Characteristics of rockburst and early warning of microseismic monitoring at qinling water tunnel

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ABSTRACT
In-depth records of the geological and rockburst data during the construction of the Qinling Water Tunnel of the Han to the Wei River project, analysis of the initial stress field distribution rules of the rock mass within a buried depth of 700 m. According to the situation of the site, strength stress ratio criterion, Russense criterion and Hoek criterion, were analysed and modified, and the rockburst tendency criterion suitable for Qinling Water Tunnel was proposed. According to the rockburst data, the rockbursts in the TBM tunnelling section of Qinling Water Tunnel were classified and counted, and the characteristics and risk reasons of rockbursts were summarized. The microseismic monitoring technology was applied to carry out the monitoring and early warning of rockburst in Qinling Water Tunnel, so as to achieve the effect of real-time monitoring. By comparing the microseismic monitoring results with the statistical data of rockburst, it was found that the microseismic monitoring has high accuracy of rockburst prediction. Finally, combined with two typical cases of rockburst prediction, it can be found that microseismic monitoring can reflect the preparation process of rockburst and use artificial intelligence for rockburst early warning, which has great practical significance for the prevention of rockburst.

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1. Introduction
Rockburst was a phenomenon of rockburst and ejection due to the sudden release of elastic strain energy in surrounding rock due to the unloading of surrounding rock excavation and the redistribution of rock stress during the excavation of rock mass in high stress area.

In South Africa, rockbursts occur frequently. In 1975 alone, 680 rockbursts occurred in 31 gold mines in South Africa (Zhang and Fu 2008), resulting in huge...
human and material losses. The earliest catastrophic event (Ortlepp 2005) that can be classified as a major rockburst was likely to occur in the Altenberg tin mine in Germany in 1640, resulting in the reopening of the mine in 1840. In 1958, a huge bump caused by rockburst occurred in Springhill No. 2 Mine (Notley 1984). Linglong gold deposit in China was affected by high geostress (Cai et al. 2001) in the mining process and involves rockburst. In June 1985 (Zhang and Lu 1991), rockburst occurred for the first time in No. 2 construction branch tunnel of Tianshengjiao II Hydropower Station. Zhou and Hong (1995) recorded more than 400 rockburst data during the construction of Taipingyi hydropower station and summarized the rockburst characteristics of the project. The maximum buried depth of the diversion tunnel of Jinping II Hydropower Station (Hou et al. 2011) was about 2525 m, and many rockbursts have hindered the progress of the site. Xu (1999) recorded more than 200 rockbursts in the Erlang mountain tunnel of the Sichuan-Tibet highway, studied the problem of rockburst and high ground stress. Qinling Water Tunnel studied in this article was also a deep tunnel where rockbursts occur frequently.

Many scholars in the world have studied and put forward many estimation criteria of rockburst risk and tendency. Representative rockburst variable formula prediction (Wu et al. 2019), empirical criterion evaluation, artificial neural network prediction, fuzzy mathematics comprehensive evaluation. The commonly used methods for rockburst evaluation (Barton et al. 1974; Russenes 1974; Hoek and Brown 1997; Wang et al. 1999; Tezuka and Niitsuma 2000; Deng and Zhou 2014) include Hoek criterion, Russenes criterion, Turchaninov criterion, erlang mountain tunnel criterion, Zhenyu Tao criterion, and Barton criterion.

Microseismic monitoring and prediction of rockburst has made great progress in recent years. Zhang et al. (2018) proposed a method for predicting regional impact risk by using microseismic energy attenuation, which shows that it was effective to predict rockburst in potential dangerous areas of deep mining by using microseismic energy attenuation. Feng et al. (2016) proposed the energy fractal calculation method of tunnel microseismic events, and established a dynamic early warning system based on the evolution of microseismic events. (Dong and Li 2013) proposed a MS/AE source localization method for P wave and S wave reaching the unknown wave velocity system (PSAFUVS) to eliminate the influence of wave velocity measurement error on the positioning error of microseismic/acoustic emission (MS/AE) monitoring system. Based on the rockburst data of the diversion tunnel of Jinping II Hydropower Station, Zhang et al. (2020) studied the time behaviour of surrounding rock failure and the microseismic of delayed rockburst. The results showed that under long-term high stress conditions, when the damage accumulated to a certain extent, the rock mass was unstable, which led to rockburst, providing reference for the prediction of delayed rockburst in deep buried tunnels. Ma et al. (2018) considered that there were some precursors before rockburst, which showed the consistency between acoustic emission and rock mass damage variables. According to the spatial and temporal distribution, three models of microseismic incubation can be summarized. Based on 3S (stress accumulation, stress shadow, and stress transfer) principle in seismology, three rockburst criteria were proposed, which provide a theoretical basis for rockburst prediction by microseismic.
Many studies have promoted the rapid development of rockburst warning (Feng and Yang 1999; Yang and Li 2000; Feng and Zhao 2002), and high-tech also makes the accuracy of rockburst warning continue to improve. In addition, studying the evolution of rock damage can bring great help to the prevention and control of rockburst in tunnels. Relevant scholars have conducted in-depth research on rock damage and brought new ideas to the prevention and control of rockburst. Zhou et al. (2020) proposed a 3D numerical mesoscale model that considers material heterogeneity and local material degradation, and the data show that the model was a powerful tool for studying the failure evolution of brittle rocks. Fu et al. (2020) established a three-dimensional discrete element grain-based stress corrosion model to investigate the time-varying behaviour of damage evolution of brittle rocks and the fracture modes on the meso-scale. Fu et al. (2020) introduced the stress corrosion model into the 3D discrete element program, established a numerical time-dependent deformation model of rock, and studied the time-dependent deformation and fracture evolution of the surrounding rock of underground caverns with circular, inverted U-shaped and rectangular cross-sections.

