



Rockburst risk assessment model based on improved catastrophe progression method and its application

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Abstract

Aiming to accurately assess the intensity of rockburst in coal mines, we propose a rockburst risk assessment model using the improved catastrophe progression method based on its sudden, complex, and non-linear characteristics. A risk assessment indicator system for rockburst is established based on the occurrence conditions of rockburst, which comprehensively considers 10 main influencing factors. We introduce a combined weighting method consisting of the variation coefficient method and analytic hierarchy process (AHP) to determine the weight and ranking of evaluation indicators, which improves the catastrophe progression method. Finally, by applying 10 coal mine cases into the established model and comparing them with the unimproved catastrophe progression method and several other risk assessment methods, we conclude that the accuracy of the model in assessing rockburst intensity level has increased by a maximum of 42.85%. Our work proves the effectiveness and practicality of the risk assessment model, which can provide good theoretical guidance for assessing rockburst intensity level in coal mines. Furthermore, based on the model risk assessment results and comparative analysis, this paper provides feasible suggestions for reducing the intensity of rockbursts.

Keywords Rockburst · Risk assessment model · Catastrophe progression method · Combined weighting · Analytic hierarchy process

1 Introduction

Rockburst is a coal-rock dynamic disaster characterized by its suddenness, complexity, and nonlinearity, resulting from the coupled effect of natural geological conditions and engineering disturbances (Wei et al. 2018; Wang and Du 2020; Mi et al. 2022; Yin et al. 2021). In recent years, with the increasing depth of coal mining, the in-situ stress increases constantly, and the geological and physical properties of coal seams and their roof and floor become more complex. Moreover, the influence of external dynamic load disturbances, such as large-scale roof

movement and fault slip in the mining area, exacerbates the occurrence and severity of dynamic rockburst (Ranjith et al. 2017; Zhang et al. 2021a, b; Li et al. 2019; Gao et al. 2020; Zhang et al. 2023). As the most common type of coal mine disaster, dynamic rockburst not only causes significant economic losses but also poses a serious threat to the safety of workers (He et al. 2022; Cai et al. 2020). Therefore, it is of great significance to assess rockburst in a reasonable and accurate manner. However, due to its complexity, a sound risk assessment method system has not been established so far (Hou et al. 2021; Ghasemi et al. 2020).

Many scholars around the world have conducted extensive research on this and proposed numerous methods for assessing rockburst. According to different calculation methods, they are mainly divided into three categories: theoretical empirical analysis method, field monitoring and testing method, and applied mathematical model method (Li 2020).

The theoretical empirical analysis method is a risk assessment method based on the mechanism of rockburst

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and engineering practice experience. Generally, it analyzes the stress–strain state of rock and combines it with existing evaluation indicators. Its biggest advantages are its low cost, simple operation, and strong practicality. However, this method involves past experience, which results in lower risk assessment accuracy. This type of method mainly includes strength theory empirical criterion (Ma et al. 2018), energy theory empirical criterion (Miao et al. 2016), brittleness theory criterion (Wang et al. 2015), and stiffness theory criterion (Tang and Xia 2010).

The field monitoring and testing method uses instruments to monitor certain necessary conditions for the occurrence of rockburst, or directly test the rock mechanical properties in the field to determine the possibility, timing, and range of its occurrence. The commonly used monitoring and testing methods include pulverized coal drilling cuttings method (He et al. 2021b, a), borehole stress meter method (Stas et al. 2007), support load method, roadway deformation measurement method, acoustic emission method (Zhai et al. 2020), microseismic method (Xue et al. 2021; Chen et al. 2022). This type of method can make risk assessments in a timely and larger range, but its cost is higher.

The method of applying mathematical models is a way to assess the occurrence of rockburst in unknown areas based on the existing geological data and the results of rockburst occurrence by establishing a mathematical model. This method is generally based on multiple indicators related to rockburst or by training computer programs with a large amount of data. It is currently the most commonly used method for assessing rockburst, including neural network method (Feng et al. 2019; Du et al. 2021), fuzzy comprehensive evaluation method (He et al. 2021a, b), gray correlation theory method (Zheng et al. 2019), cloud model method (Wang et al. 2020), catastrophe progression method (Jin et al. 2013). Machine learning-based risk assessment methods require a large amount of sample information, and accuracy cannot be guaranteed when the number of learning samples is insufficient. When the number of samples is too large, it also affects its generalization. At the same time, most existing literature uses samples from the same mining area for training and risk assessment, so the applicability to mining areas without samples is not strong. The risk assessment method based on theoretical analysis has problems such as difficulty in determining indicator membership and weight, and the calculation process is not easy to converge (Xue et al. 2020; Xu et al. 2018; Wang et al. 2022; Zhang et al. 2021a, b).

Therefore, this paper innovatively introduces the variation coefficient method for objective weighting and the Analytic Hierarchy Process (AHP) for subjective weighting. The weights and ranking of each evaluation indicator

are determined by fusing the subjective and objective weighting in a proportion of 50% each, taking into account the degree of importance that experts subjectively attach to each rating indicator and the inherent laws between evaluation indicators. This reduces the impact of the order between evaluation indicators in the mutation progression method on the evaluation results, added accuracy to the evaluation system. Taking into account up to 10 relevant main influencing factors, a risk assessment model for rockburst intensity level is constructed, which makes the risk assessment results more accurate and has a wider range of applications.

