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A coal bursting liability evaluation model based on fuzzy set theory and analysis of three influencing factors

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The classification of coal bursting liability is of great significance for the prevention and control of rock burst. To address the shortcomings in existing bursting liability classification methods, a comprehensive evaluation model for bursting liability based on a combination of weighted-fuzzy set theory and three influencing factor analyses is proposed. The model selects four evaluation indicators: dynamic failure time (DT), elastic energy index (W_{ET}), bursting energy index (K_E), and uniaxial compressive strength (R_C). Two types of membership functions, trapezoidal fuzzy numbers (TFN) and Gaussian fuzzy numbers (GFN), are used to quantitatively describe the fuzziness between indicator levels. The Delphi method and a random forest feature identification method are combined to obtain a subjective and objective combined weighting, determining the optimal combination weight of the four indicators. Based on Zadeh operator (ZO), maximum-minimum operator (MMO), weighted-average operator (WAO), and all-around restrictive operator (ARO), calculations are carried out for the synthesis of indicator weights and memberships. Maximal membership principle (MMP) and Credible identification principle (CIP) are utilized as evaluation principle to assess the bursting liability level, constructing 16 fuzzy comprehensive evaluation models. The impact of membership functions, fuzzy operators, and evaluation principle on evaluation results are systematically analyzed based on the discrimination results of 127 sample sets. The results show that the optimal fuzzy comprehensive evaluation model is constructed using the trapezoidal fuzzy numbers, weighted average operator, and maximal membership principle (TFN-WAO-MMP), with a classification accuracy of 97.64%. Finally, the optimal model is applied to 10 engineering instances, and the evaluation results are consistent with the actual situation, verifying the reliability and effectiveness of the model. Overall, these findings contribute to the development of a more sophisticated and accurate method for assessing the rock burst tendency of coal specimens. By leveraging the theory of fuzzy sets, this approach provides a more nuanced and nuanced evaluation of rock burst tendency, and thus offers

the potential to improve workplace safety and efficiency in the coal mining industry.

KEYWORDS

rock burst, coal's bursting liability, synthetic weights, fuzzy set theory, comprehensive evaluation

1 Introduction

As mining operations and underground excavation increase in scale and depth, elevated stress and excavation disturbances inevitably cause brittle fracturing of deep rock masses, leading to more frequent occurrences of complex geological disasters, such as rock bursts, which pose a serious threat to the safe and efficient development of deep mineral resources (Li et al., 2021; Ling hu et al., 2021; Dong et al., 2022; Wang et al., 2022; Fu et al., 2022; Zhao J. et al., 2022; Wang C. et al., 2024; He et al., 2023; Qiu et al., 2023; Zhao et al., 2024). Rock burst, a phenomenon of coal ejection occurring during the coal seam mining process, entails the release of kinetic energy accompanied by sound, vibration, air blasts, or shock waves. In severe cases, it can lead to the destruction of the roof and floor, or even demolish the mine drifts, potentially resulting in casualties. It represents one of the typical geological disasters in mining engineering (Wang, 2012; Patynska, 2013; Du, 2022; Tahmasebinia et al., 2023). The bursting liability of coal refers to the ability and inherent property of coal to generate impact damage, which is the internal cause and critical condition for rock burst occurrence (Wang, 2012; Wang et al., 2017a; Zhang et al., 2022). According to existing research statistics (Ju et al., 2021), coal seams with strong bursting liability account for 59.04% in the rock burst mines in China, while those with weak bursting liability account for 39.76% and mines with coal seams without bursting liability make up only 1.2% of rock burst incidents. Apart from China, over 450 rock bursts have been detected in the Ostrava-Karvina coalfield since the last century (Ptacek et al., 2017). On 22 February 2020, a rock burst accident occurred at the Longgu mine of Shandong Xinjulong Coal Industry Co., Ltd., resulting in four fatalities. The direct cause was the weak bursting liability of the coal seam and its roof and floor strata in the accident area. Under the influence of large-scale structural stress adjustment and mining disturbance on the working face, the rock burst accident was triggered. Figure 1 shows the damage of the on-site tunnel (Rock-Burst Research Center, 2020).

The classification of coal bursting liability is the basic work to prevent rock burst, and also the main basis to evaluate the risk degree of rock burst (Bieniawski, 1967; Kidybiński, 1981; Tan, 1988; Michel et al., 1994; Zhu et al., 2022; Konicek et al., 2013; Zhao et al., 2023; Wang et al., 2019a). The current national standard in China, "Classification and laboratory test method on bursting liability of coal" (GB/T 25217.2-2010) (Standards Press of China, 2010), uses four evaluation indicators: dynamic failure time (DT), elastic energy index (W_{ET}), bursting energy index (K_E), and uniaxial compressive strength (R_C). Based on the fuzzy comprehensive evaluation method, 73 combinations of evaluation results are given, but there are still 8 combinations that are difficult to determine clearly. In recent years, many scholars have conducted in-depth research on the classification of coal's bursting liability levels and proposed various

classification indicators and methods. Khan et al. (2022) proposed the elastic modulus damage index (EMDI) based on the energy evolution characteristics under different load rates, and used it as a discriminant indicator for coal's bursting liability; Zhang et al. (2019) comprehensively considered the elastic and damage effects of coal and rock masses, proposed a modified bursting energy index (K_{ED}), and verified its rationality through PFC2D simulation; Gong et al. (2021) proposed the residual elastic energy index based on the linear energy storage law of rock materials; Wang et al. (2019b) introduced the distance discriminant analysis (DDA) method to evaluate the bursting liability of coal samples, avoiding the impact of correlation between evaluation indicators on the discrimination results; Zhou et al. (2021) used the AHP-entropy weight method to determine the weight of evaluation indicators and proposed an improved classification model for bursting liability of coal samples based on the theory of unascertained measures (Model comparison is shown in Table 1).

In summary, while there have been many achievements in the research of coal bursting liability classification, the following shortcomings still urgently need to be addressed:

- (1) Bursting liability is influenced by various factors, and accurate determination is difficult using only a single classification indicator, while the discrimination results of different indicators sometimes contradict each other. Although GB/T 25217.2-2010 provides discrimination results under 73 different indicator combinations, the boundaries between different levels are not "clear-cut" and the transition between adjacent levels has a certain fuzziness, resulting in difficulty in determining coal sample bursting liability in 8 combinations.
- (2) Due to the high degree of dispersion in coal sample test data, there is a problem of evaluation indicator weight offset between different coal bursting liabilities. Existing bursting liability assessment methods often overlook this issue, which affects the accuracy and reliability of evaluation results to a certain extent. Current weight determination methods can be mainly divided into two categories: the subjective weighting method, which is greatly influenced by the subjective intentions of decision-makers and experts, has a high degree of subjectivity and is difficult to optimize based on engineering data; and the objective weighting method, which is entirely determined by objective data, neglects expert subjective opinions, and is prone to be influenced by data fluctuations.

To address the limitations of existing methods for assessing the bursting liability of coal samples, this paper introduced fuzzy set theory to describe the fuzziness between data and levels. The Delphi random forest combined weighting method was used to determine the weights of evaluation indicators in order to reduce the interference of data fluctuations on weights and make the indicator weights more reasonable. Considering the three influencing factors



FIGURE 1
Damage situation of the roadway at Longgu Mine from 24 m to 40 m on the upper entrance of Sanlian Tunnel.

TABLE 1 Model comparison of the bursting liability evaluation.

References	Year	Method	Merits	Key issues
Khan et al.	2022	Parameter-based	Convenient and effective	unilateral
Zhang et al.	2019	Parameter-based	New indices	Complex calculation
Gong et al.	2021	Parameter-based	Convenient	Empirical
Wang et al.	2019	DDA	Avoiding the impact of correlation	Empirical
Zhou et al.	2021	Machine learning	High accuracy	Labeled data

of membership function, fuzzy operator and evaluation principle comprehensively, 16 fuzzy comprehensive evaluation models for bursting liability were established. Performance comparison and analysis of the above models were conducted using 127 sample sets, and the best model was selected for engineering application.

2 Principle

2.1 Fuzzy set theory

The theory of fuzzy sets, first proposed by L.A. Zadeh in 1965, employs membership degree as a means of expressing transitional states between concepts, which are often ambiguous or uncertain in nature. As such, this approach is particularly well-suited to addressing problems characterized by uncertainty or indeterminate boundaries. In recent years, fuzzy set theory has found widespread application in many areas of engineering science (Şebnem, 2019; AI et al., 2023).