The research fields of artificial intelligence include expert systems, machine learning, evolutionary computing, etc. In recent years, machine learning has attracted widespread attention in the field of seismology. It can improve traditional seismic detection and phase recognition methods (Jia et al. 2019), so that traditional methods can achieve better accuracy and efficiency. Feng et al. (1998) used a neural network model based on field rockburst data to predict rockbursts in deep gold mines in South Africa; Zhan et al. (2017) predicted the rockburst intensity level based on the artificial intelligence expert system method; Peng et al. (2010) combined artificial intelligence methods such as wavelet neural network and catastrophe theory to establish a rockburst prediction system that combines long-term prediction and short-term prediction; Zeng and Wu (2015) introduced the support vector machine algorithm of artificial intelligence, established a microseismic prediction model based on the support vector machine, and achieved good results in microseismic prediction; Perol et al. (2018) introduced a highly scalable convolutional neural network for seismic detection and localization, and localized seismic events in Oklahoma; Wang et al. (2021) used three tree-based ensemble methods to examine a rockburst database composed of 102 rockburst case data from 14 hard rock mines from 1998 to 2011, and found that the Bagging algorithm was the best predictive method for rockburst in hard rock mines. Zhou et al. (2020) used the neural bee model, the accuracy of rockburst prediction and the breadth of application have been well optimized.

Based on the statistical analysis of rockburst in Qinling water tunnel project, this article revised three methods of rockburst tendency assessment combined with the actual situation, and found a suitable method of rockburst tendency assessment. In addition, the rockburst data of TBM tunnelling section were analysed to summarize the general situation and causes of rockburst risk, and real-time continuous microseismic monitoring was carried out on multiple working faces in the engineering site. Combined with two actual cases, it can be found that the microseismic monitoring technology adopted not only has high accuracy of rockburst prediction, but also has a good effect on rockburst early warning and prevention combined with artificial
Figure 1. Detailed location and engineering layout of Qinling Water Tunnel.

(a) Qinling Water Tunnel of the Han to the Wei River Project was in Shaanxi Province, this was the location of the Shaanxi Province in China

(b) The sketch Plane layout of water conservancy project of Qinling Water Tunnel

(c) Construction plan including tunnel excavation section and excavation method
intelligence prediction, which effectively promotes the smooth implementation of Qinling Water Tunnel project.

2. Engineering overview

The Qinling Water Tunnel of the Han to the Wei River Project in Shaanxi Province (Figure 1a) crosses the Yangtze River and the Yellow River and crosses the Qinling Mountains with a total length of about 98.30 km. The longitudinal slope was 1/2500 (the ratio of the elevation difference between the two points and its horizontal distance was 1/2500) which was divided into the third section of the Yellow III River and the cross ridge section (Figure 1b). This article mainly carries out the rockburst monitoring of the excavation tunnel in the cross ridge section. The total length of the tunnel was 81.779 km, and the tunnel has been completed about 77 km. The TBM method was used to construct the main ridge section of the Qinling Mountains. The remaining section was about 4.7 km not penetrated, and the maximum depth of the remaining section was 2012 m. In the section of the Qinling Water Tunnel where rockbursts have occurred, the stress test results show that the initial maximum principal stresses all exceed 20 MPa, and the highest reaches 40 MPa. According to the test results of ground stress in the engineering area, the regression analysis formula was used to predict that the maximum principal stress can reach 100 MPa when the maximum buried depth of the TBM working area of the Qinling Tunnel was near 2012 m. High ground stress, complex geological conditions, difficult construction. Rockburst, high temperature, and water inrush were the main difficulties in the excavation. The main ridge section was divided into two TBM excavation working faces of South of the mountains and North of the mountains, as shown in Figure 1c. South of the mountains TBM was divided into two excavation sections. The first excavation
The second excavation section plans K39 + 551–K43 + 360.

Rockburst was one of the main geological disasters in the Qinling Water Tunnel project, which causes serious damage to the initial support system such as steel mesh, steel arch frame and so on. The explosion of large stones caused by rockburst poses a great threat to the safety of construction machinery and personnel, and seriously restricts the progress of the project. Figure 2 was the statistical data of the buried depth distribution of Qinling Tunnel. It can be seen from the figure that the Qinling Tunnel was a deep-buried tunnel, and the buried depth of the tunnel chamber was distributed in the range 100–1500 m. The length of the 500–1000 m high buried deep tunnel can reach 34.1 km, and the length of the tunnel section with the buried depth of more than 1000 m reaches 27.2 km. The statistical data show that the buried depth of the second tunnelling section of TBM in South of the mountains was larger than that of the first tunnelling section.

3. Engineering geology

The tunnel line of Qinling Water Tunnel was located in the western mountainous area of Qinling Mountains, which mainly includes three major geomorphic units: the middle and low mountainous area of South of the mountains, the middle and high mountainous area of ridge, and the middle and low mountainous area of North of the mountains. The strata that Qinling Tunnel passes through were affected by multi-stage tectonic movement, fault structure was developed and magmatic activity was strong. As shown in Figure 3, the lithology of Qinling was mainly metamorphic sandstone, phyllite, schist, quartzite, granulite, marble, gneiss and granite, granodiorite, diorite, etc. The lithology of North of the mountains cave was mainly diorite, and the lithology of South of the mountains cave was mainly granite. In the field construction, there were many engineering geological problems such as high ground stress, rockburst, water inrush, surrounding rock instability, soft rock deformation, high ground temperature, harmful gas, and radioactivity.
Based on the surface geological survey and comprehensive analysis of geophysical prospecting, drilling, and test data, and in accordance with the ‘Water Resources and Hydropower Engineering Geological Investigation Specification’, the surrounding rocks of the Qinling Tunnel were classified and scored. As shown in Table 1, Type II–Type IV surrounding rocks account for 26.5%, 45.4%, and 21.7% of the total length, and a total of 93.6% of the total length.

Rockburst was closely related to the initial stress field of the rock mass and the nature of the rock. According to the statistical analysis of the Qinling Tunnel measured data, the distribution characteristics of the initial stress field of the rock mass within the buried depth of 700 m was obtained.

