 m. The stratum is weak, with high water content and strong heterogeneity. Type IV surrounding rock is mainly distributed in the fault fracture zone and the contact zone of different lithology. The rock mass is broken and is mostly in granular structure, with a total length of about 500 m; class III surrounding rock is mainly distributed in the basalt and medium thick limestone section, with a total length of about 4000 m, of which the basalt section is about 3460 m long, which is distributed near the tunnel entrance to the entry mileage of 3870 m. The tunnel in this section has a large buried depth, the maximum buried depth is about 1000 m, and the rock mass is relatively complete. The limestone section is about 600 m long and is distributed near the tunnel exit. In the range of 4–10 km, the grade of surrounding rock varies greatly.

2.2. Rock Strength. The higher the strength of rock, the greater the elastic energy accumulated before failure, so the higher the possibility of rockburst. The length of Yufengsi tunnel through hard basalt accounts for about 40% of the total length, and thick sandstone and thick limestone account for about 50%. The complete massive basalt is mainly located between 300 and 3800 m of tunnel mileage, the local hard thick sandstone is between 3800 and 10200 m, and the hard thick limestone is mainly located between 10200 and 10900 m near the tunnel exit.

Basalt, sandstone, and limestone samples were collected in the study area, and uniaxial and triaxial stress tests were carried out. The test results show that the three kinds of rock failure are shear failure (Figure 2). The uniaxial strengths of sandstone, limestone, and basalt are 143 MPa, 116 MPa, and 102 MPa, respectively. With the increase of surrounding rock, the strengths of three kinds of rock samples increase sharply; limestone has the largest elastic modulus, followed by sandstone and basalt.
value is obtained by Kriging interpolation method. Then, the coordinate value is imported into the discrete element software 3DEC. The specific numerical model is shown in Figure 3. The material parameters of rock mass are shown in Table 1.

### 3.2. Boundary Conditions.

The four basic factors that cause the distribution of in situ stress are vertical stress field, horizontal tectonic stress field in \( X \)-direction, horizontal tectonic stress field in \( Y \)-direction, and shear tectonic stress field, as shown in Figure 4. The method of applying self-weight stress field is to apply vertical constraint to the bottom of the model and normal constraint to the side of the model. According to the properties of rock mass, the density is applied to obtain the gravity load. The application method of \( X \)-direction horizontal tectonic stress field is to apply stress on both sides of the model in \( X \)-direction to simulate tectonic stress. The application method of horizontal tectonic stress field in \( Y \)-direction is to apply stress on both sides of the model in \( Y \)-direction to simulate tectonic stress. The shear tectonic stress field is obtained by applying shear stress to four sides.

### 3.3. Principle and Results of In Situ Stress Inversion Based on Multiple Regression Analysis.

In multiple regression analysis, independent variables must have a significant impact on dependent variables and have a close linear correlation. There is a linear correlation between independent variables and dependent variables. There should be a certain degree of mutual exclusion between independent variables; that is, the degree of correlation between independent variables should not be higher than that between independent variables and dependent variables. Independent variables should have complete statistical data. Therefore, the stress values obtained under the above four boundary conditions are selected as independent variables. The measured in situ stress is taken as the dependent variable, as shown in the following formula:

\[
\tilde{\sigma}_k = b_0 + \sum_{i=1}^n b_i \sigma_i^k.
\]  

In the above formula, \( \tilde{\sigma}_k \) is the measured in situ stress value of the measuring point, and \( k \) is the mark of the measuring point. \( b_0 \) is the free term and \( b_i \) is the multiple regression coefficient. \( n \) is the number of working conditions. In \( \sigma_i^k \), \( k \) is the numerical solution consistent with the measured point coordinates, and \( i \) is the working condition number. In this paper, the first condition is vertical stress, the second condition is \( X \)-direction tectonic stress, the third condition is \( Y \)-direction tectonic stress, and the fourth condition is shear tectonic stress.