Given a domain of discourse U , its fuzzy set (Eq. 1) is defined as:

$$U_A: U \rightarrow [0, 1] (x \in U, U_{A(x)} \in [0, 1]) \quad (1)$$

Where: A is a fuzzy set defined on the domain U ; $U_{A(x)}$ is the degree of membership of element x in A ; U_A is the membership function defined on the domain U .

2.2 Fuzzy comprehensive evaluation method

Fuzzy comprehensive evaluation uses fuzzy set theory to describe the fuzziness between evaluation indicators and levels of the evaluation objects, and comprehensively evaluate based on this (Zadeh, 1965; Tabbussum et al., 2021). Firstly, two domains are determined: the factor set $U = \{u_1, u_2, \dots, u_m\}$ contains m indicators, where u_i ($i=1, 2, \dots, m$) are factors that affect the evaluation objects; $V = \{v_1, v_2, \dots, v_n\}$ is the evaluation set, where v_j ($j=1, 2, \dots, n$) are possible status levels, and the indicators and levels are subjectively determined according to engineering practical situations. Based on the membership function, a single-factor evaluation is performed on u_i of the factor set U , and the degree of membership of each level in the corresponding evaluation set of u_i is determined, constructing a fuzzy matrix R . The weight set W is constructed according to the weight of each indicator, and then the comprehensive evaluation set B is obtained through fuzzy operation $B=W \circ R$, and finally, the fuzzy comprehensive evaluation result is obtained based on evaluation principle.

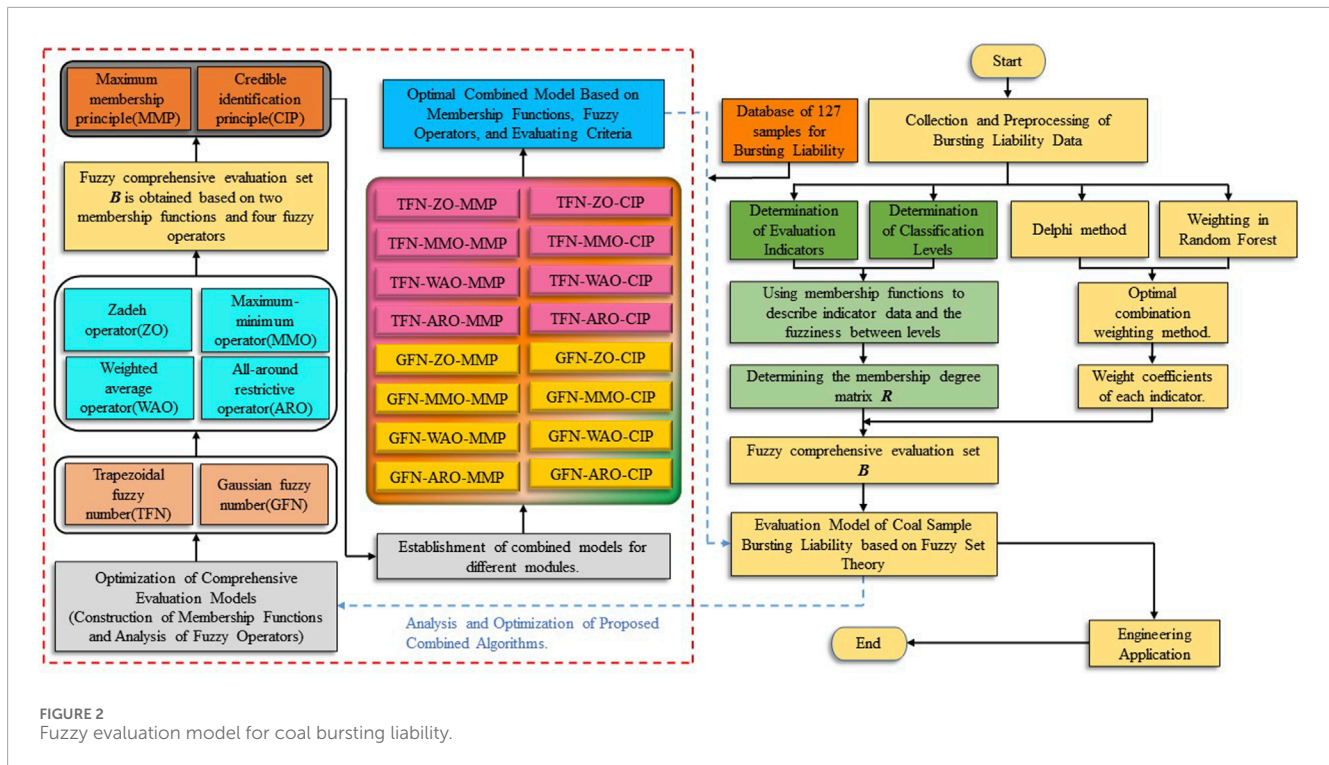


FIGURE 2
Fuzzy evaluation model for coal bursting liability.

3 Establishment of fuzzy comprehensive evaluation model

3.1 Research route and content

This paper proposes a comprehensive evaluation model for the bursting liability of coal based on fuzzy set theory and discusses the impact of main modeling factors such as membership function, fuzzy operator and evaluation principle on evaluation results, and selects the best comprehensive evaluation model. Figure 2 shows the basic process of constructing and selecting the best model for the fuzzy evaluation of coal bursting liability. The main research content of this paper is:

- (1) Construct an indicator system for classifying the bursting liability of coal.
- (2) Based on fuzzy set theory, use trapezoidal fuzzy numbers (TFN) and Gaussian fuzzy numbers (GFN) to describe the fuzziness between indicator data and levels from both linear and nonlinear perspectives.
- (3) Adopt the Delphi method-Random Forest combined weighting approach to obtain the optimal combination weights for each evaluation criterion.
- (4) Synthesize the weights of indicators and membership degrees using Zadeh operator (ZO), maximum-minimum operator (MMO), weighted-average operator (WAO), and all-around restrictive operator (ARO) to obtain the fuzzy evaluation set B .
- (5) Use the maximum membership principle (MMP) and credible identification principle (CIP) to determine the priority of each evaluated object.

- (6) Based on fuzzy set theory and three influencing factors, construct 16 models for evaluating the bursting liability of coal samples, and select the optimal model through comparative analysis.

3.2 Establishment of metrics system and sample index

Scientific selection of indicators is crucial to ensure accurate determination of bursting liability. Determining the bursting liability of coal primarily involves identifying the accumulated elastic energy within the coal prior to impact damage and the release rate and proportion of energy during the damage process. Therefore, this study selects dynamic failure time (DT), elastic energy index (W_{ET}), bursting energy index (K_E), and uniaxial compressive strength (R_C) as the evaluation indicators based on strength theory, energy theory, and related research results (GB/T 25217.2-2010). There are three reasons for selecting these four indicators: 1) They can effectively reflect the energy changes of coal during the processes of energy storage and energy consumption (damage); 2) Each indicator is easy to obtain and interpret; 3) They have been extensively tested through experiments and engineering examples and are the most commonly used evaluation indicators in determining bursting liability.

Based on the established metrics system, a sample database was constructed by collecting 127 sets of typical bursting liability samples. (Yan et al., 2011; Song et al., 2012; Li et al., 2014; Wan et al., 2014; Dong et al., 2015; Chen et al., 2016; He et al., 2016; Wang et al., 2017b; Deng et al., 2017; Li et al., 2021) (Partial sample data is shown in Table 2, full data is available in Supplementary Appendix SA). The samples were collected from

TABLE 2 Partial bursting liability data.

Sample No.	Evaluation indicators				Bursting liability level
	DT/ms	W_{ET}	K_E	R_C/MPa	
1	461	2.23	1.45	7.3	2
2	537	2.08	2.38	7.79	2
3	674	2.23	2.46	8.66	2
4	409	2.16	1.39	8.16	2
5	2,943	1.103	2.17	2.193	3
...
122	49.667	8.472	65.92	31.661	1
123	357	4.6	2.9	11.5	2
124	494	1.37	2.88	10.81	2
125	415	4.38	1.13	8.2	2
126	254	1.59	1.46	12.64	2
127	161.4	2.253	3.382	13.79	2

40 coal mines in 12 provinces in China, with specific distribution shown in Figure 3.