The horizontal principal stress increases with the increase of buried depth as a whole, showing a good linear relationship. The maximum horizontal principal stress gradient was greater than the vertical stress gradient, reflecting the strong geological structure of the Qinling orogenic belt. The difference between the maximum horizontal principal stress and the minimum horizontal principal stress gradient was large, showing strong directivity.

### 4. Rockburst tendency assessment method

Rockburst tendency assessment was an indispensable part of preventing rockburst during construction, and rockburst tendency assessment was based on the analysis and research on the formation mechanism of rockburst. Many scholars have put forward a variety of hypotheses and rockburst criterion methods (Kidybiński 1981; Hou and Wang 1989; Shan 1992; Wang et al. 1998; Jiang et al. 2003) by studying and analysing the mechanism of rockburst formation. Based on the actual rockburst measurement of the excavated section of the Qinling Tunnel, three different criteria, namely the strength-to-stress ratio criterion, the Russense criterion, and the Hoek criterion, were used for analysis. The traditional criterion was revised and a rockburst suitable for the Qinling Tunnel was proposed, and the rockburst grade was determined based on this. The method of modifying the traditional criterion was first to carry out microseismic monitoring of the tunnel, and according to the monitoring results, it was found that there may be rockburst risk ahead. Then the actual field parameters required by each traditional criterion were measured, such as uniaxial compressive strength, maximum ground stress, and maximum tangential stress of the rock, and then the predicted rockburst grade was calculated based on the traditional criterion. After the rockburst occurred in the tunnel section, according to the range of rockburst, influence depth, sound and vibration characteristics, rock movement and morphological characteristics of rockburst, rockburst duration and damage degree of rockburst and other factors, combined with the own situation of Qinling tunnel site

| Surrounding rock category | Length (m) | Percentage of total tunnel length (%) |
|---------------------------|-----------|---------------------------------------|
| I  | 3050 | 3.7 |
| II | 21695 | 26.5 |
| III | 36990 | 45.4 |
| IV | 17875 | 21.7 |
| V  | 2169 | 2.7 |
such as geological characteristics, construction conditions, supporting structure, etc., the actual rockburst grade was determined, and the prediction grade was compared with the actual rockburst grade, in order to correct the corresponding values of different rockburst grades in the traditional criterion.

4.1. Strength-to-stress ratio criterion

Traditional method for rockburst grading (Xu et al. 2018) using rock strength and ground stress ratio. The ratio of the saturated uniaxial compressive strength $R_c$ (MPa) of the rock and the maximum ground stress $\sigma_{\text{max}}$ (MPa) on site can divide the rockburst into four levels, as shown in the following formula.

$$
R_c/\sigma_{\text{max}} = 
\begin{align*}
4.0-7.0 & \quad \text{Slight rockburst} \\
2.0-4.0 & \quad \text{Medium rockburst} \\
1.0-2.0 & \quad \text{Strong rockburst} \\
<1.0 & \quad \text{Extremely strong rockburst}
\end{align*}
$$

Wang et al. (2011) used Hoek-Brown strength criterion to analyse the relationship between rock mass strength, rock mass quality classification parameters and rock uniaxial compressive strength, and further confirmed the reliability of the criterion of the ratio of rock mass strength to stress; Wu (2011) through the research and analysis of the rockburst of the Daba mountain Tunnel, it was believed that the intensity–stress ratio criterion only considers the maximum principal stress in the ground stress, and the occurrence of rockburst was mainly affected by the stress difference, so the stress–intensity ratio was selected as the rockburst The criterion was more reasonable; Chen et al. (2015) redefines the strength–stress ratio criterion formula, which was defined as the ratio of the dry uniaxial compressive strength of the rock to the measured maximum principal stress, and proposes a new ground stress classification scheme (quantitative criteria); Kou et al. (2019) simplified the strength-to-stress ratio criterion in the evaluation of the in situ stress field of the Banzhulin Tunnel on the Xubi Railway, in order to simplify the calculation, the compressive strength was removed from the extreme value and the average was taken, take the average $R_c=50$ MPa, and the buried depth of the tunnel was reversed based on the ratio result. In this article, combined with the actual rockburst measurement of the excavated section, the numerical judgment range of the strength–stress ratio result was revised, and the revised strength–stress ratio criterion suitable for this project was proposed, as shown in Table 2.

| Rockburst classification | Slight rockburst | Medium rockburst | Strong rockburst | Extremely strong rockburst |
|--------------------------|-----------------|------------------|-----------------|---------------------------|
| Strength-to-stress ratio criterion | 4.0–7.0 | 2.0–4.0 | 1.0–2.0 | <1.0 |
| Revised strength–stress ratio criterion | 3.8–7.5 | 2.2–3.8 | 1.0–2.2 | <1.0 |
4.2. Russense criterion

The Norwegian scholar Russense proposed the Russense criterion (Hou et al. 1992), which was widely used in practical engineering. He uses the maximum tangential stress $\sigma_{\theta_{\text{max}}}$ of the cavern and the radial point load strength $I_s$ of the rock to draw the rockburst intensity relationship diagram, and passes the point load strength of the rock was converted into the uniaxial compressive strength $R_c$, and according to the Russense diagram, the criterion formula was as follows.

$$\frac{\sigma_{\theta_{\text{max}}}}{R_c} = \begin{cases} 
<0.20 & \text{No rockburst} \\
0.20-0.30 & \text{Slight rockburst} \\
0.30-0.55 & \text{Medium rockburst} \\
\geq 0.55 & \text{Strong rockburst} 
\end{cases}$$

Hou et al. (1992) based on the Russense criterion, consider the combination of surrounding rock stress $r_1$ and $r_2$, a new rockburst strength determination formula was established on this basis; the Chinese scholar Zhenyu Tao studied the Russense criterion and the Barton criterion, affirmed the advantages of the Russense criterion and promoted the Zhenyu Tao criterion (Tao 1987); Zhang et al. (2004) used the analysis of rock stress state to study and promote the Russense criterion, and established a rockburst expressed by the buried depth of the cavern. According to the criterion, the formula for the critical depth of rockburst was derived. Based on the actual measurement data of the Han to the Wei rockburst section, after statistical comparative analysis, the revised Russense criterion was proposed after research, and the comparison with the pre-modified Russense criterion was shown in Table 3.