The regression coefficient is solved by the least square method. According to the actual measurement of in situ stress, there are 15 measuring points, and each measuring point has 6 observation components. The sum of squares of the residual error of the least square method is shown in the following formula:
In the above formula, $m = 15$, $\sigma_{jk}$ is the $k$th observation point, and $j$ is the stress component obtained by numerical simulation.

$$Q_{\text{res}} = \sum_{k=1}^{m} \sum_{j=1}^{6} \left( \sigma_{jk} - b_0 - \sum_{i=1}^{n} b_i' \sigma_{jk}^i \right)^2.$$ (2)
Table 1: Physical and mechanical properties of surrounding rock.

| Lithology | Density $\rho_d$ | Uniaxial compression test $\sigma_c$ | $E$ | $\mu$ | 10 MPa | 20 MPa | 40 MPa | 60 MPa |
|-----------|-----------------|----------------------------------|-----|-------|--------|--------|--------|--------|
| Sandstone | 2.710           | 143.58                           | 6.14| 0.328 | 187.63 | 257.19 | 265.12 | 380.00 |
| Limestone | 2.797           | 116.17                           | 70.64| 0.229 | 270.26 | 314.68 | 349.07 | 468.34 |
| Basalt    | 2.965           | 102.76                           | 52.24| 0.129 | 222.78 | 307.29 | 345.94 | 418.57 |

Figure 3: Calculation model diagram.

Figure 4: Schematic diagram of model boundary conditions. (a) $Z$-direction load. (b) $X$-direction structural load. (c) $Y$-direction structural load. (d) Shear tectonic stress.
According to the principle of the least square method, the optimal solution is obtained when the sum of the squares of the residuals between the observed value and the regression value reaches the minimum.

\[
\begin{pmatrix}
6m \\
\sum_{k=1}^{m} \sum_{j=1}^{6} \sigma_{jk}^m \\
\sum_{k=1}^{m} \sum_{j=1}^{6} \sigma_{jk}^m \\
\sum_{k=1}^{m} \sum_{j=1}^{6} (\sigma_{jk}^m)^2 \\
\end{pmatrix}
\begin{pmatrix}
b_0 \\
b_1 \\
b_2 \\
\end{pmatrix}
= 
\begin{pmatrix}
\sum_{k=1}^{m} \sum_{j=1}^{6} \sigma_{jk} \\
\sum_{k=1}^{m} \sum_{j=1}^{6} \sigma_{jk} \\
\sum_{k=1}^{m} \sum_{j=1}^{6} \sigma_{jk}^2 \\
\end{pmatrix}
\begin{pmatrix}
b_0 \\
b_1 \\
b_2 \\
\end{pmatrix}.
\]  

The matrix of undetermined coefficient \(b\) is obtained by solving (3), and the distribution of regional geostress is obtained according to equation (1). The results show that the free term \(b_0\) is 1.66, the self-weight stress field regression coefficient \(b_1\) is 1.33, the \(x\)-direction tectonic stress field regression coefficient \(b_2\) is 5.31, the \(y\)-direction tectonic stress field regression coefficient \(b_3\) is 4.68, and the horizontal shear tectonic stress field \(b_4\) is 9.98.

According to the statistical principle and multiple regression significance experimental analysis, the correlation coefficient \(R = 0.996\) indicates that there is a high degree of correlation between the independent variable and the dependent variable, and the \(F\) significance statistic is \(1.16 \times 10^{-8}\), which also indicates that the regression effect is significant.

Stress field inversion regression formula is as follows:

\[
\sigma_{\text{inversion value}} = 1.66 + 5.31\sigma_x + 4.68\sigma_y + 1.33\sigma_z + 9.98\sigma_{xy}. 
\]  

In the above formula: \(\sigma_{\text{inversion value}}\) is the inversion value of in situ stress, \(\sigma_x\) is the stress produced by the tectonic compression movement in \(X\)-direction, \(\sigma_y\) is the stress produced by the tectonic compression movement in \(Y\)-direction, \(\sigma_z\) is the in situ stress component produced by the gravity stress, and \(\sigma_{xy}\) is the in situ stress component produced by the plane shear stress.

