Study on Rockburst Proneness Evaluation and Prevention and Control Countermeasures of Over-kilometer Shaft

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Abstract. In view of the problem of rockburst in over-kilometer shaft, based on 220 rockburst cases at home and abroad, combined with forward and backward cloud generator to determine the each rockburst proneness evaluation index belongs to the certainty and reasonable numerical characteristics of each rockburst level. Indexes weight are determined by using the improved CRITIC method. An improved multidimensional normal cloud-critic rockburst proneness evaluation model is proposed. Compared with the evaluation results of the entropy weight method-cloud model and the cloud model for rockburst proneness based on the index distance and the uncertainty measure, which verifies the effectiveness of the model. At the same time, the magnitude of \( \sigma_d/\sigma_c \) is obtained plays a dominant role in the occurrence degree of rockburst. Based on this, taking elastic strain energy, average energy release rate and plastic zone volume as evaluation indexes, the rockburst prevention and control countermeasures with reducing \( \sigma_d/\sigma_c \) and energy release rate as the core are put forward: optimizing bore speed, implementing stress release holes on palm surface and bolt-shotcrete support. Optimizing bore speed can reduce the average energy release rate of surrounding rock; Uniform arrangement of stress release holes around the palm surface can effectively reduce the stress concentration behind the palm surface, and form a large low-pressure crushing zone around it. By bolt-shotcrete support, the energy release rate of surrounding rock of shaft wall can be reduced. The above three methods are jointly implemented to effectively prevent and control rockburst. The research results can provide an effective basis for identification of rockburst hazard area and establishment of prevention and control measures in deep engineering.

1. Introduction

Rock burst is a common geological disaster in underground engineering. It often shows that the surrounding rock mass suddenly collapses with violent shock waves and rapidly releases huge energy. It has the characteristics of transient and strong destructive power, which poses a great threat to personnel safety and equipment. Therefore, the evaluation and prevention of rockburst proneness is a subject that needs to be further studied and solved.

Domestic and foreign scholars have done a lot of work on the study of rockburst tendency and achieved fruitful results. At present, empirical methods and mathematical algorithms are most widely used in the evaluation of rockburst proneness. According to incomplete statistics, there are more than 100 kinds of rockburst proneness evaluation indexes established based on empirical methods. These
indexes evaluate the rockburst proneness of rocks from the perspectives of stress, deformation and energy. Among them, the typical and widely used indexes are the following: strength brittleness coefficient (B) method [1], improved brittleness index BIM [2], elastic index (Wet) [3], Russenes [4], Turchaninov [5] and so on. However, due to the complex influencing factors of rock burst, the empirical method alone cannot meet the demand. With the rapid development of artificial intelligence and deep learning, some scholars have widely used mathematical methods to evaluate rockburst proneness. These methods can be divided into three categories: uncertainty theory, unsupervised learning and supervised learning. Such as fuzzy mathematics [6], rough set theory [7], nonlinear grey classification model [8], fuzzy self-organizing neural network [9], extenics [10], particle swarm projection pursuit algorithm [11], ant colony clustering algorithm, support vector machine [12]. These methods have achieved certain results in the evaluation of rockburst proneness, but the above methods have certain limitations due to the suddenness, randomness and complexity of rockburst [13]. The uncertainty theory proposed by Li Deyi [14] provides a new idea for solving the evaluation of rockburst tendency.

Wu Wenping [15] In view of the rock burst problem of No. 2 diversion tunnel of Jinping Hydropower Station, the rock burst accident is effectively reduced by reducing the excavation rate and spraying 15 cm thick steel fiber concrete immediately after excavation, using water-rising anchor rod as temporary support and system anchor rod as permanent support. Su Guoshao [16] studied the relationship between different excavation rates and elastic release energy, and concluded that the elastic release energy of surrounding rock decreased with the decrease of excavation rate. Feng Xiating et al. [13] proposed the dynamic prevention and control method of rockburst inoculation process: according to the latest evaluation or early warning results of rockburst area and grade, the dynamic optimization of excavation, stress release and support scheme was carried out, and the method was successfully used to prevent and control the occurrence of rockburst in a tunnel.