The box plots and Spearman correlation coefficients for the four evaluation indicators selected in this study are shown in Figure 4. Figure 4A–D indicate that the selected data distributions are uniform, and some abnormal values present in the test samples have been taken into account in consideration of realistic field conditions. This can validate the applicability and reliability of the proposed model in engineering applications. Figure 4E shows the correlation between the four indicators, indicating that the correlation between the indicators is weak or non-existent. This suggests that the selected indicators in this study are scientifically and reasonably chosen.

According to GB/T 25217.2-2010, Table 3 shows the classification criteria for bursting liability, which divides it into three levels: strong bursting liability (Class 1), weak bursting liability (Class 2), and no bursting liability (Class 3). As shown in Table 1, the sample database contains 53, 67, and 7 samples with strong, weak, and no bursting liability, respectively. The bursting liability evaluation index also has a corresponding quantitative grading, and there is a determined quantification range for a specific set of samples.

3.3 Determine index weights

Due to the discreteness of coal sample data in various parts of the coal seam, it is difficult to conduct specific coal seam discrimination analysis using the commonly used fixed national standard weights. So it can only be used for coal sample bursting liability discrimination at the laboratory scale, which cannot meet the needs of engineering applications and cannot supplement the

problem of difficult determination of indicator weights caused by the discreteness of coal sample properties. Therefore, this article adopts the Delphi random forest subjective and objective combination weighting method to determine the weight of bursting liability indicators. It can integrate the advantages of expert engineering skills and coal seam physical and mechanical data driving, and can solve the problem of discrete coal sample properties in indicator weight determination.

3.3.1 Method for determining weights of bursting liability index based on delphi method

The Delphi method, also known as expert opinion method or expert inquiry survey method (Borch-Johnsen et al., 2023), is essentially a feedback anonymous inquiry method. Its principle is to use an ordered and anonymous continuous individual inquiry plan, and through controlled in-formation feedback to respondents, to clarify and select the judgments given by the expert group for a certain issue when accurate information is difficult to obtain. The steps of the Delphi method are: ①Selecting members of the expert group; ②Designing evaluation inquiry forms; ③Expert inquiry and feedback; ④Determining weights (Eq. 2) and processing results (Eq. 3). The formula for calculation is as follows:

$$E = \sum_{w=1}^s a_w/s \tag{2}$$

$$V_I = D_i/E_i \tag{3}$$

Where, E is the mean value of index evaluation importance; a_w represents the evaluation score of the w -th expert, with a range of 1–10 points, where 1 represents extremely unimportant and 10 represents extremely important; s is the number of expert



consultations; V_I is the coefficient of variation of index importance evaluation, which represents the degree of dispersion of evaluation scores for the same index by different experts; D_i is the standard deviation of index importance evaluation; and E_i is the mean value of importance evaluation for the i -th index.

Then, the weights of each evaluation indicator are normalized (Eq. 4)

$$A_j = E_i / \sum_{i=1}^g E_i \tag{4}$$

Where, g is the number of evaluation indicators for bursting liability.

Based on the Delphi method and expert consultations, the data obtained was normalized, and the weights of each evaluation indicator were calculated. The results in Table 4, indicate that the opinions of the four experts on each evaluation indicator are relatively consistent, with coefficient of variation less than 0.25, indicating the reasonability of the subjective weights obtained. Therefore, the weights of the four indicators determined by the Delphi method are 0.30, 0.20, 0.20, and 0.30, respectively.

3.3.2 Method for determining weights of bursting liability index based on delphi method

The Random forest (RF) algorithm is a supervised tree ensemble model consisting of multiple classification trees (Khan et al., 2023). It can perform feature selection at each internal node of the tree, and by comparing the feature importance values of each evaluation index, it can obtain the importance ranking of the indices in the evaluation of Bursting Liability. Mean square error (MSE) or out-of-bag (OOB) error rate is usually used as the evaluation index for measuring the feature importance. In this paper, MSE is used as the cost function to determine the importance of each index parameter. The specific steps are as follows:

- (1) Calculate mean square error S_{ME} (Eq. 5)

$$S_{ME} = \frac{\sum_{i=1}^n (v_j - \bar{v})^2}{n} \tag{5}$$

Where, n represents the sample size, v_j represents the bursting liability level of each indicator parameter in the sample, and \bar{v}

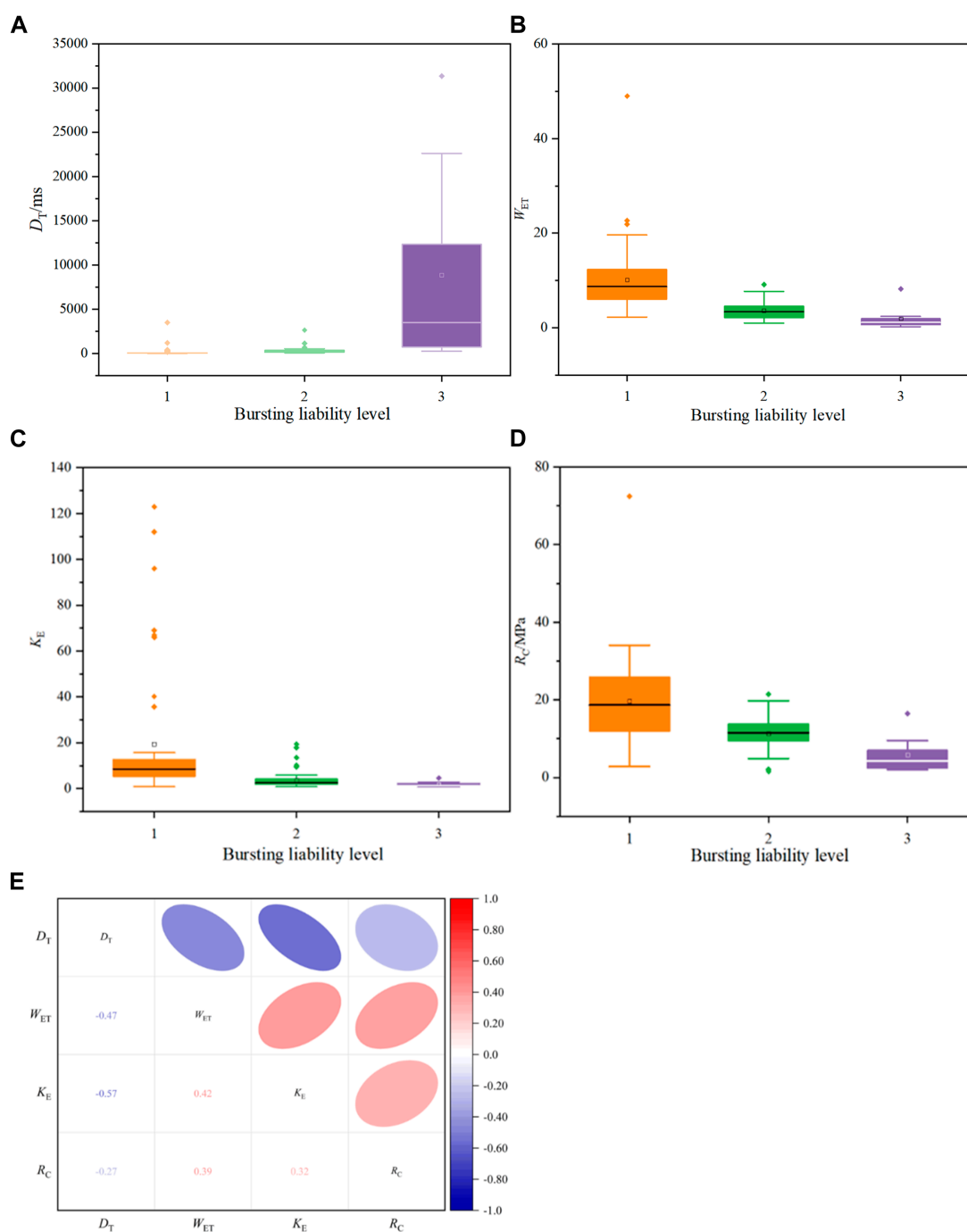


FIGURE 4 Box plots and correlation coefficients of different evaluation indices in sample data. (A) D_T ; (B) W_{ET} ; (C) K_E ; (D) R_C ; (E) Correlation coefficients of different evaluation indices.

TABLE 3 Classification criteria for bursting liability.