Table 3. Comparison table before and after correction of Russense criterion.

| Rockburst classification | No rockburst | Slight rockburst | Medium rockburst | Strong rockburst |
|--------------------------|-------------|-----------------|-----------------|-----------------|
| Russense criterion       | <0.20       | 0.20–0.30       | 0.30–0.55       | \geq 0.55       |
| Revised Russense criterion | <0.30       | 0.30–0.50       | 0.50–0.70       | \geq 0.70       |

4.3. Hoek criterion

Hoek and Brown (1997) analysed the observation results based on actual cases of mining tunnels in South Africa, and used the ratio of the maximum principal stress $\sigma_{\text{max}}$ in the far field to the short-term uniaxial compressive strength $R_c$ of the rock as the evaluation index for brittle failure. This criterion puts forward the formula method to determine the grade of rockburst and slab as follows.

$$\frac{\sigma_{\text{max}}}{R_c} = \begin{cases} 
<0.34 & \text{Slight rib spalling} \\
0.34-0.42 & \text{Severe rib spalling} \\
0.42-0.56 & \text{Medium rockburst} \\
>0.70 & \text{Strong rockburst} 
\end{cases}$$

Zhu et al. (2013) summarized many theories about the Hoek-Brown strength criterion in the past, and proposed a generalized three-dimensional Hoek-Brown strength criterion; Xu et al. (2018) took the rockburst of a railway tunnel engineering
in western China as the background, the rock mass strength was calculated using the generalized Hoek-Brown criterion. According to the actual situation of rockburst, an improved method of rockburst prediction based on the ratio of rock mass strength and maximum ground stress was proposed. However, the rockburst manifestations in the Qinling Water Tunnel of Han to the Wei Project were mainly plate-like spalling and flaky spalling, which were similar to the instability form of the Hoek criterion. Hoek criterion has reference value for the identification of rockburst from Han to the Wei, combined with the actual measurement data of the Han to the Wei rockburst section, and after statistical comparative analysis, the revised Hoek criterion was proposed, as shown in Table 4.

The revised Hoek criterion has a more accurate range than before the revision, and was more suitable for the actual rockburst situation at the site. The revised Hoek criterion has been successfully applied in the construction of the Qinling Water Tunnel of the Han to the Wei Project, it Playing a key role in preventing rockbursts, effectively ensuring the safety of on-site construction.

5. Statistics of rockburst characteristics

Owing to the characteristics of large buried depth, high rock temperature and complex geological conditions of Qinling Water Tunnel, the rockburst of Qinling Water Tunnel was relatively frequent. As shown in Figure 4, the impact of rockburst disaster on site was more serious, as shown in the blasting, excavation and support operation process or after the completion of construction, the initial support system and steel arch were broken and crushed, respectively. And the volume of rockburst was large, the collapsing cavity caused by rockburst was deep, and the maximum collapse depth was even more than 10 m, which brings great security threats to the site construction and hinders the construction progress. The lithology of rockburst hole section was mainly granite, diorite and so on, and mostly block structure.

According to on-site microseismic monitoring and on-site real-time rockburst feedback data statistics, since 2017, South of the mountains drilling and blasting method excavation section statistics have obvious collapse cavity rockburst 67 times; from March 2015 to December 2018, 397 rockbursts occurred in the first tunnelling section of South of the mountains TBM method; From April 2019 to September 2020, 1031 rockbursts occurred in the second tunnelling section. From July 2018 to September 2020, there were 1275 rockbursts in the North of the mountains TBM tunnelling section.

By referring to the classification standards of rockburst of Jinping II Hydropower Station and Erlang mountain tunnel of Sichuan-Tibet highway by Zhang et al. (2014) and Xu et al. (2002), the corresponding rockburst grades were divided from the aspects of rockburst occurrence range, influence depth, sound and vibration characteristics, rock movement and morphological characteristics, rockburst duration and

| Form of destruction | Slight rib spalling | Severe rib spalling | Medium rockburst | Strong rockburst |
|---------------------|---------------------|---------------------|------------------|------------------|
| Hoek criterion      | <0.34               | 0.34–0.42           | 0.42–0.56        | >0.70            |
| Revised Hoek criterion | 0.09–0.20         | 0.20–0.30           | 0.30–0.45        | >0.45            |
rockburst hazard degree, combined with the geological characteristics, construction conditions, and support structure of Qinling Tunnel site. The rockburst times of North of the mountains TBM tunnelling section and the first and second tunnelling

Figure 4. Hazard map of rockburst scene in Qinling Water Tunnel, this shows the damage done to the site by the rockburst.

Figure 5. Rockburst statistics of North of the mountains TBM tunnelling section.

Figure 6. Rockburst statistics of the first tunnelling section of South of the mountains TBM.
sections of South of the mountains TBM method were classified and counted according to the grades. Figures 5–7 show the rockburst statistics of North of the mountains TBM tunnelling section and the first and second tunnelling sections of South of the mountains TBM method.

It can be seen from the Figure 5 that from July 2018 to September 2020, among the rockbursts occurred in the TBM tunnelling section of North of the mountains, the number of rockbursts with strong grade and medium to strong grade reached 642 and 367, respectively, while the number of slight rockbursts was only 42, and the rockburst risk was high.

As shown in the Figure 6, during the period from March 2015 to December 2018, the rockburst in the first tunnelling section of South of the mountains TBM method was relatively good. Among the 397 rockbursts, the number of minor rockbursts reached 279, and the number of extremely strong and strong rockbursts was only 1 and 4, respectively.