Through the simulation inversion results, the distribution maps of the maximum, middle, and minimum principal stress fields in Yufengsi tunnel area are obtained (Figures 5–7). The stress distribution of rock mass in tunnel site has the following characteristics.

The in situ stress field is obviously affected by lithology, topography, and faults. The stress concentration is strong in the valley. On steep ridges and isolated hilltops, the stress relaxes and decreases. The contour of the maximum principal stress is basically consistent with the topographic change on the profile, and the value is high in the mountain area, but the contour of the basin is shifted downwards. With the increase of buried depth, the stress value increases. Near the tunnel exit, the difference between the maximum principal stress and the minimum principal stress reaches 40 MPa, and the tunnel is obviously affected by the bias stress environment.

4. Prediction and Analysis of Rockburst Based on Deep Neural Network

4.1. Evaluation Index and Sample Data. There are external and internal reasons for rockburst. The external reason is that rockburst usually occurs in underground rock mass with high ground stress. Due to the excavation of caverns in the rock mass, the spatial environment of rock mass is changed, and the stress redistribution and stress concentration around the caverns are caused. The internal reason is that rockburst usually occurs in hard rock, and its mineral structure is dense and hard. The brittle failure of surrounding rock due to excavation unloading leads to the sudden release of elastic strain energy stored in rock mass, which eventually leads to the failure of surrounding rock, such as burst loosening, spalling, and ejection, resulting in rockburst. At the same time, it is found that the stress level of rockburst is higher, and the intensity of rockburst is closely related to the degree of stress concentration. Considering the main factors affecting the occurrence and intensity of rockburst, the four indexes are selected.

The factors that affect the rockburst in tunnel are more complex, which is particularly important for the selection of the indexes to evaluate the occurrence of rock burst. Through the mechanism of rockburst and investigation statistics, this paper holds that rockburst usually occurs in the area with high stress concentration, so the maximum principal stress is selected as one of the evaluation criteria. Rockburst is a result of energy accumulation and instantaneous explosion of rock. Therefore, the rock hardness, namely, uniaxial strength and tensile strength, is also an
important index. The higher the index, the greater the energy stored between the occurrence and failure of rock, and the elastic energy index of rock is also regarded as one of the evaluation indexes.

Through the analysis of rockburst at home and abroad, the sample data are obtained by taking the maximum principal stress, uniaxial strength, tensile strength, and elastic energy index as the rating indexes in Table 2.

4.2. BP Neural Network Model Based on Genetic Algorithm Optimization. BP neural network optimized by genetic algorithm is divided into three parts: BP neural network structure determination, genetic algorithm optimization, and BP neural network prediction. The structure of BP neural network is determined according to the number of input and output parameters of the fitting function, and then the individual length of genetic algorithm is determined. Genetic algorithm optimization uses genetic algorithm to optimize the weights and thresholds of BP neural network. Each individual in the population contains a network ownership value and threshold. Individual fitness value is calculated by fitness function. Genetic algorithm finds the corresponding individual with the optimal fitness value through selection, crossover, and mutation operation. BP neural network prediction uses genetic algorithm to get the optimal individual, assign the initial weights and thresholds of the network, and output the prediction function after training.