Although the above methods have achieved certain results, there are still some problems. For the evaluation of rockburst proneness, on the one hand, there are too few rockburst data for modeling, and the validity of the established model needs to be further verified. On the other hand, the evaluation standard of rockburst proneness comes from empirical indicators, and these empirical indicators have poor evaluation effect on rockburst proneness. In addition, most evaluation methods use the weight of rock burst tendency evaluation index, and the size of the index weight often affects the final evaluation results. Therefore, it is meaningful to establish a more perfect and operable rockburst proneness evaluation model.

In the research of rock burst prevention and control: Although many scholars research on rock burst prevention and control is based on the engineering background which is basically related to the tunnel, there are few cases in the deep shaft rock burst prevention and control. However, regardless of the engineering background, the main characteristics of rock burst are energy release. When the strain energy of local accumulation of surrounding rock exceeds the energy storage limit of rock mass, the energy release of rock mass occurs and the rock burst occurs. The stress environment of tunnel and shaft construction is different, so it is necessary to carry out rock burst prevention and control countermeasures for shaft construction. This paper focuses on the optimal excavation rate of shaft and the optimal stress release hole arrangement of shaft face.

Based on the uncertainty artificial intelligence of Li Deyi et al., this paper takes the multidimensional normal cloud model which can consider multiple influencing factors as the core of establishing the rock burst tendency evaluation model. Using the rock burst examples at home and abroad, combined with the improved CRITIC method considering the amount of information and the correlation between indicators, an improved multidimensional normal cloud-CRITIC model is constructed. At the same time, the model is used to evaluate the rockburst tendency of the ultra-kilometer shaft in Xincheng Gold Mine. Referring to the experience of tunnel rockburst prevention and control, combined with the construction condition of deep shaft, the energy release rate is controlled by optimizing the bore speed, laying stress release holes and supporting on the tunnel face, so as to prevent and control rockburst.

2. Multidimensional normal forward cloud model theory
The multi-dimensional normal forward cloud model is a transformation model that realizes the transformation from qualitative concept to quantitative value, reflecting the uncertainty of natural language concept [14]. It is defined as follows [14]: Suppose that \( U \{ x_1, x_2, \ldots, x_m \} \) is an m-dimensional quantitative domain represented by precise values, and \( U \{ x_1, x_2, \ldots, x_m \} \) be a qualitative concept on X. If the quantitative value \( x \in U \), and \( X \{ x_1, x_2, \ldots, x_m \} \) is a random realization of qualitative concept C, if \( X \{ x_1, x_2, \ldots, x_m \} \) satisfies the normal distribution \( X \sim \text{N}(\text{En}^N, \text{He}^N) \), then \( X \{ x_1, x_2, \ldots, x_m \} \sim \text{N}(\text{En}, \text{He}) \) and \( X \{ x_1, x_2, \ldots, x_m \} \) satisfies the certainty of \( \mu(x) = e^{\sum_{j=1}^{m} \frac{(x_j - \text{En}_j)^2}{2(\text{He}_j)^2}} \) (\( j = 1,2,\ldots,m \))

In the formula: Ex is the expectation of the spatial distribution of cloud droplets in the domain, which is the most representative point of qualitative concepts. En is entropy, which is the uncertainty measure of qualitative concept and is determined by the randomness and fuzziness of concept. He is a hyper entropy, which is an uncertainty measure of entropy, and is determined by the randomness and fuzziness of entropy. Then the distribution of \( X \{ x_1, x_2, \ldots, x_m \} \) on \( U \{ x_1, x_2, \ldots, x_m \} \) is called m-dimensional normal cloud [14]. Expectation Ex, entropy En, hyper entropy He are called three numerical characteristics of cloud model [14].

The implementation process of forward cloud generator of multidimensional cloud normal forward cloud model is shown in Figure 1.