2 Theoretical methods

2.1 Catastrophe progression method

The catastrophe progression method decomposes the evaluation objective into multiple evaluation indicators at different levels, generates a catastrophe membership function by combining catastrophe theory with fuzzy mathematical functions, and then uses a normalization formula to quantitatively calculate and obtain the total membership function for decision-making evaluation (Xia et al. 2017). The principle is to use evaluation indicators as control variables to convert control variables of different qualitative states into state variables of the same qualitative state. The number of state variables and control variables determines different catastrophe models. The commonly used elementary models have a state variable dimension of 1 and a control variable dimension of 1 to 5, respectively: fold catastrophe model, cusp catastrophe model, swallowtail catastrophe model, butterfly catastrophe model, and Indian cottage catastrophe model. These models are provided in Table 1 (Singh et al. 2022).

The basic steps to improve the evaluation of the catastrophe progression method are as follows:

- (1) Establishing a catastrophe progression evaluation indicator system. The overall indicator system is decomposed into multiple levels based on the functional principle of each evaluation indicator until each evaluation indicator can be measured separately. Since the number of control variables in commonly used catastrophe models generally does not exceed 5, the number of evaluation indicators at each level does not exceed 5.
- (2) Dimensionless treatment of each evaluation indicator. Since the indicators in the evaluation system have different units and dimensions, unified calculations cannot be performed between indicators. Therefore, it is necessary to perform dimensionless

Table 1 Five common catastrophic models

Catastrophic model	Control variable	Potential function	Normalization formula
Fold catastrophe model	1	$F(x) = x^3 + \mu x$	$x_\mu = \sqrt{ \mu }$
Cusp catastrophe model	2	$F(x) = x^4 + \mu x^2 + \nu x$	$x_\mu = \sqrt{ \mu }, x_\nu = \sqrt[3]{ \nu }$
Swallowtail catastrophe model	3	$F(x) = x^5 + \mu x^3 + \nu x^2 + \omega x$	$x_\mu = \sqrt{ \mu }, x_\nu = \sqrt[3]{ \nu }, x_\omega = \sqrt[4]{ \omega }$
Butterfly catastrophe model	4	$F(x) = x^6 + \mu x^4 + \nu x^3 + \omega x^2 + tx$	$x_\mu = \sqrt{ \mu }, x_\nu = \sqrt[3]{ \nu }, x_\omega = \sqrt[4]{ \omega }, x_t = \sqrt[5]{ t }$
Indian cottage catastrophe model	5	$F(x) = x^6 + \mu x^4 + \nu x^3 + \omega x^2 + tx^2 + sx$	$x_\mu = \sqrt{ \mu }, x_\nu = \sqrt[3]{ \nu }, x_\omega = \sqrt[4]{ \omega }, x_t = \sqrt[5]{ t }, x_s = \sqrt[6]{ s }$

processing on each indicator. The evaluation indicators include positive indicators (the larger the indicator, the more likely the occurrence of rockburst) and negative indicators (the smaller the indicator, the more likely the occurrence of rockburst), which can be expressed as

$$\text{positive indicator : } x_{ij}' = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \quad (1)$$

$$\text{negative indicator : } x_{ij}' = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \quad (2)$$

where x_{ij} refers to the original data of the j th evaluation indicator in the i th evaluation sample, and x'_{ij} refers to the data after dimensionless processing.

- (3) Determining the weight and ranking of evaluation indicators using the combined weighting method. The objective weight is determined using the variation coefficient method, and the subjective weight is determined using the AHP. Finally, the combined weight of each indicator is calculated and ranked based on a 1:1 ratio.
- (4) Calculating the fuzzy catastrophe level value. First, the corresponding catastrophe model is selected based on the number of control variables in the evaluation indicator system. Then, the ranking of each evaluation indicator is determined based on the importance of each indicator obtained in step (3). Finally, the fuzzy catastrophe level value is calculated by normalizing the weighted sum of the evaluated indicators.
- (5) Following the principle of the normalization formula evaluation. The fuzzy catastrophe membership degree is obtained layer by layer from the indicator layer to the criterion layer. In the process of normalization formula evaluation, they should follow the principle of complementarity or non-complementarity. The principle of complementarity means

that different evaluation indicators can be substituted for each other and can compensate for each other’s shortcomings without preconditions. The principle of non-complementarity means that different evaluation indicators cannot be substituted for each other and cannot compensate for each other’s shortcomings. If the indicator layer satisfies the principle of complementarity, the membership degree of the criterion layer is calculated using the “average value” method, e.g., $x = (x_a + x_b + x_c)/3$ in the swallowtail catastrophe model; If they comply with the principle of non-complementarity, the value is calculated using the standard of “minimum value” to calculate the catastrophe membership degree of the criterion layer, e.g., $x = \min\{x_a, x_b, x_c\}$ in the swallowtail catastrophe model (Chen et al. 2020). Similarly, the total catastrophe membership degree of the rockburst risk assessment can be calculated.