As shown in the Figure 7, during the period from April 2019 to September 2020, the number of strong rockbursts in the second tunnelling section of South of the mountains TBM reached 550, and the number of medium and medium-strong rockbursts also reached a total of 328, with high rockburst risk.

By comparison, it can be found that the occurrence times of rockburst in the North of the mountains and South of the mountains tunnelling sections were significantly different, mainly due to the different lithology of the two tunnel sections. The lithology of North of the mountains cave was mainly diorite, while the lithology of South of the mountains cave was mainly granite. The uniaxial tensile strength of diorite was higher than that of granite. Under the same stress, diorite was easier to store energy and granite was easier to produce micro-fracture.

Figure 8 was the daily frequency comparison chart of microseismic events in the first and second tunnelling sections of South of the mountains TBM. By comparing the daily frequency of microseismic events in the first tunnelling section of TBM from September 2017 to December 2018 and the second tunnelling section of TBM from March 2019 to September 2020, it can be seen that the microseismic activity of the second tunnelling section was significantly improved compared with the first tunnelling section, and the proportion of strong rockburst in the second tunnelling section of South of the mountains TBM method was significantly increased. The lithology of the two excavation sections in South of the mountains was granite. Under the same lithology, with the increase of the buried depth of the second excavation section, the in situ stress was continuously improved, and more rock micro-fractures were produced under high stress, thus the potential rockburst risk was increased.
6. Rockburst monitoring and early warning

6.1. Early warning of rock burst by microseismic monitoring

As an important means of rockburst monitoring and early warning, microseismic monitoring has been widely used in more and more projects at home and abroad, which was of great significance to prevent rockburst disasters (Blake 1987; Li 2009; Ma et al. 2016; Feng et al. 2017; Ghosh and Sivakumar 2018). In order to accurately predict the specific location of rockburst in Qinling Tunnel, microseismic monitoring and early warning technology were mainly used for rockburst early warning. This section carries on the field microseismic technology application and case analysis of Qinling water tunnel.

6.1.1. Microseismic monitoring technology and field microseismic data statistics

The microseismic monitoring system of ESG company in Canada was introduced. The positioning principle was determined by the elastic wave received by sensors at different locations in space. Owing to the different source locations, the time when the sensor receives the elastic wave was not the same. After more than three sensors receive the elastic wave, the spatial location of the source was roughly determined. With the continuous forward tunnelling of the tunnel face, the effect of real-time monitoring was achieved by moving the monitoring equipment forward.

Figure 9 was the topology map of the microseismic monitoring network in TBM section of Qinling Water Tunnel. By installing a high sensitivity microseismic sensor coupled with the rock mass in the range 50–150 m behind the tunnel face, the micro-fracture signal in the rock mass was received. The signal was transmitted to the signal acquisition system and the seismic recorder through the dedicated cable, and the digital signal was converted to the data acquisition and storage system through the optical cable or the network wire. After processing by the outdoor workstation, it was transmitted to the cloud server and the big data calculation and...
analysis centre. Finally, the monitoring daily report was formed and the analysis results were sent to the participating construction units. This method can obtain accurate microseismic monitoring data at the first time, which provides a guarantee for the on-site work command and dispatching work and the smooth implementation of the project.

The results of microseismic monitoring in Qinling Water Tunnel were expressed by the density cloud map of microseismic events, the distribution map of microseismic events and the corresponding relationship map between the daily frequency of microseismic events and rockburst. The strength of microseismic events usually has the characteristics. (1) The density map of microseismic events refers to the aggregation degree of microseismic events in a certain range. The more the number in unit volume, the deeper the colour, which means the higher the risk of rockburst. (2) The distribution map of microseismic events. Each sphere represents a microseismic event, the colour depth represents the magnitude intensity, and the volume size represents the energy level. (3) The corresponding relationship map between the daily frequency of microseismic events and rockburst shows that there was a strong correlation between the frequency of microseismic events and the risk of rockburst.

Since 2016, the microseismic monitoring of three drilling and blasting working faces and three TBM working faces has been carried out in Qinling Water Tunnel. At present, there were two working faces of South of the mountains TBM and North of the mountains TBM were still monitoring. After all the tunnels have been opened, the length of continuous microseismic monitoring single hole will reach 13,280 m.
According to the rockburst monitoring results of each working face of Qinling Tunnel, six monitoring working faces were counted from three aspects of excavation method, monitoring time and monitoring mileage, as shown in Table 5.

### 6.1.2. Prediction analysis of microseismic activity

Based on the microseismic data of Qinling water tunnel obtained by microseismic monitoring technology, the energy distribution of microseismic events in a certain period of time was counted to predict the rockburst grade. The microseismic activity prediction analysis of Qinling water tunnel construction section was based on the proportion of strong energy levels, it was to predict the corresponding level of microseismic events according to the proportion of microseismic events in different microseismic energy intervals.

1. The No. 4 tunnel of Qinling Water Tunnel excavated by drilling and blasting method was monitored for 8 months and excavated for 1046 m. A total of 4076 effective microseismic events were collected, of which 51 times reached the strong level, and the proportion of strong energy level was 1.25%. There were 18 rockbursts in the working face, of which 15 were accurately predicted in advance, and the accurate prediction rate accounted for 83.33%.

2. In the upper and lower working faces of No. 4 tunnel excavated by drilling and blasting method, 11,612 effective microseismic events were collected in the two working faces, of which 379 times reached the strong level, and the strong energy level accounted for 3.26%. The upstream monitoring lasted 14.5 months, and the excavation was 1389 m. The statistics of rockbursts were 23 times, of which 19 times were accurately predicted in advance, accounting for 82.61%. The downstream monitoring lasted 16.5 months, and the excavation was 1196 m. The statistics of rockbursts were 26 times, of which 24 times were predicted accurately in advance, accounting for 92.31%.