**Figure 1.** Forward cloud generator

**Figure 2.** Backward cloud generator (No certainty information is required)

Multidimensional normal forward cloud model algorithm steps [14] are as follows:

1. Generating normal random number \( \text{En}^{\prime} \{ \text{En}_1^{\prime}, \text{En}_2^{\prime}, \ldots, \text{En}_m^{\prime} \} \), \( \text{En}^{\prime} \sim \text{N}(\text{En}, \text{He}^2) \);
2. Generating normal random number \( X \{ x_1, x_2, \ldots, x_m \} \), \( X \sim \text{N}(\text{Ex}, \text{En}^2) \);
3. Calculation of certainty:
\[
\mu(x) = e^{\sum_{j=1}^{m} \frac{(x_j - \text{En}_j)^2}{2(\text{He}_j)^2}} \] (\( j = 1,2,\ldots,m \))

4. Generating cloud droplets of multidimensional cloud model;
5. Repeat steps (1) to (4) to generate n cloud droplets.

### 3. Rock burst proneness evaluation model based on multidimensional cloud model

The multidimensional cloud model is used to evaluate the rock burst proneness, and the results are easily affected by numerical characteristics determination method and the weight determination method. Therefore, this paper uses different numerical characteristics, different weight determination methods, combined with the rock burst data set, and based on the accuracy of the evaluation results (test sets / modeling sets + test sets), 9 combination methods are formed to select the optimal rock burst proneness evaluation model, as shown in Figure 3, Q1-S1, Q represents the weight. S represents numerical characteristics, 1 represents method 1.
3.1. Selection of rockburst proneness index

There are more than one hundred kinds of evaluation indexes of rock burst proneness at present, and selecting suitable indexes is a crucial step to evaluate rock burst proneness. Referring to J. Zhou et al. [4], considering energy, stress, brittleness and other factors, elastic deformation energy index, maximum shear stress, uniaxial compressive strength, uniaxial tensile strength, brittleness coefficient and stress coefficient are selected as evaluation indexes of rock burst proneness, as shown in Table 1.

3.2. Establishment and data processing of rock burst data sets

By consulting a large number of literatures related to rockburst tendency evaluation, 271 groups of rockburst cases at home and abroad [17-20] are collected in this paper. In order to eliminate the influence of abnormal data on the model evaluation effect, the box diagram method, which is not limited by data distribution and is widely used, is used to process data. After the box diagram method to complete the abnormal data detection, a total of 51 abnormal data, normal data 220, as shown in Table 1. Referring to the hold-out method used to evaluate the model in machine learning, the dataset consisting of 220 normal data is divided into two mutually exclusive sets $U$, one as the modeling sets $TR$ and the other as the test sets $TS$ $(U = TR \cup TS, TR \cap TS = \phi )$. In the process of execution, the model sets $TR$ are used to construct the rockburst tendency evaluation model, and the test sets $TS$ are used to complete the evaluation of the model. In addition, the ratio of the number of data contained in the modeling sets $TR$ and the test sets $TS$ have crucial impact on the model performance and evaluation results. The common practice is to use $2/3 - 4/5$ of the samples for modeling, and $1/3 - 1/5$ of the samples are tested. In this paper, the modeling sets $TR$ contains 175 samples, and the test sets $TS$ contains 45 samples. The test sets $TR$ accounts for 79.55%, and the test sets $TS$ accounts for 20.45%.

**Table 1.** Statistical features of the recorded rock burst case data

| Rockburst intensity | Indicators | $\sigma_\theta$ (MPa) | $\sigma_s$ (MPa) | $\sigma_t$ (MPa) | $\sigma_\theta/\sigma_s$ | $\sigma_s/\sigma_t$ | $W_{ct}$ |
|---------------------|------------|----------------------|------------------|-------------------|-----------------------|-------------------|---------|
| None rock burst     |            |                      |                  |                   |                       |                   |         |
| Number of instances | 52         | (12 as test sample)  |                  |                   |                       |                   |         |
3.3. Determining methods of numerical characteristics