2.2 Combined weighting method

Due to the strong subjectivity and empirical nature of the subjective weighting method’s expert scoring, and the poor universality and participation of the objective weighting method, it cannot reflect the degree of attention that users attach to different attribute indicators. Therefore, to make the rating results more authentic and reliable, we use the additive combined weighting method with the subjective and objective weighting methods to weigh each evaluation indicator.

According to the principle of the combined weighting method and to avoid the problems of absolutization and subjectification in the traditional weight allocation process, combining the subjective and objective weighting at a ratio of 50% each (Wang et al. 2021) yields the combined weight of the j th evaluation indicator as:

$$\psi_j = 0.5\omega_{j1} + 0.5\omega_{j2} \quad (3)$$

where ω_{j1} is the subjective weight, and ω_{j2} is the objective weight.

2.2.1 Objective weighting method

The variation coefficient method is used for the objective weighting of indicators. The variation coefficient method calculates the quotient between the standard deviation and the average value of data, which is a method of measuring difference between indicators (Zhang et al. 2020). The weighting involves calculating the average value, standard deviation, coefficient of variation, and weight of each evaluation indicator after dimensionless processing.

Average value of the evaluation indicator : $\bar{x}_j = \frac{1}{n} \sum_{i=1}^n x_{ij}$ (4)

Standard deviation of the evaluation indicator : $\sigma_j = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_{ij} - \bar{x}_j)^2}$ (5)

Variation coefficient of the evaluation indicator : $CV_j = \frac{\sigma_j}{\bar{x}_j}$ (6)

Weight of the evaluation indicator : $\omega_j = \frac{CV_j}{\sum_{j=1}^n CV_j}$ (7)

where, $\sum_{j=1}^n \omega_j = 1$.

2.2.2 Subjective weighting method

AHP is currently the most commonly used subjective weighting method, which establishes a hierarchical evaluation structure of objectives and determines the weights based on the importance of each indicator to the upper level (Wang et al. 2021; Senan et al. 2023).

- (1) Establishing a hierarchical structure of the indicator system. The target layer, the criteria layer, and the indicator layer are defined based on the hierarchical relationship between the various factors and indicators in the research system, the problems to be solved, the factors to be considered, and the final consideration indicators, respectively.
- (2) Based on expert scoring, the judgment matrix between each level can be written as follows to express the relative importance of each indicator,

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{8}$$

The judgment matrix has the following properties:

$$r_{ij} = \frac{1}{r_{ji}} \tag{9}$$

where r_{ij} is the indicator importance ratio, indicating the importance of element a_i over element a_j . Generally, it is expressed quantitatively on a scale of 1 to 9, where 1 represents equal importance, and the importance increases as the value increases.

(3) Consistency testing. Because the judgment matrix is based on expert experience, errors are inevitable, so the following consistency test formula is used for testing,

$$CR = \frac{CI}{RI} = \frac{\lambda_{\max} - m}{RI(m - 1)} \tag{10}$$

where CI is a consistency indicator; RI is an average random consistency indicator; λ_{\max} is the maximum eigenvalue of the judgment matrix R ; m is the order of the judgment matrix; and CR is the consistency ratio of the judgment matrix. It is generally believed that when $CR < 0.1$, the consistency of the judgment matrix meets the requirements, otherwise the judgment matrix needs to be corrected.

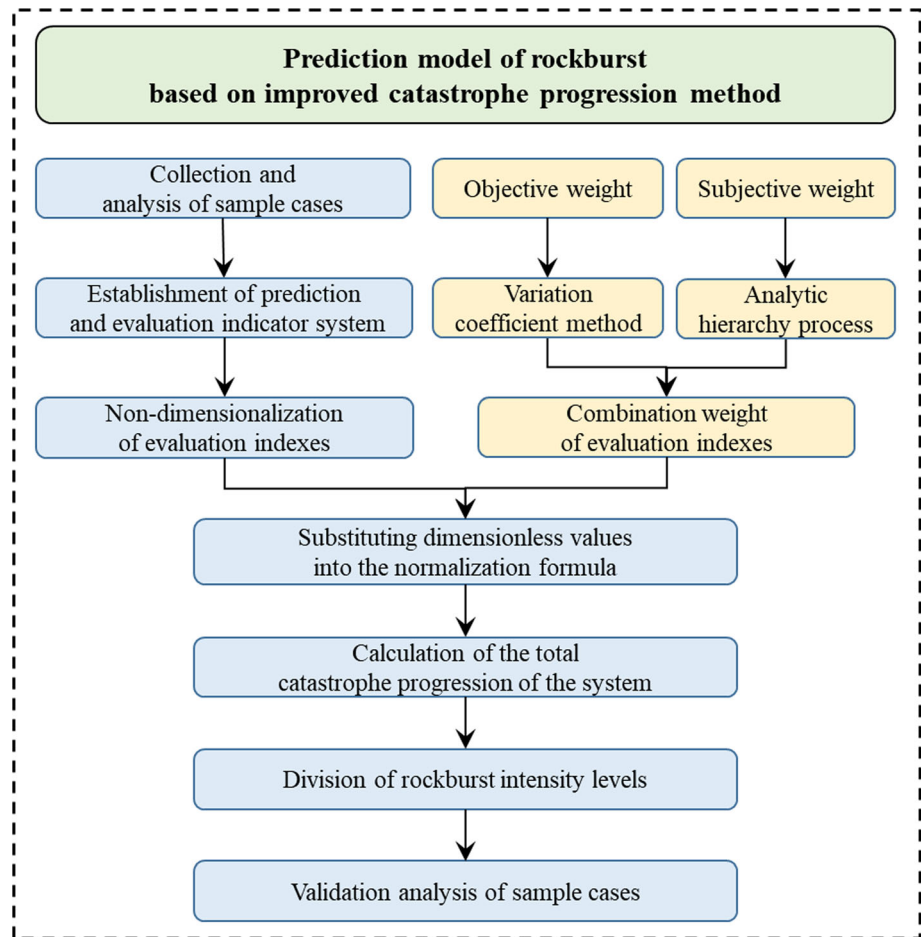
(4) According to the weight calculation formula, the weight of each corresponding indicator is calculated as,