Bursting liability type	D_T /ms	W_{ET}	K_E	R_C /MPa
Strong bursting liability (Class 1)	≤ 50	≥ 5.0	≥ 5.0	≥ 14
Weak bursting liability (Class 2)	50–500	2.0–5.0	1.5–5.0	7–14
No bursting liability (Class 3)	> 500	< 2.0	< 1.5	< 7

TABLE 4 Calculation results of indicator weights using the Delphi method.

Evaluation indicators	Expert rating				Average (<i>E</i>)	Coefficient of variation (VI)	Weights (<i>A_j</i>)
	<i>a</i> ₁	<i>a</i> ₂	<i>a</i> ₃	<i>a</i> ₄			
<i>DT</i> /ms	10	9	9	8	9.00	0.08	0.30
<i>W</i> _{ET}	5	6	6	7	6.00	0.12	0.20
<i>K</i> _E	6	6	7	6	6.25	0.07	0.20
<i>R</i> _C /MPa	9	10	9	9	9.25	0.05	0.30

represents the average value of the total bursting liability level in the sample.

(2) Calculate the mean squared error of the node *S*_{ME,ω} (Eq. 6)

$$S_{ME,\omega} = \frac{n_l \cdot S_{ME,l} + n_r \cdot S_{ME,r}}{n_m} \tag{6}$$

Where, *n_l* represents the number of nodes on the left, *S*_{ME,*l*} is the *S*_{ME} of the left node, *n_r* represents the number of nodes on the right, *S*_{ME,*r*} is the *S*_{ME} of the right node, and *n_m* represents the number of parent nodes.

(3) Calculate the importance score *V*_{IM,*im*} (Eq. 7) of a certain index *u_i* at node *m*

$$V_{IM,im} = S_{ME,m} - S_{ME,\omega lj} - S_{ME,\omega rj} \tag{7}$$

Where, *S*_{ME,*m*} is the *S*_{ME} of node *m*, *S*_{ME,*ωlj*} is the *S*_{ME,ω} of the left node after branching; and *S*_{ME,*ωrj*} is the *S*_{ME,ω} of the right node after branching.

(4) Calculate the importance *V*_{IM,*tj*} (Eq. 8) of a certain index *u_i* in decision tree *t*

$$V_{IM,tj} = \sum_{m \in M} V_{IM,im} \tag{8}$$

Where, *M* is the set of nodes in decision tree *t* where the *j*-th bursting liability evaluation index appears.

(5) Calculate the overall importance score *V*_{IM,*i*} (Eq. 9) of a certain index *u_i*

$$V_{IM,i} = \sum_{m \in M} V_{IM,im} \tag{9}$$

(6) Obtain the feature importance *I*_{F,*i*} (Eq. 10) for a certain index *u_i*

$$I_{F,i} = \frac{V_{IM,i}}{\sum_{i=1}^c V_{IM,t}} \tag{10}$$

Where, $\sum_{i=1}^c V_{IM,i}$ is the sum of the overall importance score for all indices, *c* is the number of indices.

Based on the random forest feature recognition method, after calculating and normalizing the feature importance through the above steps, the weight of the four indices are 0.25, 0.25, 0.23, and 0.27 respectively.

TABLE 5 Combination weight calculation results.

Evaluation indicators	<i>a_i</i>	<i>λ_i</i>	<i>W_i</i>
<i>DT</i> /ms	0.30	0.25	0.30
<i>W</i> _{ET}	0.20	0.25	0.20
<i>K</i> _E	0.20	0.23	0.20
<i>R</i> _C /MPa	0.30	0.27	0.30

3.3.3 Weight determination based on comprehensive weighting method

The combined weight (Eq. 11) is obtained by using the multiplication synthesis normalization method (Xu et al., 2022) to integrate the subjective weight (obtained by Delphi method) and objective weight (obtained by random forest feature recognition method) calculations mentioned above. The formula for the multiplication synthesis normalization method is:

$$W_i = \frac{a_i \lambda_i}{\sum a_i \lambda_i} \tag{11}$$

Where, *W_i* represents the combined weight, *a_i* represents the subjective weight obtained through the Delphi method, and *λ_i* represents the objective weight obtained through the random forest feature recognition method.

The calculated combined weights are shown in Table 5 as follows:

3.4 Establishing membership functions

Membership functions are the basis of fuzzy set theory, which are qualitative descriptions of the intermediate transitions in objective things and directly related to the discrimination results (Bonab et al., 2022). Because the objects studied in fuzzy set theory have fuzziness, there are differences in the understanding and interpretation of the same fuzzy concept by different people, making the determination of membership functions subjective. When using fuzzy mathematics to represent fuzzy phenomena, suitable membership functions should be selected based on the characteristics of the objects to match experimental facts (Adoko et al., 2013; Biasetton et al., 2022; Abdolrasol et al., 2023).

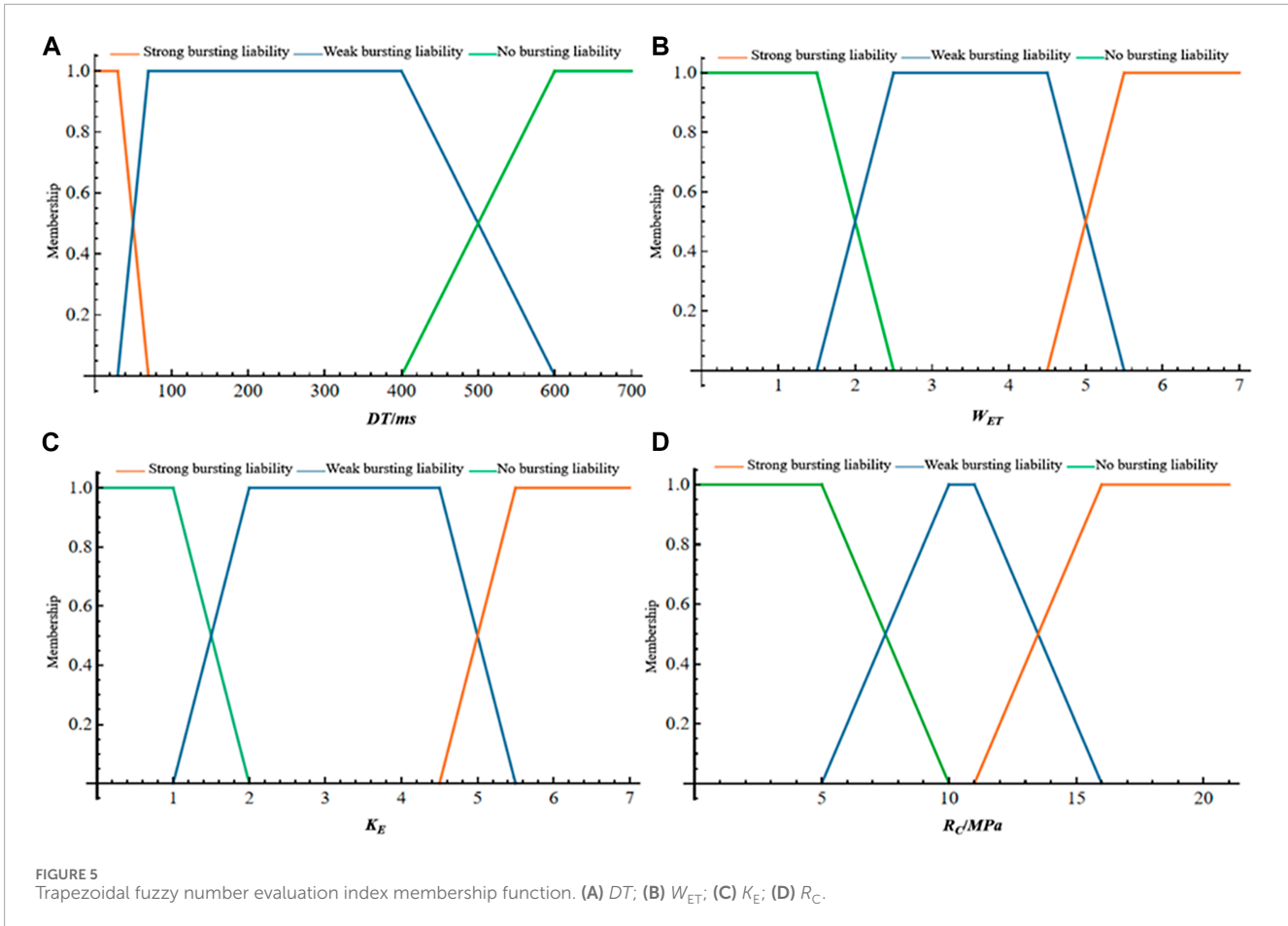


FIGURE 5 Trapezoidal fuzzy number evaluation index membership function. (A) DT ; (B) W_{ET} ; (C) K_E ; (D) R_C .