3.3.1 Numerical characteristics determination method I

Numerical characteristics determination method I is mainly constructed by multi-index evaluation criteria of rockburst proneness. The numerical characteristics obtained by this method are independent of rockburst data, and the forward cloud generator is used to realize rockburst proneness evaluation by multidimensional cloud model. The calculation steps are as follows[21]:

**STEP1**: Establishment of multi-index evaluation criteria for rockburst proneness;

**STEP2**: The determination of expectation $Ex$:

Suppose that a variable $A$ has a value range of $A\{X_{\text{min}}, X_{\text{max}}\}$, then $Ex = (X_{\text{min}} + X_{\text{max}})/2$, where $X_{\text{min}}$ and $X_{\text{max}}$ represent the maximum and minimum boundary values of variable $A$, respectively. If variable $A$ is the corresponding single boundary variable, as $A\{X_{\text{min}}, +\infty\}$ or $A\{-\infty, X_{\text{max}}\}$, the default boundary parameters or expected values can be determined according to the maximum and minimum boundary values of the, and then calculated.

**STEP3**: Determination of entropy $En$:

The determination of numerical characteristics $En$ of multidimensional cloud model need to be determined according to the maximum value of a certain evaluation index parameter. For the same evaluation index parameter, the numerical characteristics $En$ of multidimensional cloud model under different rockburst grades is the same, which can be obtained by $En = (Ex_{\text{max}})/3$, and $En$ represents the maximum expectation of each rockburst grade of a certain evaluation index parameter.

**STEP4**: Determination of hyper entropy $He$:

The determination of numerical characteristics of multidimensional cloud model $He$ needs to be determined according to the entropy $En$. The greater of $En$, the greater of $He$. In general $0.01 \leq He \leq 0.5$, if $He > 0.5$, the distance between cloud droplets and cloud droplets is too large and too scattered, it cannot reasonably represent the qualitative concept.
3.3.2 Numerical characteristics determination method 2

Numerical characteristics determination method 2 is mainly constructed by rock burst data modeling sets and multidimensional normal reverse cloud generator. The numerical characteristics obtained by this method depend on rock burst data, and the forward cloud generator is still used in the evaluation of rock burst proneness using multidimensional cloud model. The calculation formula is as follows[22]:

\[
E_x = \frac{1}{N} \sum_{i=1}^{N} x_i, E_n = \frac{\text{max}(X) - \text{min}(X)}{6}, He = k
\]  \hspace{1cm} (3)

In the formula, \( x_i \) is the rock burst data value of a certain index, \( N \) is the number of rock burst data of a certain index, \( k \) is a constant, and its size is related to \( E_n \).

3.3.3 Numerical characteristics determination method 3

The multi-dimensional normal backward cloud model is a conversion model from quantitative value to qualitative concept, which can convert a certain number of data into qualitative concepts represented by numerical characteristics (Ex, En, He). The realization process is to input the sample point data, and use the backward normal cloud generator based on principle of statistics (without certainty information) output to represent the numerical characteristics of qualitative concepts, as shown in Figure 2.[23]. Formulas for calculating numerical characteristics of multidimensional normal cloud models with different indices and grades:

\[
E_x = \frac{1}{M} \sum_{i=1}^{M} x_i, E_n = \frac{1}{2} \sqrt{\sum_{i=1}^{M} [x_i - E_x]^2}, He = k
\]  \hspace{1cm} (4)

In the formula: \( x \) is the rock burst data value of a certain index, \( M \) is the number of rockburst data for a given indicator. \( k \) is a constant, and its size is proportionate to \( E_n \).