$$\omega_j = \frac{\left(\prod_{i=1}^n \left(R_{ij} / \sum_{j=1}^n R_{ij} \right) \right)^{\frac{1}{n}}}{\sum_{i=j}^n \left(\prod_{j=1}^n \left(R_{ij} / \sum_{j=1}^n R_{ij} \right) \right)^{\frac{1}{n}}}, \quad j = 1, 2, \dots, n \tag{11}$$

3 Establishment of risk assessment model

The specific steps for establishing a rockburst risk assessment model are shown in Fig. 1, which involves improving and optimizing the catastrophe progression method through objective weighting using the variation coefficient method and subjective weighting using the analytic hierarchy process.

Fig. 1 Establishment of a rockburst risk assessment model



3.1 Establishment of evaluation indicator system

Rockburst refers to a phenomenon of dynamic instability where the elastic strain energy accumulated in coal and rock mass is suddenly released under certain conditions due to stress concentration. The intensity level of rockburst is affected by various factors such as the strike of coal seams, in-situ stress, and physical and mechanical properties of coal. We select common factors such as maximum principal stress, coal seam burial depth, inclination, complexity, thickness, uniaxial compressive strength, impact energy indicator, and roof bending energy indicator, which are in accordance with previous research experience and the chapter II of “*Implementation Rules for the Prevention and Control of Coal Mine Rockburst*”, (State Administration of Coal Mine Safety 2018). In addition, it also takes into account the minimum principal stress and coefficient of variation, which are not commonly used but significantly impact rockburst. Together, they serve as the primary evaluation indicators for assessing rockburst. The minimum principal stress and coal seam thickness are negative indicators, while the rest are positive indicators. They are divided into three categories: in-situ stress distribution,

geological conditions, and mechanical properties. In accordance with the evaluation requirements of the catastrophe progression method, an evaluation indicator system for rockburst risk is constructed, as shown in Fig. 2.

3.2 Sample selection and dimensionless processing of indicators

In this study, the identification results of rock-burst tendency of the following 10 mines are obtained as samples through extensive investigation and data search. The samples come from 10 major mining areas in the top 5 important coal producing provinces in China, which have the most rockburst mines. It covers a variety of coal quality characteristics and geological conditions, and each evaluation index data is highly dispersed, which can represent the basic situation of most rockburst mines. Therefore, the selected sample has sufficient diversity. The sample data materials are all from on-site geological reports of various mines, which poses certain difficulties in investigation and search. At the same time, 10 samples have satisfied the calculation needs and fully tested the model. Therefore, 10 highly diverse mine data were ultimately selected as