The nonlinear function to be fitted in this paper has four input parameters and one output parameter, so the structure of BP neural network is set as 4-6-1; that is, there are four nodes in the input layer, six nodes in the hidden layer, and one node in the output layer $4 \times 6 + 6 \times 1 = 30$ weights, $6 + 1 = 7$ thresholds, so the individual coding length of genetic algorithm is $30 + 7 = 37$. 20 groups of rock burst data are selected as input data and 10 groups are selected as test data. The sum of absolute prediction errors of training data is taken as individual fitness value. The smaller the individual fitness value is, the better the individual is. The flow chart of BP neural network optimized by genetic algorithm is shown in Figure 8.
4.3. Rockburst Prediction. According to the neural network inversion results, the first section 0–500 m belongs to the basalt slight rockburst section. The second section is the basalt serious rockburst section, from the tunnel entrance mileage of 500 m to 3750 m. The third section is a slight rockburst section, from the tunnel entrance mileage of 3750 m to 5500 m. The fourth section is a medium rockburst section, with the mileage from 5500 m to 9200 m. The fifth section is a serious rockburst section, from 920 m to 11000 m. It can be seen from Figure 9 that the risk degree of rockburst is highly correlated with the maximum principal stress.

5. Advanced Treatment of Rockburst Danger Area

According to the harm of rockburst to engineering construction, rockburst can be divided into three different levels: “slight rockburst,” “medium rockburst,” and “strong rockburst.” Through the above research, the risk characteristics of rockburst in different areas are obtained. The prevention methods of rockburst with different intensity are described below.

In the section of slight rockburst, the excavation footage shall be controlled within 3 m. The water gel explosive with
high fierceness and high power matching with hard rock is selected. The surrounding hole spacing is increased to reduce the impact of blasting on surrounding rock. Strengthen the management of smooth blasting technology, so as to achieve smooth excavation contour and avoid stress concentration caused by uneven surface. Water is added to soften the surrounding rock surface, and high-pressure water is sprayed directly on the excavation exposed surface to soften the surface.

In medium strength rockburst section, advanced in situ stress relief blasting is adopted: the main construction technology of stress adjustment blasting includes the layout of advanced stress relief holes and the design of charge quantity. Generally speaking, the blastholes are required to be evenly arranged on the working face, and the distance between blastholes is about 2 m. The drilling depth is controlled by 2 times of single cycle footage, and the angle is controlled within 5°–10°. The length of the hole charge is 1.5–2.0 m, and the charge quantity is 1–2 kg. In actual construction, it is appropriate that the rock mass can be formed by blasting without breaking, and it is prior to the hole blasting, as shown in Figure 10. Combined with advanced blasting, the excavation footage should be controlled within 2 m, with smooth blasting and high-pressure water spraying.

In the strong rockburst section, the same advanced in situ stress relief blasting technology as the medium rockburst section is adopted, and the vault is properly densified. Two-bench method is adopted for excavation, and the excavation step is controlled within 2 m. At the same time, smooth blasting technology is adopted. High-pressure water spraying softens the surrounding rock on the tunnel surface. The stress release holes are constructed on the side wall of the tunnel with the depth of 3–5 m and the spacing of 0.8 m.

6. Conclusion

Based on the inversion of the initial geostress field in the study area, combined with the neural network calculation model optimized by genetic algorithm, a rockburst prediction model is established:

(1) It is considered that the main controlling factors of rock burst prediction are uniaxial compressive strength, uniaxial tensile strength, maximum principal stress, and elastic energy index. Based on this, a neural network model based on genetic algorithm optimization is established.

(2) By collecting and training the existing rockburst data, the analysis shows that the rockburst risk is closely related to the maximum principal stress characteristics, uniaxial strength, tensile strength,
and elastic energy index of rockburst. At the same time, although the buried depth of the tunnel exit section is shallow, the risk of rockburst is high due to the stress concentration in the valley area and the large deviatoric stress.

(3) The rockburst prediction model based on in situ stress field inversion and neural network is applied to the rockburst prediction analysis, and the results are basically consistent with the actual engineering situation. At the same time, based on the division of rockburst risk areas, according to different rockburst levels, the corresponding treatment methods are proposed to avoid the occurrence of rockburst disasters.

Data Availability

The data are available and explained in this article; readers can access the data supporting the conclusions of this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Authors’ Contributions

The manuscript was approved by all authors for publication.

Acknowledgments

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