In order to select the appropriate membership functions for the classification of bursting liability, this paper establishes indicator membership functions from linear and nonlinear perspectives to describe the fuzziness between indicator data and levels.

3.4.1 Weight determination based on comprehensive weighting method

Trapezoidal fuzzy number are a type of linear membership function that has the advantages of low construction difficulty and strong engineering practicality. Compared with other linear membership functions such as triangular fuzzy numbers, which are difficult to characterize properties with wide peaks, the most likely interval of trapezoidal fuzzy numbers makes up for the above shortcomings. Moreover, the most likely value of triangular fuzzy numbers is usually replaced by the mean, which is not suitable for situations with large discreteness, and large discreteness is an essential characteristic of coal sample data (Mastalerz et al., 1999; Biassetton et al., 2022). Referring to the studies of Khairuddin et al. (2021) and Thangavel et al. (2022), trapezoidal fuzzy numbers are constructed for the evaluation of the level of bursting liability.

First, the corresponding membership function distribution is determined based on the indicator type. For indicators with smaller values being better (i.e., the smaller the value, the stronger the bursting liability), the distribution function of level v_1 adopts a decreasing half-trapezoid distribution function (Eq. (12)) of slightly

smaller, the distribution function of level v_2 adopts a middle-type trapezoid distribution function (Eq. (13)), and the distribution function of level v_3 adopts an increasing half-trapezoid distribution function (Eq. (14)) of slightly larger. For indicators with larger values being better (i.e., the larger the value, the stronger the bursting liability), the distribution function of level v_1 adopts an increasing half-trapezoid distribution function (Eq. (14)) of slightly larger, the distribution function of level v_2 still adopts a middle-type trapezoid distribution function (Eq. (13)), and the distribution function of level v_3 adopts a decreasing half-trapezoid distribution function (Eq. (12)) of slightly smaller. Then, according to the classification criteria for bursting liability and expert experience, the parameters a , b , c , and d included in the distribution corresponding to different levels are determined, and the membership degree is calculated by substituting the data into the corresponding membership function. The trapezoidal fuzzy number graph is shown in Figure 5.

- (1) Expression for the decreasing half-trapezoid distribution function of slightly smaller

$$v_j(u_i) = \begin{cases} 1, & u_i < a \\ \frac{b-u_i}{b-a}, & a \leq u_i \leq b \\ 0, & b < u_i \end{cases} \quad (12)$$

- (2) Expression for the middle-type trapezoid distribution function

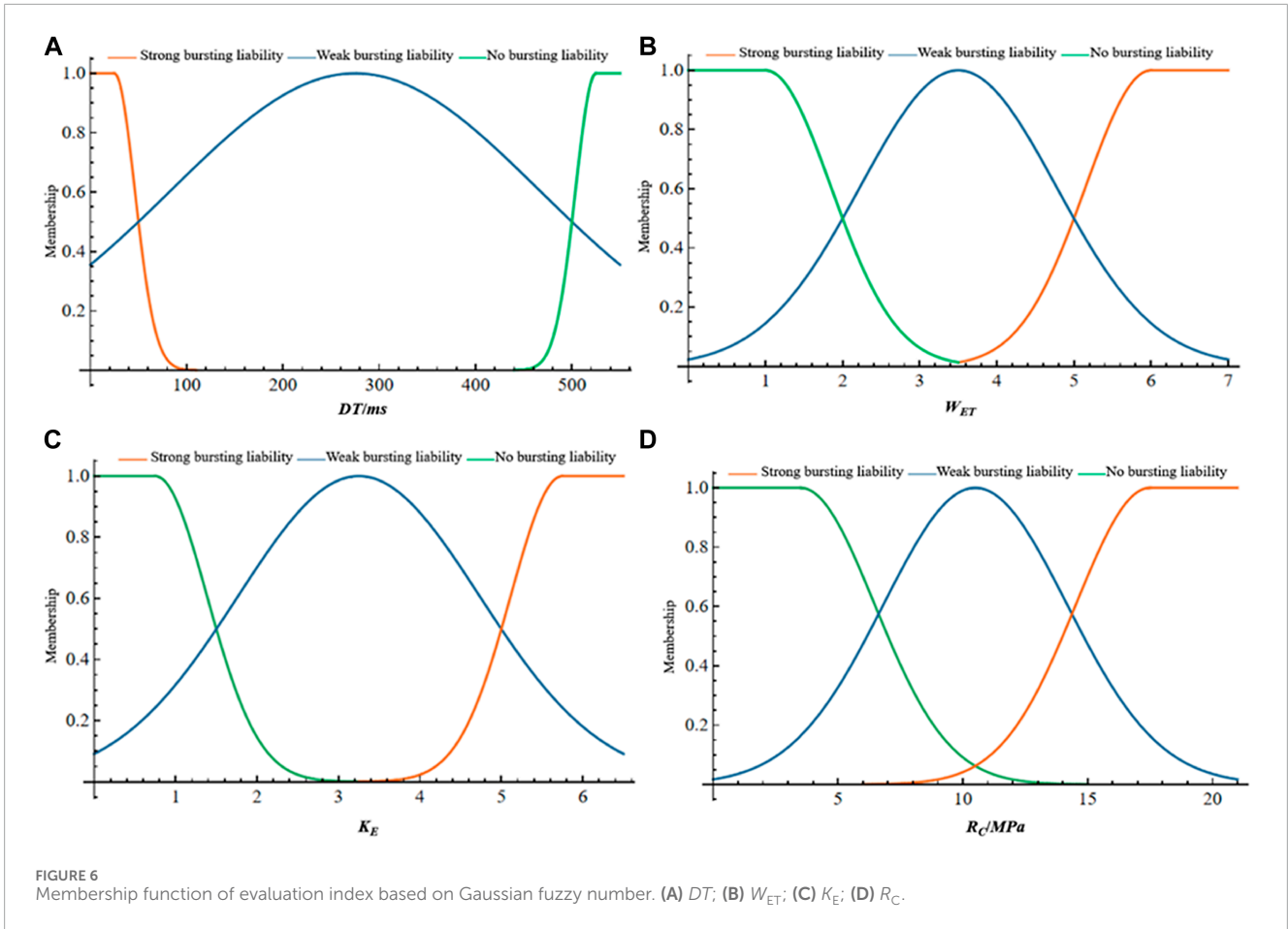


FIGURE 6 Membership function of evaluation index based on Gaussian fuzzy number. (A) DT ; (B) W_{ET} ; (C) K_E ; (D) R_C .

$$v_j(u_i) = \begin{cases} \frac{u_i - a}{b - a}, & a \leq u_i < b \\ 1, & b < u_i < c \\ \frac{d - u_i}{d - c}, & c \leq u_i \leq d \\ 0, & x < a \text{ or } d < x \end{cases} \quad (13)$$

(3) Expression for the increasing half-trapezoid distribution function of slightly larger

$$v_j(u_i) = \begin{cases} 0, & u_i < a \\ \frac{u_i - a}{b - a}, & a \leq u_i \leq b \\ 1, & b < u_i \end{cases} \quad (14)$$

3.4.2 Weight determination based on comprehensive weighting method

Gaussian fuzzy number is used to construct nonlinear fuzzy relationship membership functions (Dombi, 1990). Based on the research of Reddy et al. (2009), Gaussian fuzzy numbers can be constructed (half-Gaussian fuzzy numbers are used when near the extreme value), and the membership function is shown in Figure 6.