3.4. Determining methods of weight

In the evaluation method of rockburst proneness, the determination of weight is very important, and its distribution is reasonable or not directly related to the rationality and reliability of the evaluation results, the z-score method is selected to standardized rockburst data. In this paper, the entropy weight method, CRITIC method and dynamic weighting method based on index distance and uncertainty are selected for further research[24]. Among them CRITIC method was proposed by D. Diakoulaki et al. [25] in 1995. Its idea is to comprehensively measure the objective weight of indicators by combining the information content of evaluation indicators and the correlation between indicators. However, there are two problems in the use of this method. First, due to the different dimensions and orders of magnitude of each rockburst proneness evaluation index, it is unreasonable to use standard deviation to measure the variability of the index. Second, the correlation between each rockburst proneness index is positive or negative, and the correlation between the negative correlation with the same absolute value and the index reflected by the positive correlation should be the same. Therefore, the method is improved in two aspects[26]. (1) The coefficient of variation is introduced to replace the standard deviation to measure the variability of the index. (2) When calculating the quantitative coefficient of the independence degree of each index, \( 1-r_{ij} \) is changed into \( 1-|r_{ij}| \).
3.5. Implementation procedure
(1) According to the selected rock burst proneness evaluation index, the rock burst cases data set are established and the abnormal data are tested. The processed rock burst cases data are divided into modeling sets and test sets, and the rock burst proneness evaluation grade is determined.
(2) Numerical characteristics of the multidimensional cloud model of l rockburst grades of b indexes are calculate.
(3) Weight of b rockburst proneness evaluation indexes are calculated.
(4) A multidimensional normal forward cloud generator is used to generate a b-dimensional cloud model, that is, a cloud model considering l rockburst grades and b indicators are generated.
(5) The rock burst proneness evaluation of test sets are completed by using test sets combined with rock burst proneness evaluation index weight and b-dimensional cloud model: According to the above established rockburst proneness evaluation model, the measured values of each rockburst proneness indexes are input. Combined with the multi-dimensional normal forward cloud generator and the weight of evaluation indexes, the comprehensive determination degree is obtained according to formula (9), and the comprehensive evaluation of rockburst proneness is completed according to the maximum determination principle:

\[ \mu_k[\bar{X}(x_1, x_2, ..., x_b)] = \exp \left( \sum_{j=1}^{b} \omega_j (x_j - E_{x_j})^2 / 2(E_{n_j})^2 \right) \]  \hspace{1cm} (5)

Formula: \( \mu_k[\bar{X}(x_1, x_2, ..., x_b)] \) is the degree of certainty that the position belongs to Class k rockburst. \( \omega_j \) is weight for indicator \( j \). \( x_j \) is measured value for indicator \( j \). \( E_{x_j} \) is the expectation of the \( j \) index belonging to class \( k \) rockburst. \( E_{n_j} \) is normal random number for indicator \( j \). Here, \( a = 6, l = 4 \).

3.6. Comparison of evaluation results of rockburst proneness
By comparing and analyzing the rockburst proneness evaluation results obtained by different methods(Figure4), it can be seen that the accuracy rate of the evaluation results obtained by using the multi-dimensional normal cloud-CRITIC model is 84.25%(Q2-S3), which is in good agreement with the actual rockburst on the site. Compared with Q1-S1(48.73%)，Q3-S2(61.55%)，Q2-S2(72.4%) and so on, the evaluation accuracy rate is higher, indicating that the evaluation model constructed in this paper is feasible and reasonable in the rockburst proneness evaluation of underground engineering.

![Figure4. Comparison of evaluation accuracy of different rock burst proneness evaluation methods](image-url)
Using the CRITIC method and the modeling sets MJ containing 175 groups of samples, the weight distribution of each rockburst proneness index is obtained as shown in Table 3.

Table 2. Basic parameters of CRITIC method

| Parameter | Mean value | Standard deviation | Variable coefficient | Quantization coefficient | Comprehensive weight information content | Weight |
|-----------|------------|---------------------|----------------------|--------------------------|------------------------------------------|--------|
| $\sigma_0$ | 49.06      | 29.51               | 0.60                 | 3.92                     | 2.3563                                   | 0.1826 |
| $\sigma_c$ | 114.58     | 44.90               | 0.39                 | 4.25                     | 1.6643                                   | 0.1289 |
| $\sigma_\tau$ | 7.5        | 4.07                | 0.54                 | 3.97                     | 2.1528                                   | 0.1668 |
| $\sigma_0/\sigma_c$ | 0.44     | 0.24                | 0.54                 | 4.57                     | 2.4579                                   | 0.1905 |
| $\sigma_c/\sigma_\tau$ | 17.86    | 8.15                | 0.46                 | 4.47                     | 2.0384                                   | 0.1579 |
| $W_c$ | 4.34       | 2.06                | 0.48                 | 4.69                     | 2.2338                                   | 0.1731 |