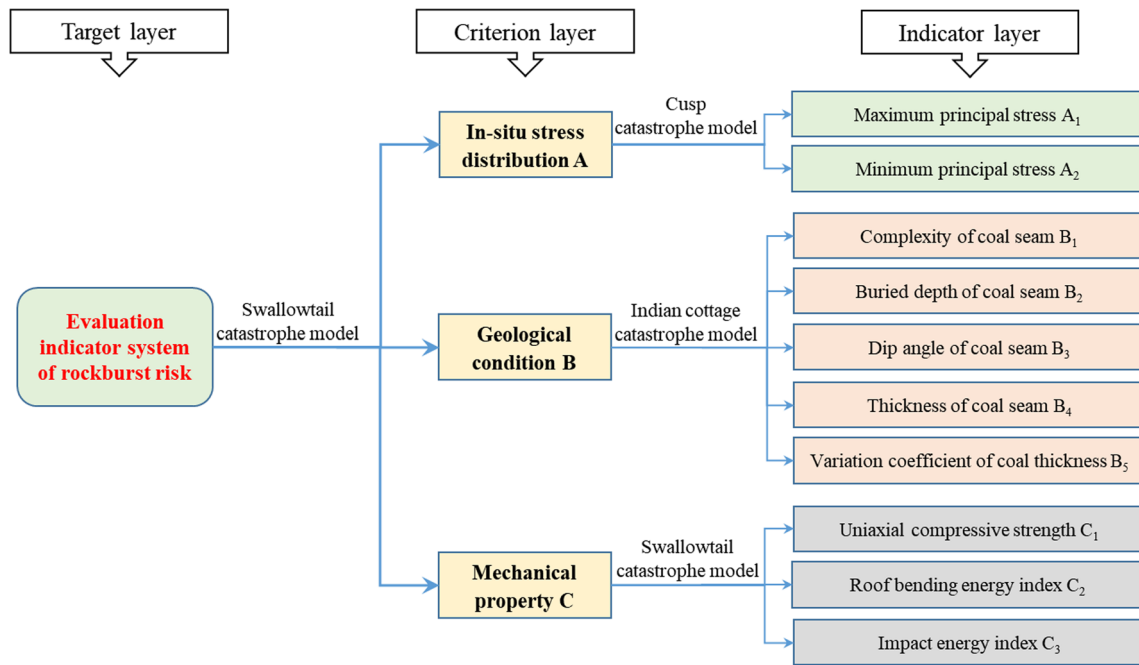


Fig. 2 Evaluation indicator system for rockburst risk

Table 2 Sample raw data

Sample	A ₁ (MPa)	A ₂ (MPa)	B ₁	B ₂ (m)	B ₃ (°)	B ₄ (m)	B ₅	C ₁ (MPa)	C ₂	C ₃	Identification results
Ji'er 3 _{upper}	29.79	5.50	4.00	895.00	6.00	5.92	0.45	16.74	80.72	6.48	Strong
Dongxia 6-1#	17.36	6.98	1.00	823.00	34.50	5.80	31.82	14.20	100.00	18.30	Strong
Junde 17#	33.42	10.81	1.00	770.00	30.00	11.93	0.35	19.35	469.39	6.42	Strong
Xing'an 11#	22.72	14.97	4.00	900.00	25.00	7.50	0.22	10.82	36.67	2.47	Weak
Xiaozhuang 4	30.17	16.04	1.00	800.00	4.50	18.01	0.48	20.62	38.42	1.73	Weak
Pengzhuang 3 _{down}	26.92	7.57	1.00	965.52	9.50	6.40	0.56	9.87	86.95	2.09	Weak
Shanjiacun 3#	20.61	8.03	1.00	425.00	17.50	6.50	0.18	7.74	65.00	2.87	Weak
Panxi 3#	33.94	17.49	1.00	1063.00	29.00	2.20	0.36	0.65	10.78	1.82	None
Tangjiahui 6	18.46	13.82	3.00	486.00	4.00	16.00	0.11	5.95	7.51	1.96	None
Fengyuan 2	31.50	21.80	1.00	855.00	20.00	1.93	0.12	1.28	33.10	1.01	None

samples. According to the standards of the “Rock Burst Measurement, Monitoring and Prevention Methods”, the rockburst risk level is divided into three levels: Strong, Weak, and None. The sample data is shown in Table 2, where the complexity of coal seam B₁ uses the numbers “1”, “2”, “3”, and “4” to indicate that the coal seam structure is simple, relatively simple, relatively complex, and complex. The evaluation indexes such as coal seam thickness B₄ and burial depth B₂ are average values.

According to Eqs. (1) and (2), each evaluation index of the 10-sample data is processed dimensionlessly, and the results are shown in Table 3.

3.3 Determination of combined weight

- (1) Determination of objective weight by the variation coefficient method.

According to the dimensionless values of each indicator in Table 3 and Eqs. (4), (5), (6), and (7), the average value, standard deviation, and variation coefficient of each evaluation indicator are calculated respectively, and the objective weight is finally obtained, as shown in Fig. 3.

Table 3 Dimensionless values of sample evaluation indicators

Sample	A ₁	A ₂	B ₁	B ₂	B ₃	B ₄	B ₅	C ₁	C ₂	C ₃
Ji'er 3 _{upper}	0.75	1.00	1.00	0.74	0.07	0.75	0.01	0.81	0.16	0.32
Dongxia 6–1#	0.00	0.91	0.00	0.62	1.00	0.76	1.00	0.68	0.20	1.00
Junde 17#	0.97	0.67	0.00	0.54	0.85	0.38	0.01	0.94	1.00	0.31
Xing'an 11#	0.32	0.42	1.00	0.74	0.69	0.65	0.00	0.51	0.06	0.08
Xiaozhuang 4	0.77	0.35	0.00	0.59	0.02	0.00	0.01	1.00	0.07	0.04
Pengzhuang 3 _{down}	0.58	0.87	0.00	0.85	0.18	0.72	0.01	0.46	0.17	0.06
Shanjiacun 3#	0.20	0.84	0.00	0.00	0.44	0.72	0.00	0.36	0.12	0.11
Panxi 3#	1.00	0.26	0.00	1.00	0.82	0.98	0.01	0.00	0.01	0.05
Tangjiahui 6	0.07	0.49	0.67	0.10	0.00	0.13	0.00	0.27	0.00	0.05
Fengyuan 2	0.85	0.00	0.00	0.67	0.52	1.00	0.00	0.03	0.06	0.00