According to the unbiased estimation theory, any u_i follows a normal distribution with $u_i \sim N(\mu_i, \sigma^2 i)$, and the sample mean m_{ij}

(Eq. 15) and sample standard deviation S_i (Eq. 16) of u_i are unbiased estimators of u_i and $\sigma^2 i$, respectively. The m_{ij} and S_i of the i -th type of evaluation index for the j -th bursting liability can be expressed as:

$$m_{ij} = \frac{1}{n} \sum_{i=1}^n u_i \quad (15)$$

$$S_i = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (u_i - m_{ij})^2} \quad (16)$$

Based on this, Gaussian fuzzy numbers (Eq. 17) can be constructed (Yazdanpanah et al., 2022):

$$v_j(u_i) = \begin{cases} 0, & u_i < a \\ \frac{u_i - a}{b - a}, & a \leq u_i \leq b \\ 1, & b < u_i \end{cases} \quad (17)$$

When $x_i = m_{ij}$, $\mu_j(u_i) = 1$, m_{ij} (Eq. 18) can be taken as the average of the upper and lower boundary values of evaluation index u_i in the j -level interval. That is:

$$m_{ij} = \frac{1}{n} \sum_{i=1}^n u_i = \frac{u_{ij}^+ + u_{ij}^-}{2} \quad (18)$$

Where, u_i^+ and u_{ij}^- represent the upper and lower bounds of evaluation index u_i in the j -level interval.

TABLE 6 Commonly used fuzzy operators.

Fuzzy operators type	Symbol	Fuzzy reasoning method.
Zadeh operator (ZO)	$M(\wedge, \vee)$	$b_j = V_{i=1}^n (a_i \wedge r_{ij})$
All-around restrictive operator (ARO)	$M(\cdot, \vee)$	$b_j = V_{i=1}^n (a_i \cdot r_{ij})$
Weighted-average operator (WAO)	$M(\cdot, \oplus)$	$b_j = \sum_{i=1}^n (a_{ij} \cdot r_{ij})$
Maximum-minimum operator (MMO)	$M(\wedge, \cdot)$	$b_j = \bigwedge_{i=1}^n (r_{ij}^{a_i}) (j = 1, 2, \dots, m)$

Additionally, the boundary values between each index level should correspond to the same membership degree for two levels. Therefore, the calculation formula for S_i is (Eqs 19, 20):

$$\exp \left[-\frac{(u_i - m_{ij})^2}{2S_i^2} \right] = 0.5 \tag{19}$$

$$S_i = \frac{u_{ij}^+ - u_{ij}^-}{\sqrt{-\ln(0.5)}} \tag{20}$$

3.5 Determination of fuzzy comprehensive evaluation set

After quantifying the evaluation index values based on the membership function, the membership degree matrix R is constructed. Each element in R corresponds to a single-factor evaluation value of an indicator, and each calculation unit corresponds to a specific judgment matrix. The membership degree values of each indicator are obtained by using the membership degree function. The fuzzy comprehensive evaluation set of bursting liability category is (Eq. 21a):

$$B = W \circ R = (w_1, w_2, \dots, w_m) \circ \begin{pmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{pmatrix} = (b_1, b_2, \dots, b_n) \tag{21a}$$

Where, “ \circ ” is the fuzzy operator.

Different fuzzy operators will change the fuzzy reasoning method and affect the inference results, leading to inaccurate and unreasonable evaluation results of fuzzy evaluation models (Thangavel et al., 2022). Therefore, it is necessary to choose the appropriate fuzzy operator according to the characteristics of the project. Currently, there are four commonly used fuzzy operators, as shown in Table 6.

3.6 Comprehensive evaluation

After obtaining the fuzzy comprehensive evaluation set B , the evaluation result vector needs to be processed in order to obtain the final evaluation result. This method of determining the evaluation result is called the evaluation principle (Zhou et al., 2022). In this

paper, the maximum membership principle (He et al., 2021) and the confidence principle (Lovett et al., 2005) are used for evaluation and comparative analysis is carried out.

3.6.1 Maximal membership principle (MMP)

If $b_j = \max(b_1, b_2, \dots, b_n)$ after obtaining the fuzzy evaluation set B , the evaluation level of the evaluated object is considered to be at level j .

3.6.2 Credible identification principle (CIP)

Suppose (C_1, C_2, \dots, C_K) is an ordered evaluation set of property space F , λ is the belief degree, and $0.5 < \lambda \leq 1$, generally taking 0.6–0.7 (Lovett et al., 2005), this paper takes 0.6.

When $C_1 > C_2 > \dots > C_K$, if it satisfies (Eq. 21b):

$$k_0 = \min \left\{ k: \sum_{l=1}^k \mu_{xl} \geq \lambda, 1 \leq k \leq K \right\} \tag{21b}$$

Then the evaluation level of the evaluated object is considered to be at level C_{k_0} .

4 Results and discussion

4.1 Model validation and evaluation

In order to validate the correctness and effectiveness of the comprehensive evaluation model constructed in this paper for classifying bursting liability levels, the effects of membership functions, fuzzy operators, and evaluation principle on the improved model evaluation results were analyzed separately. The 16 comprehensive evaluation models constructed were applied to 127 sets of test data, and the accuracy was used to evaluate the performance of the classification model. The accuracy of each evaluation model is shown in Figure 7. (The evaluation results of each model level can be found in Supplementary Appendix SA, SB).

4.2 Impact analysis of membership functions on the model

Life Science Identifiers (LSIDs) for ZOOBANK registered names or nomenclatural acts should be listed in the manuscript before the keywords with the following format:

In existing research, scholars generally focus on the application methods of evaluation models themselves and rarely systematically

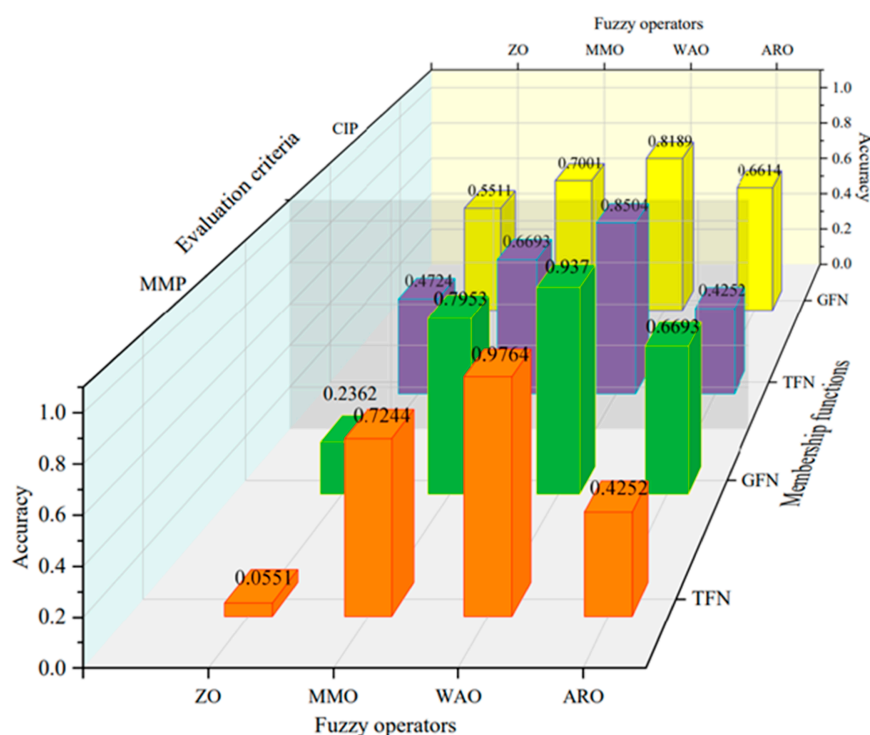


FIGURE 7 Comparison of accuracy for different fuzzy comprehensive evaluation models.

analyze the matching between mathematical factors in the modeling process and the evaluated objects and their impact on the evaluation results. This paper constructs a comprehensive evaluation model based on fuzzy set theory through theoretical analysis and calculations.

As shown in Figure 7, membership functions have different effects on the model evaluation results. The average accuracy of the model using trapezoidal fuzzy numbers and Gaussian fuzzy numbers are 57.48% and 67.42%, respectively. Although the model established using Gaussian fuzzy numbers has a higher average accuracy, the Trapezoidal fuzzy number- Weighted average operator- Maximal membership principle (TFN-WAO-MMP) model based on trapezoidal fuzzy numbers has the highest accuracy among the 16 models, reaching 97.64%.

From the evaluation results, trapezoidal fuzzy numbers (TFN) are suitable for evaluation indicators with wide peak intervals (such as D_T , R_C), and their most likely interval can better characterize the discreteness of coal sample data. They are good at dealing with “outlier” problems that some evaluation methods and machine learning models find difficult to solve. However, their linear expression method also leads to the loss of some intermediate information in the evaluation process. Gaussian fuzzy numbers have strong universality in nonlinear representation of fuzzy features and are almost applicable to all random variable distributions. They can better preserve some intermediate information and overall improve the accuracy of the model, but it is difficult to apply to special cases with wide indicator ranges and large changes.