4. Evaluation of rockburst proneness in over-kilometer shafts

The net diameter of the new main shaft in Xincheng Gold Mine is 6.7 m, the wellhead elevation is +32.9 m (surface +32.7 m), the bottom elevation is -1488.1 m, and the wellbore depth is 1521 m. The bedrock section of the wellbore is excavated by drilling and blasting method. Each cycle of blasting footage is 4 m. The formation lithology through the wellbore is mainly porphyritic granodiorite, fragmentate lithification porphyritic granodiorite and fragmentate porphyritic granodiorite. The rock hardness coefficient of the wellbore section is 8-10. The improved multidimensional normal cloud-CRITIC model rockburst proneness evaluation method proposed in this paper has achieved good results in rockburst proneness evaluation. Therefore, this method is used to evaluate the rockburst proneness of ultra-kilometers shaft in Xincheng Gold Mine. Evaluation results are shown in Table 3. After the shaft construction is under kilometers, the probability of rock burst increases greatly, and the grade of rock burst is III and above.

Table 3. Evaluation results of rockburst proneness in deep shaft

| Depth/m | Comprehensive certainty degree | Level of rockburst proneness |
|---------|--------------------------------|------------------------------|
|         | $\mu_1$ | $\mu_2$ | $\mu_3$ | $\mu_4$ |                          |
| -1000   | 0.0696  | 0.1488  | 0.1350  | 0.3654  | IV                          |
| -1023   | 0.4017  | 0.6999  | 0.8384  | 0.8678  | III–IV                      |
| -1093   | 0.0694  | 0.1261  | 0.3341  | 0.4264  | III                         |
| -1104   | 0.3363  | 0.5806  | 0.9033  | 0.8290  | III                         |
| -1190   | 0.2166  | 0.4257  | 0.8057  | 0.9282  | IV                          |
| -1202   | 0.1092  | 0.2787  | 0.3178  | 0.5736  | IV                          |
| -1286   | 0.0712  | 0.1896  | 0.3282  | 0.5428  | IV                          |
| -1312   | 0.1340  | 0.2744  | 0.6281  | 0.5632  | III                         |
| -1320   | 0.1770  | 0.3970  | 0.6785  | 0.6652  | III–IV                      |
| -1353   | 0.0169  | 0.0536  | 0.0899  | 0.2901  | IV                          |
| -1371   | 0.0416  | 0.0748  | 0.3703  | 0.5040  | IV                          |
| -1450   | 0.0489  | 0.1644  | 0.2952  | 0.6449  | IV                          |
| -1503   | 0.0391  | 0.1425  | 0.2841  | 0.5825  | IV                          |

5. Countermeasures for the prevention and control of rock burst

According to the evaluation results, combined with FLAC3D software, taking volume of plastic zone and average energy release as criteria, the rock burst was prevented and controlled by optimizing bore speed, implementing stress release holes on palm surface and supporting.

5.1. Optimizing bore speed
The volume of plastic zone increases with the increase of boring speed (Figure 5. a). The volume of plastic zone is the smallest at the bore speed of 1 m and the largest at the bore speed of 96 m. With the increase of bore speed, the elastic strain energy of rock mass aggregation decreases (Figure 5. b), and the decrease is basically unchanged in the range of 1 m ~ 6 m. When the bore speed is 12 m, 24 m, 48 m and 96 m, the elastic strain energy decreases and the release energy increases. The larger the excavation step, the larger the average energy release (Figure 5. c), the smaller the average energy release in the range of 1m ~ 6m. Therefore, considering the bore speed should be selected at 2 ~ 6 m, and the existing bore speed of 4 m in the mine meets the requirements. In order to facilitate the research and implementation of the subsequent rockburst control scheme, the subsequent research bore speed is 4 m.