3. The first tunnelling section of South of the mountains excavated by TBM method was excavated north of No. 3 branch tunnel of Qinling Water Tunnel, and was constructed relative to the working face of No. 4 branch tunnel entering southward drilling and blasting method. From September 2017 to December 2018, it took 15 months to excavate 3141 m. A total of 52,867 groups of waveforms were collected, and 4536 effective microseismic events were identified, of which 127 reached a strong level, and the strong energy level accounted for 2.8%. A total of

| Monitoring working face | Excavation methods | Monitoring time | Monitoring mileage |
|-------------------------|--------------------|-----------------|--------------------|
| No. 4 tunnel            | Borehole-blasting method | 2016.7–2016.10 3 months oblique 3 + 983−oblique 4 + 378(395 m) | |
|                         |                    | 2016.12–2017.8 8 months oblique 4 + 734−oblique 5 + 780(1046 m) | |
| No. 4 tunnel upstream   | Borehole-blasting method | 2017.9–2018.11 14.5 months K38 + 400−K37 + 011(1389 m) | |
| No. 4 tunnel downstream | Borehole-blasting method | 2017.9–2019.4 16.5 months K38 + 400−K37 + 596(1196 m) | |
| Lingnan TBM–1           | TBM                | 2017.9–2018.12 15 months K33 + 870−K37 + 011(3141 m) | |
| Lingnan TBM–2           | TBM                | 2019.4–2020.9 18 months K39 + 596−K41 + 602(2006 m) | |
| Lingbei TBM             | TBM                | 2018.6–2020.9 27 months K47 + 150−K45 + 183(1967 m) | |
261 rockbursts were counted, of which 233 were accurately predicted in advance, accounting for 89.27%.

4. The second tunnelling section of South of the mountains, excavated by TBM method, commenced construction on 27 March 2019. From 11 April 2019 to 30 September 2020, it lasted for about 18 months. It had been stopped for maintenance, drivage for 2006 m. During this period, a total of 1031 rockbursts were counted, of which about 930 were accurately predicted in advance, accounting for 90.2%.

From the above analysis of microseismic activity, it can be found that the accuracy of microseismic monitoring and prediction of rockburst was at a high level, which plays a key role in the prevention and control of rockburst, as shown in Figure 10.

6.1.3. Typical cases of practical application of microseismic monitoring

Through the analysis of a typical case of Qinling Water Tunnel site, it can be found that through the microseismic monitoring technology of Qinling Water Tunnel site, the rockburst warning on site had achieved good results, and had made outstanding contribution to engineering construction.

A typical case of strong rockburst early warning was analysed. This typical case presents the breeding and prediction process of strong rockburst, which was used as the basis for preventing rockburst. On 30 June 2018, a strong rockburst occurred in the K39+397–K39+401 section of the drilling and blasting method working face downstream of No. 4 tunnel of Qinling Water Tunnel. As shown in Figure 11, under the influence of long and large cross joints, the longitudinal length of the cavity was about 4 m, the circumferential length was about 10 m, and the deepest cavity was about 5.8 m. The maximum single rockburst energy detected by microseismic monitoring was 4.36 million J. On 1 July 2018, a strong rockburst superimposed structural

![Figure 10. General situation of the accuracy of rockburst prediction by microseismic monitoring in the Qinling Water Tunnel.](image-url)
collapse occurred again in this section, and the maximum collapse depth was more than 10 meters.

Through the microseismic density cloud map and microseismic event distribution map in Figure 12, the incubation and prediction process of the rockburst was analysed. From 20 to 21 June 2018, there were few microseismic events and almost no precursor. The density of microseismic events increased gradually from June 22 to 25, and the red risk signal appeared in the density cloud map of microseismic events on 26th. The data analysis report issued strong rockburst prevention tips, and the risk probability reached 80%. From 27 June to 29 June, the risk probability increased to 90% and continued to issue strong rockburst tips. From 30 June to 1 July, two strong rockbursts occurred. Due to the development of long joints, the depth of collapse cavity after multiple collapses was more than 10 m.

Therefore, through the real-time microseismic monitoring in this case, a complete rockburst inoculation process was recorded and the rockburst warning effect was achieved. It was proved that the microseismic monitoring has strong engineering practice and research value, which was of great significance for the prevention of rockburst.

6.2. Artificial intelligence rockburst warning. The artificial neural network algorithm has made great progress in intelligent control, pattern recognition and signal processing in recent years. In order to improve the limit of rockburst early warning based on semi-manual experience, we use big data combined with artificial intelligence optimization methods to continuously learn and practice, and realize the full-machine automatic rockburst ‘temporal and spatially strong’ accurate early warning. In this article, the artificial intelligence rockburst early warning adopts three steps. First, it
Figure 12. Qinling Water Tunnel, downstream of South of the mountains No. 4 tunnel, 20 June 2018, 6:00 to 29 June 2018, 6:00, the picture of the microseismic events.
(b) Distribution map of micro-seismic events

Figure 12. Continued.
was based on the recurrent neural network (RNN) for P wave arrival time pickup. Second, fuzzy neural network for microseismic type identification. Finally, probabilistic neural network for rockburst risk early warning.

6.2.1. Analysis of theoretical methods

Pickup of P wave arrival time was the basis of microseismic positioning, reducing the pickup error of P wave arrival time can effectively improve the accuracy of microseismic positioning. The commonly algorithms of Pickup of arrival mainly include long-short time window energy ratio method (STA/LTA), AIC method and Polarization analysis method, etc. Most of these picking methods have certain limitations, For example, the problem of STA/LTA method was that the picking accuracy was not high in the case of low signal-to-noise ratio. The problem of AIC method was that in the case of low signal-to-noise ratio, AIC will appear multiple local minima, which was difficult to accurately pick up microseismic signals, and the location of local minima does not necessarily occur microseismic events. Polarization analysis method will be interfered by surface waves, and when the surface wave energy was large, it will produce picking deviation. Some S waves in microseismic events arrive obviously but the P waves were not obvious, which brings difficulties to the Pickup of P wave arrival time. The picking method of P wave arrival time based on RNN in this article makes full use of the recurrent ability of RNN, uses the full waveform sequence and the characteristics of P wave arrival time frequency, and binary coding for learning, training and recognition, which was divided into the following five steps.