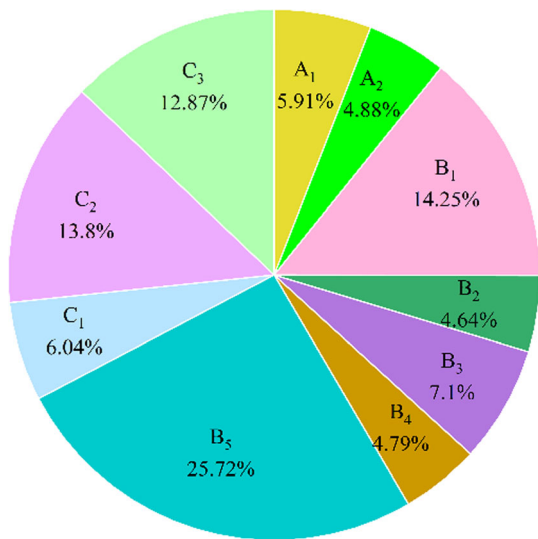


Fig. 3 Objective weight calculation results

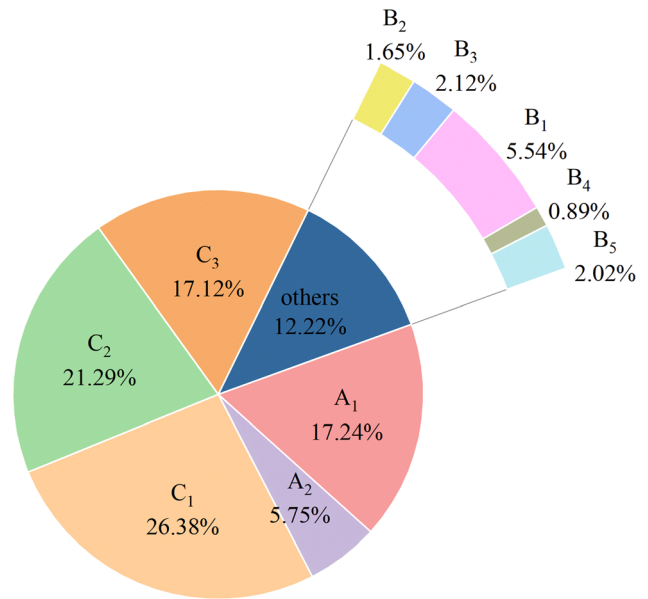


Fig. 4 Subjective weight calculation results

(2) Determination of subjective weight by the AHP.

According to the rockburst risk evaluation indicator system shown in Fig. 1, we invited three mining engineering experts and two geotechnical engineering experts to conduct subjective scoring. Establish the judgment matrix in Eq. (8) by averaging their scores, and use Eq. (10) to check consistency. Finally, the relative calculation weight results of the indicator layer and the target layer are obtained by using Eq. (11), as shown in Fig. 4.

(3) Determination of combination weights.

The combined weight of each evaluation indicator can be calculated using Eq. (3) in the combined weighting method, as shown in Fig. 5.

As can be seen from Fig. 5, the order of the importance of each evaluation indicator in the criterion layer is: C > B > A, and the importance

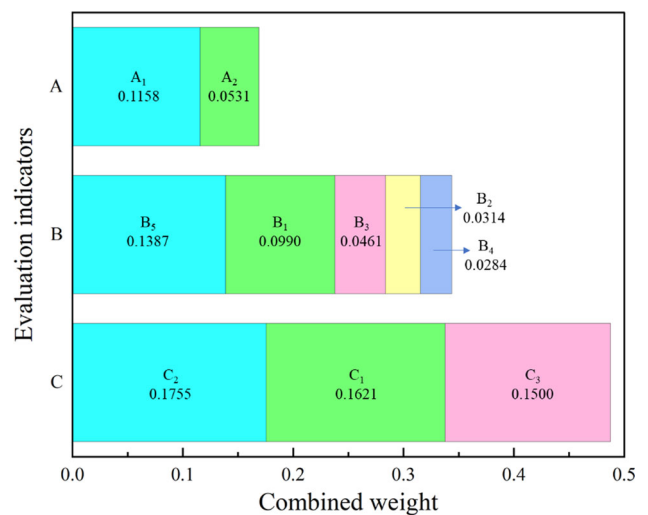


Fig. 5 Combined weight calculation results

Table 4 Numerical calculation results of system catastrophe levels

Sample	A	B	C	X	Identification results
Ji'er 3 _{upper}	0.9329	0.7006	0.6929	0.9011	Strong
Dongxia 6-1#	0.4844	0.7730	0.7754	0.8775	Strong
Junde 17#	0.9305	0.5565	0.9088	0.9193	Strong
Xing'an 11#	0.6584	0.7688	0.5295	0.8482	Weak
Xiaozhuang 4	0.7930	0.2730	0.5699	0.7824	Weak
Pengzhuang 3 _{down}	0.8575	0.5369	0.5626	0.8417	Weak
Shanjiacun 3#	0.6940	0.3618	0.5446	0.7878	Weak
Panxi 3#	0.8209	0.6075	0.1833	0.7423	None
Tangjiahui 6	0.5229	0.4412	0.3754	0.7415	None
Fengyuan 2	0.4617	0.5586	0.1840	0.6923	None

of each evaluation indicator in the indicator layer is:
 $C_2 > C_1 > C_3$, $B_5 > B_1 > B_3 > B_2 > B_4$, $A_1 > A_2$.