Figure 5. (a) Plastic zone volume comparison under different bore speeds; (b) Comparison of elastic strain energy of rock mass under different bore speeds; (c) Average energy release rate of rock mass under different bore speeds

5.2. Implementing stress release holes on palm surface
Different stress release hole layout, the final stress release effect is different[6], this design of three stress release hole layout scheme, each scheme has nine stress release holes, as shown in Figure 6. The pore size of the stress release hole is set to 0.05 m. In order to match the construction footage, the depth of the stress release hole is set to 4 m. In addition, in order to reflect the change of rock mass parameters around the stress release hole after blasting, 0.5 m around the stress release hole is set as a broken area, and the mechanical parameters of rock mass in the broken area are reduced to one-half of the original rock.

Figure 6. Layout plan of stress release holes
After the implementation of the stress release hole, the energy released by the shaft face is less than that before the control, and the volume of the plastic zone is increased. It fully shows that the
implementation of the stress release hole can effectively release the energy gathered by the shaft face in advance, increase the volume of the plastic zone of the shaft face, damage the rock mass near the shaft face, weaken the ability of gathering and releasing energy, and reduce the risk of rockburst. According to Figure 7, the stress-release hole scheme (a), compared with the other two schemes, releases the least energy on the shaft face, maximizes the volume of plastic zone, maximizes the amount of rock damage, reduces the ability of energy accumulation on the shaft face, and reduces the risk of rock burst caused by excavation on the shaft face. Therefore, the stress release hole scheme (a) should be selected for this section of shaft, that is, holes should be evenly distributed around the shaft face.

![Figure 7](image_url)

**Figure 7.** Comparison of indicators of stress release holes (plan a, b, c)

After the stress release holes are arranged, the area and volume of plastic zone on the shaft face are increased (Figure 8), further indicating that the damage zone on the shaft face became larger, the ability to gather energy is decreased, the elastic strain energy gathered is decreased, and the rock burst risk is decreased. After the stress release hole scheme (a) is arranged, the stress value of the shaft face is reduced by 25.7% (Figure 9), and a low-pressure fracture zone is formed around the stress release hole, which reduces the stress concentration of the shaft face, cuts off its connection with the high stress zone, and reduces the risk of rockburst.

![Figure 8](image_url)

**Figure 8.** Distribution of maximum principal stress with or without stress release holes (plan a)

(a) Stress release holes are not implemented  (b) Stress release holes (plan a)
In addition, it is generally believed that the maximum decrease of $\sigma_1$ is more than 20% after the stress release hole is arranged, which can be considered to be the obvious effect of the stress release hole. Define $\sigma_1$ reduction percentage = $(\sigma_1$-reduced $\sigma_1$) / $\sigma_1$ before reduction, and $\sigma_0 / \sigma_c$ reduction percentage = $(\sigma_0 / \sigma_c$-reduced $\sigma_0 / \sigma_c$) / $\sigma_0 / \sigma_c$ before reduction. By arranging monitoring points in the axial direction (four monitoring points) and radial direction (ten monitoring points) of the stress release hole, the data of $\sigma_1$ and $\sigma_1$ with or without the stress release hole are extracted, and the ratio of $\sigma_0 / \sigma_c$ is calculated, and Figure 10 is drawn. After the arrangement of each release hole in the stress release hole scheme (a), the maximum decrease of $\sigma_1$ is more than 20%. At the same time, the maximum decrease of $\sigma_0 / \sigma_c$ is also more than 20%, and $\sigma_1$ and $\sigma_0 / \sigma_c$ in the range of at least half a meter around the stress release hole are reduced. This further indicates that the overall stress regulation effect of the stress release hole scheme (a) is obvious, which has certain guiding significance for the prevention and control of rock burst on the working face.