1. Output settings: Select two categories as the output form.
2. Input settings: full waveform sequence as input.
3. Model design: three layers of LSTM (variant of RNN) were superimposed to increase the abstract ability of the model.
4. Model input: waveform sequence of length 2000.
5. Model output: The length corresponds to the input waveform, the number of each time point was composed of 0 and 1, and the trigger point was 1, which was 0, as shown in Figure 13.

After picking up the P wave information, it was necessary to identify the microseismic type. The identification of rock microseismic signal type was of great
significance for microseismic monitoring. In order to conduct time-frequency analysis of waveform, S-Transform (ST) time-frequency analysis method was used to convert the waveform of time-amplitude into the waveform data of time-frequency-amplitude. ST overcomes the defect that the time width of short-time Fourier transform window was constant and can adaptively adjust the analysis time width according to the change of frequency, which realizes the accurate expression of signal frequency. Unlike wavelet and wavelet packet transform, ST method can provide intuitive time-frequency features without selecting window functions and analysis scales, as shown in Figure 14.

After converting waveform data, six spectral features were extracted, which were P wave arrival time, maximum amplitude, duration, main frequency, bandwidth, and corner frequency. Taking the above six spectrum characteristics as the feature vector of the fuzzy neural network model and the microseismic waveform type (rock fracture waveform and blasting vibration waveform) as the judgment result, the microseismic waveform type identification can be carried out by fully training sample data. At the same time, the fish swarm algorithm was applied to the fuzzy neural network, and the parameters of the fuzzy neural network were optimized by using the fish swarm algorithm. The established fuzzy network model was stable, with fast global convergence, and had strong memory ability and promotion ability.

Based on the principle of seismology, a series of microseismic parameters with clear physical significance can be obtained by quantitative analysis of monitoring information. Based on the field construction situation, this paper summarizes the experience of rockburst in the past. According to the evolution law of microseismic, a risk early warning method of rockburst based on probabilistic neural network was proposed to predict the level and probability of rockburst. First, the correlation and principal component analysis of microseismic source parameters were carried out, and several parameters with small correlation coefficient and clear mechanical significance were selected for artificial intelligence learning. Secondly, taking the number of microseismic cumulative events, cumulative energy, $b$ value and cumulative apparent volume as feature vectors, and the level and probability of rockburst as prediction results, a probabilistic neural network rockburst risk prediction and early warning model was constructed. Finally, the level and probability of rockburst were judged, as shown in Figure 15.
6.2.2. Application analysis of artificial intelligence rockburst warning

The artificial intelligence early warning method used in this paper has good rockburst prediction effect in the field. This article analyses the application process of rockburst early warning. First of all, the P wave picking of the RNN was performed. It Combined with the Qinling Water Tunnel project site, 5000 microseismic waveforms of different types, different characteristics and different amplitudes were selected. The sampling rate of resampling was set to 5000 Hz, and the original data were translated and scaled. Finally, 2000 groups of samples were constructed to train the RNN of this model, as shown in Figure 16.

Secondly, the microseismic type identification. A total of 100 groups of waveforms were selected to form the sample data, and the fuzzy neural network structure of fish swarm optimization was constructed. Combining fuzzy algorithm and neural network algorithm organically, it combines the strong knowledge expression ability, flexible control and strong advantages of the fuzzy system, and has the strong nonlinear tracking learning ability of neural network. Six characteristics of spectrum P wave arrival time, maximum amplitude, duration time, main frequency, bandwidth and corner frequency were selected as input variables, and waveform type was used as output variable. Through the training and learning analysis of field data through the model, the prediction accuracy reaches 97%, among which the classification accuracy of rock fracture signal reaches 98%, and the identification accuracy of blasting vibration signal was 96%. The prediction accuracy can provide reference for the identification of microseismic monitoring events in the field, as shown in Table 6.

The microseismic monitoring and rockburst of No. 4 tunnel of Qinling Water Tunnel from 30 December 2016 to 25 August 2017 were counted. According to the prediction results of engineers on rockburst, 193 samples were formed. Select 175 samples as training set and the rest as test set. The predicted rockburst probability and rockburst level were coded. The four-layer network structure of probabilistic

![Probabilistic neural network model structure.](image)

**Figure 15.** Probabilistic neural network model structure.

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neural network (input layer, mode layer, summation layer and output layer) was used to learn rockburst risk samples, and cross validation was used to improve the utilization rate of samples and reduce the risk of overfitting. Table 7 was based on the
finiteness of field data and the actual engineering situation, accelerating the test effect of the model, and taking the artificial prediction results as the real rockburst risk results for the model test. The test results show that the accuracy of the model for the prediction set reaches 84.6%; the accuracy of the training set reaches 86.7%, with high estimation accuracy. It shows that the model was not only suitable for training samples, but also has good judgment accuracy for samples not involved in training. Therefore, the method of rockburst risk early warning based on probabilistic neural network was feasible and effective.

The following was a practical case of rockburst warning based on real-time monitoring of microseismic monitoring technology and artificial intelligence. As shown in Figure 17, 28 microseismic events were collected at No. 4 hole from 8:00 on 13 September 2018 to 8:00 on 15 September 2018 with cumulative energy of \(502.44 \times 10^9\) J, \(b\) value of 0.85 and cumulative apparent volume of \(336.33 \times 10^6\). Through artificial intelligence analysis, it was considered that slight to moderate rockburst may occur in the range of about 30 meters ahead of the face of the palm, which needs to be prevented.