3.4 Calculation of catastrophe level value

From Fig. 1, it can be observed that the indicator layer A_n to the criterion layer A, the indication layer B_n to the criterion layer B, the indicator layer C_n to the criterion layer C, and the criterion layer to the target layer conform to the cusp catastrophe model, the Indian hut catastrophe model, the swallowtail catastrophe model, and the swallowtail catastrophe model, respectively, in the common catastrophe model presented in Table 1. Therefore, according to the importance order of each evaluation indicator determined in Sect. 3.3, it is substituted into the normalized formula of the catastrophe model in Table 1 for calculation. Moreover, the selected rockburst risk assessment indicators in this paper exhibit a strong correlation, satisfying the principle of complementarity. Therefore, the “average value” method is used to calculate the normalized value of the system. The calculation results are shown in Table 4.

3.5 Relationship between rockburst level and catastrophe level

Figure 6 shows the catastrophe level values calculated in Table 4 and the rockburst identification level of each sample.

As can be seen from Fig. 6, the larger the catastrophe level, the higher the rockburst level. The catastrophe level value based on the combined weighting catastrophe progression model has a good positive correlation with the rockburst level, with clear differences between levels. Therefore, the catastrophe level value can be used as a new standard for assessing the rockburst level. Based on the observation in Fig. 6, the catastrophe level can be divided into intervals to represent the rockburst level. The no impact propensity is represented by $X < 0.75$, the weak

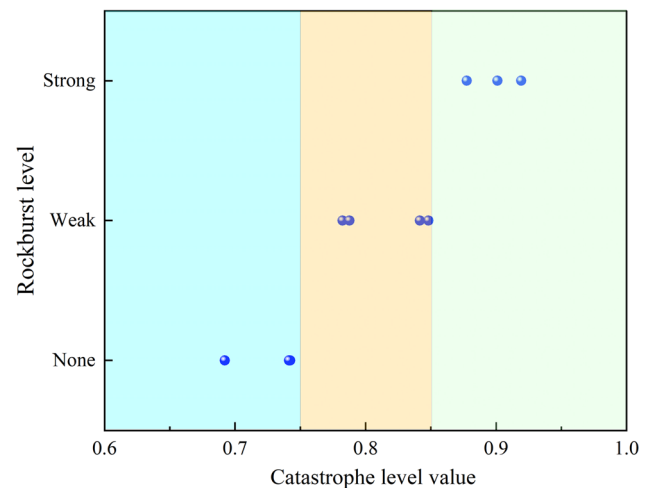


Fig. 6 Relationship between rockburst level and catastrophe level value

impact propensity is represented by $0.75 \leq X < 0.85$, and the strong impact propensity is represented by $X \geq 0.85$.

3.6 Validation analysis and comparison

The calculated catastrophe level values for the 10 samples in this work are used to determine the rockburst level by comparing them to the division intervals. The results are then compared to the risk assessment made using the unimproved catastrophe progression method and the single indicator risk assessment method, which includes uniaxial compressive strength, impact energy indicator, and bending energy indicator. The classification criteria for rockburst levels in the single indicator risk assessment method are mainly based on the classification and evaluation criteria in national standards such as “Standard for the Determination of Coal Seam Burst Tendency” and “Standard for the Determination of Rockburst Tendency”, as shown in Table 5. The results of this analysis are presented in Table 6.

Table 5 Classification criteria for assessing rockburst with a single indicator

Impact propensity	None	Weak	Strong
Uniaxial compressive strength /MPa	$C_1 < 7$	$7 \leq C_1 < 14$	$C_1 \geq 14$
Bending energy indicator /kJ	$C_2 \leq 15$	$15 < C_2 \leq 120$	$C_2 > 120$
Impact energy indicator	$C_3 < 1.5$	$1.5 \leq C_3 < 5$	$C_3 \geq 5$

Table 6 Comparison of risk assessment results by different methods

Sample	Single indicator risk assessment results			Risk assessment results of the catastrophe progression method		Identification results
	Uniaxial compressive strength	Impact energy indicator	Bending energy indicator	unimproved	improved	
Ji'er 3 _{upper}	Strong	Strong	Weak	Strong	Strong	Strong
Dongxia 6–1#	Strong	Strong	Weak	Strong	Strong	Strong
Junde 17#	Strong	Strong	Strong	Strong	Strong	Strong
Xing'an 11#	Weak	Weak	Weak	Strong	Weak	Weak
Xiaozhuang 4	Strong	Weak	Weak	Weak	Weak	Weak
Pengzhuang 3 _{down}	Weak	Weak	Weak	Strong	Weak	Weak
Shanjiacun 3#	Weak	Weak	Weak	Weak	Weak	Weak
Panxi 3#	None	Weak	None	Weak	None	None
Tangjiahui 6	None	Weak	None	None	None	None
Fengyuan 2	None	None	Weak	None	None	None

As shown in Table 6, when the catastrophe level values calculated by the improved combined weighting catastrophe progression method for sample data are substituted to the rockburst intensity level, the rockburst results assessed for all 10 samples are consistent with the rockburst propensity identification results, achieving a risk assessment accuracy of 100%. However, in the single indicator risk assessment method, the risk assessment accuracy of the results obtained based on the uniaxial compressive strength, impact energy indicator, and bending energy indicator are 90, 80, and 70%, respectively. The accuracy of the risk assessment results using the unimproved catastrophe progression method is 70%. Therefore, the combined weighting catastrophe progression method established in this paper is accurate and reliable for assessing rockburst intensity level.