Figure 9. Distribution of plastic zone with or without stress release holes (plan a)

Figure 10. Stress decreases after stress release holes are implemented (plan a)

5.3. Supporting

With the increase of excavation times, the energy release of the surrounding rock of the shaft wall is also gradually increasing. Therefore, it is necessary to control its deformation by supporting and reducing the energy release rate, so as to alleviate the risk of rockburst in the shaft wall. Shaft wall supporting scheme is: concrete C30, thickness 300mm, anchor type R25N (parameters as shown in table 4), anchor length 2.5m, anchor spacing 1m $\times$ 1m, each row 20, layout 4 rows. In FLAC3D, SHELL element is used to simulate concrete and CABLE element is used to simulate anchor rod.

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Through fish language, SHELL element node, CABLE element node and shaft wall mesh element node are shared to form a force-bearing whole, so as to simulate better support effect.

Table 4. Bolt parameter (R25N)

| Elastic modulus/ GPa | Grout cohesive strength per unit length/ (kN·m⁻¹) | Grout stiffness per unit length/ (N·m⁻²) | Grout exposed perimeter/ mm | Cross-sectional area/mm² | Tensile yield strength/ (N·mm⁻²) |
|---------------------|-----------------------------------------------|---------------------------------------------|----------------------------|--------------------------|--------------------------------|
| 200                 | 1180                                          | 2.35×10¹⁶                                   | 119.38                     | 244                      | 805                            |

Without support, the energy release is reduced by 1000 kJ after the stress release hole (plan a) is implemented in the surrounding rock of the shaft wall. It is again proved that the pressure relief and energy dissipation effect of the stress release hole is significant. On this basis, the energy release is reduced by 400 kJ again after the support of the surrounding rock of the shaft wall. Compared with the no support-no stress release hole, the energy release is reduced by 1 400 kJ (Figure 11). The combined implementation of support and stress release hole plays a more active role in reducing the energy release rate, which is more conducive to the prevention and control of rockburst.

**Figure 11.** Comparison of energy changes before and after support (The measures for prevention and control, bore speed: 4m, excavation for -1 450 to -1 454 m)

6. Conclusions

Each figure should have a brief caption describing it and, if necessary, a key to interpret the various lines and symbols on the figure.

(1) Based on the evaluation index of rockburst proneness $\sigma_0$, $\sigma_c$, $\sigma_r$, $\sigma_0/\sigma$, $\sigma_c/\sigma_r$, $W_{el}$, the multidimensional normal cloud-CRITIC model is constructed by using multidimensional cloud model, CRITIC method, the entropy weight method, dynamic weighting method based on index distance and uncertainty and 220 rockburst cases (modeling sets MJ, test sets MC), and the validity and rationality of the model are proved by the test sets.

(2) The weight of each rockburst proneness evaluation standard can be obtained from the test sets MC combined with CRITIC method, and the weight is $\sigma_0/\sigma_c$ (0.1905)$>$ $\sigma_0$ (0.1826)$>$ $W_{el}$ (0.1731)$>$ $\sigma_r$ (0.1668)$>$ $\sigma_c/\sigma_r$ (0.1579)$>$ $\sigma_c$ (0.1289), indicating that $\sigma_0/\sigma_c$ plays a major role in the occurrence of rockburst events compared with other indicators, which can provide a basis for the construction and prevention of rockburst.

(3) Considering the average energy release rate, plastic zone volume and elastic strain energy, the reasonable range of shaft excavation rate in Xincheng Gold Mine is 2 ~ 6 m, and the existing excavation rate of 4 m meets the requirements. The stress release holes are uniformly arranged around the working face of the shaft, and the stress release effect is good, which can reduce the stress...
concentration behind the working face, and form a low-pressure fracture zone around the working face, reducing the energy release rate of the working face. The wall is supported to reduce the energy release rate of shaft wall rock. The rock burst prevention and control measures with the core of optimizing bore speed- arranging stress release holes on the working face – supporting have played a good role in the prevention and control of rock burst.

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