4.3 Impact analysis of membership functions on the model

As shown in Figure 7, different fuzzy operators have a significant impact on the evaluation results of the model. The average accuracy of the model using Zadeh operator, maximum-minimum operator, weighted average operator, and all-around restrictive operator (ARO) are 26.38%, 69.69%, 91.34%, and 42.52%, respectively. It can be seen that the accuracy of the model using the weighted average operator is significantly higher than the other three operators, while the accuracy of the model using the Zadeh operator is the worst. The accuracy of the evaluation model using the maximum membership principle under different operators fluctuates greatly, with the highest difference reaching 92.13% and the lowest being 25.20%. The evaluation model using the weighted average operator has the highest accuracy under both evaluation principle (maximum membership principle, credible identification principle), which can better represent the fuzzy relationship between the evaluation indicators and the bursting liability category.

From the analysis of the evaluation process, the weights of the four indicators in the bursting liability discrimination are relatively balanced, making it difficult to distinguish between importance. The characteristic of the Zadeh operator is that the main factor plays a decisive role, and it is not sensitive to weights and ignores the impact of intermediate factors on bursting liability, resulting in inaccurate evaluation. The maximum-minimum operator is an improvement based on the Zadeh operator. Although it weakens the role of the main factor, it is essentially a main factor prominent type. From the results, the number of samples that are difficult to distinguish is

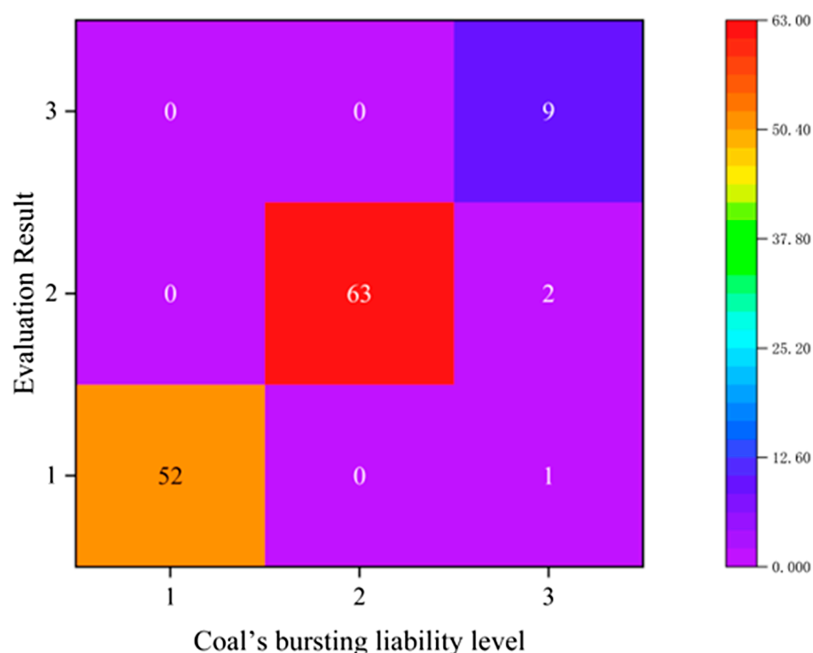


FIGURE 8
Confusion matrix of the TFN-WAO-MMP combined model.

reduced significantly compared to the Zadeh operator. The all-around restrictive operator is the opposite of the Zadeh operator, focusing on the impact of secondary factors on the evaluation result, which leads to a large number of samples that are difficult to distinguish under both evaluation principle. The weighted average operator considers the impact of all factors, and its weight function has a significant effect, providing clear discrimination results for all samples.

4.4 Impact analysis of evaluation principle on the model

As shown in Figure 7, evaluation principles have different impacts on the accuracy of the model, with average accuracies of 54.53% and 60.43% for models based on the maximum membership principle and the credible identification principle, respectively. The credible identification principle performs better in models with a large number of difficult-to-distinguish samples, with a higher average accuracy than the model based on the maximum membership principle. However, the model using the maximum membership principle has a higher maximum accuracy, and the model using the weighted average operator based on the maximum membership principle has an accuracy as high as 97.64%.

From the evaluation results, although the credible identification principle can comprehensively consider intermediate information and solve unclear grading evaluation situations, it overemphasizes intermediate factors, ignores the impact of main or secondary factors on the evaluation result, and as a result, the maximum accuracy of the model is not high enough, and it is difficult to fully consider all factors. The maximum membership principle

can comprehensively consider the impact of all factors, but it is also prone to overemphasize the extreme values and lead to unreasonable evaluations. Therefore, it needs to be used in conjunction with the weighted average operator for model construction.

4.5 Model selection

Based on the analysis of the research above, combined with the accuracy comparison of various comprehensive evaluation models in Figure 7, the best model selected in this paper is the TFN-WAO-MMP combined model.

Confusion matrix is a standard visualization tool used to describe model classification performance (Kardani et al., 2021). In this paper, the determination of bursting liability is a three-class classification problem. Therefore, we can use the confusion matrix to visually describe the performance of the TFN-WAO-MMP combined model, as shown in Figure 8. The numbers on the diagonal from the upper right corner to the lower left corner in the figure indicate the number of samples where the evaluation values and actual values are consistent. The other positions indicate the number of samples where the evaluation values and actual values do not match. It can be seen that the TFN-WAO-MMP combined model has good performance in determining the bursting liability.

5 Engineering application

In order to further verify the effectiveness and practicality of the best model, the Trapezoidal fuzzy number- Weighted

TABLE 7 Engineering examples and determination results.

NO.	Sample source	Evaluating index				Bursting liability level	Best model	GB/T25217.2-2010	Field situation
		DT/ms	W_{ET}	K_E	R_C/MPa				
1	Chaoyang Mine, Level 1, 3,100 mining area, coal seam 3 under coal	23	49	5.09	6.47	1	1	1	Repeated occurrences of strong shock wave and weak bursting dynamic phenomena.
2	Zhaozhuang Mine, 3# coal seam, 1,306 working face	196	1.93	1.08	6.88	2	2	2	Intermittent coal bumps and slabbing phenomena occurred during the mining process.
3	Qianqiu Mine, bottom coal of coal seam 2	224	6.44	6.32	15.4	2	2	2	Repeated occurrences of rock bursts and other dynamic phenomena in the mine.
4	Guangzheng Coal Mine	260	2.4	0.76	30.31	3	3	*	No dynamic phenomenon
5	Yuwu Coal Industry, upper stratification of 3# coal	468	3.1	1.09	5.81	2	2	*	Several occurrences of roof collapse accidents have happened near the goaf.
6	Yuwu Coal Industry lower stratification of 3# coal	313	2.65	1.35	7.05	2	2	*	Several occurrences of floor heave accidents have happened near the goaf.
7	Huating Chenjiagou Coal Mine, 8,512 working face coal seam	206	9.37	3.12	6.47	1	1	*	Coal and surrounding rock have been severely damaged due to frequent coal mine explosions at the working face.
8	Fuli Coal Mine, 22 coal	147	13.28	4.77	6.88	1	1	*	The mine dynamic events have occurred frequently.

(Continued on the following page)

TABLE 7 (Continued) Engineering examples and determination results.