4 Discussion

The risk assessment results of different methods show that the accuracy of the risk assessment results obtained from uniaxial compressive strength in the single indicator risk assessment method is up to 90%. Moreover, through comparing and analyzing the uniaxial compressive strength

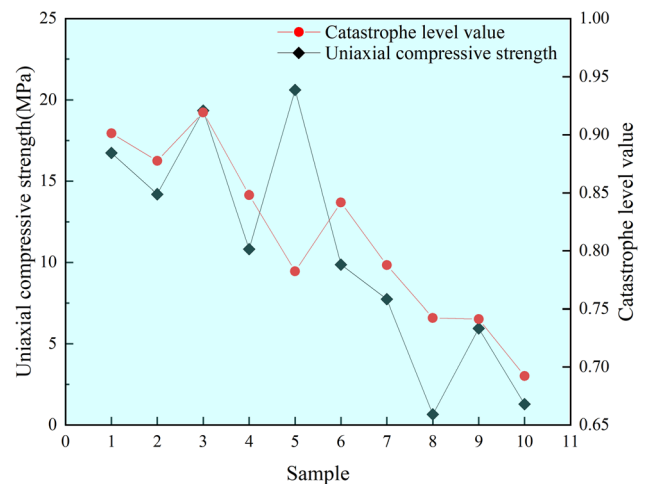


Fig. 7 Relationship between uniaxial compressive strength and catastrophe level

in the original data with the catastrophe level values obtained from the model in the paper, it can be concluded that the variation trend of the uniaxial compressive strength and the catastrophe levels is highly similar (except for individual cases, such as sample 5), as shown in Fig. 7. Therefore, it can be considered that uniaxial compressive strength plays an important role in assessing the propensity

for rockburst in coal mines. Reducing the uniaxial compressive strength of coal can effectively prevent the occurrence of rockburst, which is consistent with the research results of many scholars who have reduced the strength of coal seams by means of water injection (Liu et al. 2021) and microwave radiation (Guozhong et al. 2021). This further verifies the feasibility and accuracy of the rockburst risk assessment model.

In this paper, a risk assessment model for rockburst based on combined weighting catastrophe progression method is established and applied to an engineering example, which is verified to be feasible and effective. However, due to the complexity of rockburst and numerous influencing factors, although the risk assessment model selects 10 key indicators of three influencing factors, namely, in-situ stress distribution, geological conditions, and mechanical properties, for analysis, the conditions for occurrence of rockburst in practical projects are far more complex and involve various evaluation indicators. Furthermore, there is also a coupling effect between various evaluation indicators. Therefore, to assess the intensity level of rockburst more scientifically and accurately, it is also necessary to improve the selection of evaluation indicators for the impact factors of rockburst, so as to continuously optimize the risk assessment indicator system and the calculation method of weight. In addition, while the model has been applied and verified in this case, its applicability to other cases needs to be verified.

5 Conclusions

In this paper, ten main factors affecting rockburst are selected to develop an evaluation indicator system for rockburst risk assessment based on the combined weighting method and catastrophe progression method. Subsequently, this model is applied to engineering practice. The following conclusions can be drawn from this study.

- (1) Based on selecting 8 commonly used indicators such as maximum principal stress, coal seam burial depth, inclination angle, complexity, thickness, uniaxial compressive strength, impact energy index, and roof bending energy index, and considering the minimum principal stress and coefficient of variation that are not commonly used but have a large influence on rockburst, they are collectively used as the main evaluation indicators for assessing rockburst, making the evaluation index system more comprehensive.
- (2) The combined weighting method of objective weighting of variation coefficient and subjective weighting of the analytic hierarchy process is used to weight each evaluation indicator determine the relative importance of each indicator at the indicator layer and criterion layer, which can effectively avoid the problem of absoluteness and subjectivity in the process of traditional weight distribution.
- (3) By applying the evaluation indicator data of 10 mines to the rockburst risk assessment model based on the combined weighting catastrophe progression method and comparing it with the risk assessment results from the unimproved catastrophe progression method, the accuracy of the risk assessment is improved by 42.85%. Therefore, it can be concluded that the risk assessment model established in this paper is both accurate and reliable.
- (4) According to the comparative analysis between the model risk assessment results and the original indicators, it is concluded that the intensity level of coal mine rockburst can be reduced by decreasing the uniaxial compressive strength of the coal seam. This finding confirms the research results of other scholars and verifies the accuracy of the model once again.

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Author contributions WX: conceptualization, methodology, investigation, writing—original draft. HW: conceptualization, funding acquisition, resources, supervision, writing—review & editing. JF: investigation, data collection and analysis. WW: investigation, data analysis and interpretation. XY: investigation, data processing.

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Data availability The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of Interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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