According to on-site feedback, three moderate rockbursts and several minor rockbursts occurred in Pile No. 4 + 290–4 + 300 from 19 to 20 September 2018. The

| Sample number | P wave arrival time (ms) | Maximum amplitude (V) | Duration (ms) | Basic frequency (Hz) | Bandwidth (lg(f)) | Corner frequency (lg(f)) | Wave type |
|---------------|--------------------------|------------------------|---------------|----------------------|--------------------|--------------------------|-----------|
| 1             | 109.2                    | 3.73                   | 76            | 785                  | 0.87               | 3.71                     | Vibration of blasting |
| 2             | 100.1                    | 4.09                   | 82            | 893                  | 0.79               | 3.83                     | Vibration of blasting |
| 3             | 90.3                     | 0.19                   | 43            | 932                  | 0.14               | 3.61                     | Rock bump burst   |
| 4             | 91.7                     | 0.15                   | 49            | 1135                 | 0.09               | 3.53                     | Rock bump burst   |
| 5             | 109.2                    | 4.10                   | 71            | 1327                 | 0.90               | 4.11                     | Vibration of blasting |
| ...           | ...                      | ...                    | ...           | ...                  | ...                | ...                      | ...         |
| 100           | 89.3                     | 0.11                   | 41            | 1164                 | 0.11               | 3.23                     | Rock bump burst   |

Table 6. Sample for the identification of microseismic types.

| Sample number | The cumulative number of events | Cumulative energy \((10^9)\) | \(b\) value | Cumulative visual volume \((10^6)\) | Artificial prediction grade | AI predicts rockburst | Artificial prediction probability (%) | AI Forecast Probability (%) |
|---------------|---------------------------------|-----------------------------|-----------|-----------------------------|---------------------------|------------------------|----------------------------------------|---------------------------|
| 176           | 111                             | 837.01                      | 1.18      | 457.77                      | Medium                    | Medium                 | 70                                     | 75                        |
| 177           | 99                              | 734.54                      | 0.82      | 423.17                      | Medium                    | Medium                 | 70                                     | 75                        |
| 178           | 73                              | 502.44                      | 0.75      | 261.07                      | Medium                    | Medium                 | 70                                     | 75                        |
| 179           | 86                              | 641.97                      | 0.71      | 336.33                      | Medium                    | Slight                 | 70                                     | 50                        |
| 180           | 77                              | 537.68                      | 0.95      | 322.37                      | Slight                    | Slight                 | 50                                     | 50                        |
| 181           | 68                              | 476.32                      | 0.76      | 294.13                      | Slight                    | Slight                 | 50                                     | 50                        |
| 182           | 50                              | 363.13                      | 0.87      | 201.60                      | Medium                    | Slight                 | 50                                     | 50                        |
| ...           | ...                             | ...                         | ...       | ...                         | ...                      | ...                    | ...                                    | ...                       |
| 193           | 35                              | 246.88                      | 1.01      | 145.98                      | Slight                    | Slight                 | 50                                     | 50                        |

Table 7. Prediction results based on practical data for the Han to the Wei River project (comparison between forecast and artificial forecast).
actual case proves that artificial intelligence accurately predicts the occurrence and grade of rockburst, and has good application effect.

7. Conclusions

Rockburst was a common disaster in underground engineering construction, and it brings great challenges to the safety of on-site efficient construction, maintenance personnel and equipment. Therefore, it was of great significance to analyse the characteristics of rockburst generated at the construction site and accurately carry out
rockburst warning to prevent on-site rockburst. This article collects and analyses the rockburst data of Qinling Water Tunnel, and uses accurate and effective microseismic monitoring technology for rockburst warning.

Horizontal principal stress generally increases with the increase of buried depth, showing a good linear relationship. The maximum horizontal principal stress gradient was greater than the vertical stress gradient, reflecting the strong characteristics of geological structure in Qinling orogenic belt. The gradient difference between maximum horizontal principal stress and minimum horizontal principal stress was large, showing strong directivity. Through the comparison and practical application of the strength-stress ratio criterion, Russense criterion and Hoek criterion in Qinling Water Tunnel, it was found that the modified Hoek rockburst criterion was most suitable for the actual rockburst situation in Qinling Water Tunnel.

The lithology of North of the mountains was mainly diorite, and South of the mountains was mainly granite. The uniaxial tensile strength of diorite was higher than that of granite. Under the same stress, diorite was easier to store energy and produce less micro-fracture than that of South of the mountains tunnelling section. Therefore, different lithology was the cause of different rockburst times in the two excavation sections; Under the same lithology of the two heading sections in South of the mountains, with the increase of the buried depth of the second heading section, the ground stress was continuously improved, and more micro-fractures of rock mass were generated under the action of high stress, resulting in a greater risk of in the second heading section. On-site microseismic monitoring technology was used to predict rockburst. The accurate prediction rates of rockburst in No. 4 branch tunnel and the upper and lower working faces of No. 4 tunnel excavated by drilling and blasting method reached 83.33%, 82.61%, and 92.31%, respectively. The accurate prediction rates of rockburst in the first and second excavation sections of South of the mountains by TBM method were 89.27% and 90.20%, respectively.

Through two case studies of strong rockburst early warning and record of occurrence process and application of artificial intelligence, complete rockburst incubation process can be obtained by microseismic time map, and artificial intelligence can be effectively applied to microseismic data processing and rockburst risk early warning, which provides a reliable basis for the prevention and control of rockburst disasters. It was proved that the microseismic monitoring technology used in this paper effectively provides rockburst warning function, achieves the purpose of preventing rockburst for Qinling Water Tunnel, and provides effective rockburst warning and prevention experience for related projects. The mechanism of rockburst incubation was more complicated. Strengthening the research of rockburst mechanism to find the objective and essential rockburst criterion was the key to improving the prediction level. Tunnel mining parameters and the overall mountain geological structure were all related to rockburst. In the future, relevant research on these aspects should be deepened to help improve the level of rockburst prediction.

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