NO.	Sample source	Evaluating index				Bursting liability level	Best model	GB/T25217.2-2010	Field situation
		DT/ms	W_{ET}	K_E	R_C/MPa				
9	Xinjiang Wudong Coal Mine, B3 and B5 coal seam of the 400 m level	391	4.64	0.9	15.4	2	2	*	The B3+6 coal seam and its surrounding rock in Wudong coal mine have been frequently affected by dynamic impacts.
10	A certain mine in Inner Mongolia	722	1.9	1.54	30.31	3	3	*	No dynamic phenomenon

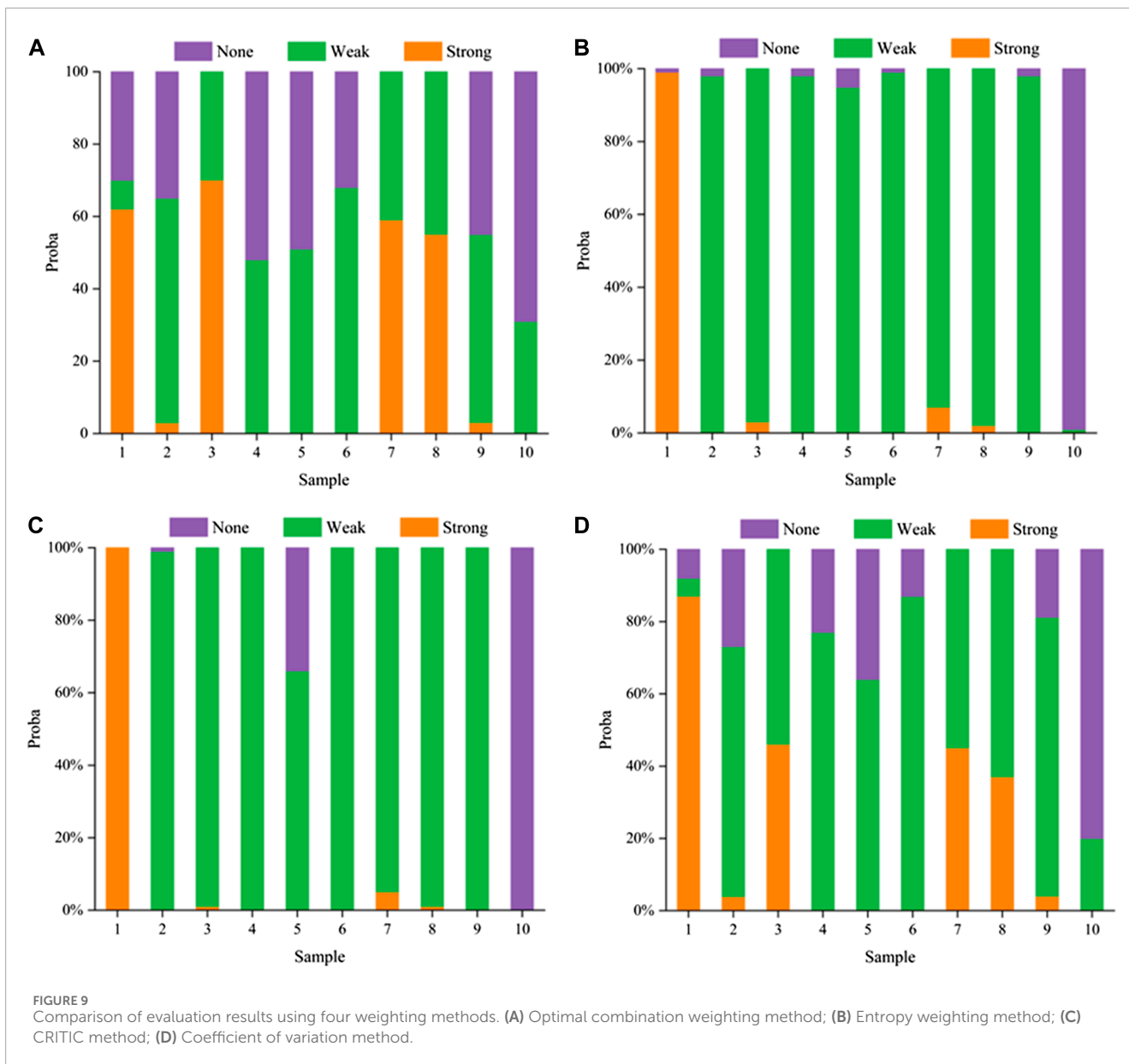
average operator- Maximal membership principle (TFN-WAO-MMP) combined model selected in this paper was used to determine the bursting liability of 10 engineering examples in Table 7, and the results were compared with the results given by the national standard GB/T 25217.2-2010. As shown in Table 7, the best model in this study produced consistent results with the standard for example, 1 to Example 3 but the national standard cannot determine the bursting liability levels of Example 4 to Example 10. However, the results obtained by the best model are in line with the actual engineering situations.

Figure 9 presents a comparison of the evaluation results of the combined weighting method proposed in this study with those of the entropy weighting method, CRITIC method, and coefficient of variation method applied to the optimization model. Figure 9A shows the evaluation results of the optimal combined weighting method proposed in this study, which is consistent with the actual engineering situation, and its accuracy is significantly higher than that of the objective weighting method. Figure 9B–9D show that when the indicator data fluctuates, the weights determined by the objective weighting method are unreasonable and bias towards a certain indicator, making it difficult to comprehensively consider various indicators. This indicates that the accuracy of the coal bursting liability evaluation model based on the combined weighting-fuzzy set theory is high and verifies the feasibility and effectiveness of the model in coal bursting liability evaluation.

In this study, specific analysis was conducted with Example 7. During the excavation of the 8512-working face in the Chenjiagou coal mine in Huating, the mining pressure was apparent, and “coal explosion” sounds occurred. The surrounding rock of the roadway deformed significantly, and local support bodies had been damaged. The specific occurrence of mining pressure was that there was a total of 17 recorded “explosion sounds” in the return airway of the 8512-working face. According to incomplete statistics, 1,558 anchor rods and cables were broken due to the pressure. There were 14

recorded “explosion sounds” in the transportation return airway of the 8512-working face. According to incomplete statistics, 1980 anchor rods and cables were broken due to pressure. During the coal bursting liability identification test, individual coal samples under their natural state experienced sudden explosive dynamic destruction, pulverized into debris, and were ejected at a relatively high speed. This indicates that the coal sample’s bursting liability is strong under its natural state. It can be seen that the discriminant result of the optimal model constructed in this study is consistent with the engineering field situation, and other models make false judgments.

To sum up, the combination model TFN-WAO-MMP constructed based on the combined weighting-fuzzy set theory can accurately determine the level of coal bursting liability level. The main advantages include: 1) Compared with traditional fuzzy evaluation methods, TFN-WAO-MMP better retains the fuzzy information of the data, makes full use of engineering data to accurately evaluate the level of bursting liability. When constructing the membership function, it considers more comprehensively (such as normalization, non-negativity, and additivity of the membership degree), which can solve the problem of eight samples that are difficult to distinguish in the current national standard. 2) Compared with existing comprehensive evaluation methods and machine learning methods, TFN-WAO-MMP is not restricted by sample data and can obtain related parameters only by expert evaluation method based on the index grading criteria. Moreover, the model is simple and practical, which can evaluate the bursting liability level of underground engineering without sample data and has strong applicability. 3) The Delphi-random forest combination weighting method proposed in this study can solve the problem of objectivity weighting method being greatly affected by data fluctuations and improve the shortcomings of the subjective weighting method being limited by the discreteness of coal sample data and the difficulty in updating weights at all stages, thus improving the rationality and reliability of indicator weights.



6 Conclusion

- (1) To address the deficiencies in the current discrimination methods, this study conducted a comprehensive evaluation of coal impact tendency using the combined weighting-fuzzy set theory. The Delphi method and random forest weighting method were used to determine the weights of each evaluation index. The optimal combination weighting method was determined using multiplication synthesis method. Based on two membership functions, four fuzzy operators, and two evaluation principle, 16 fuzzy mathematical comprehensive evaluation models were established.
- (2) Based on 127 sets of sample discrimination results, the impact of membership functions, fuzzy operators, and evaluation principle on the model evaluation results was systematically analyzed. The Trapezoidal fuzzy number-

Weighted average operator- Maximal membership principle (TFN-WAO-MMP) combined model was selected as the optimal fuzzy comprehensive evaluation model, with an accuracy of 97.64%.

- (3) The Delphi method and random forest-optimal combined model were applied to 10 engineering examples, and the discrimination results were completely consistent with the actual situation. Compared with other evaluation methods, this method improved the efficiency of evaluation and avoided the effect of data fluctuations on weight determination. It also improved the rationality and reliability of indicator weights and effectively solved the problem of the eight samples that are difficult to distinguish in the national standard. This study is a beneficial supplement and improvement to the national standard and existing evaluation methods.

Data availability statement

The original contributions presented in the study are included in the article/[Supplementary Material](#), further inquiries can be directed to the corresponding author.

Author contributions

CW: Writing–review and editing, Conceptualization, Funding acquisition, Methodology, Software, Supervision. ZJ: Writing–review and editing, Writing–original draft. XL: Project administration, Supervision, Writing–review and editing. TW: Investigation, Software, Writing–review and editing. YL: Writing–review and editing. SZ: Formal Analysis, Writing–review and editing. QW: Investigation, Methodology, Validation, Visualization, Writing–original draft, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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