Rock Burst Evaluation Using the CRITIC Algorithm-Based Cloud Model

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Under high-stress conditions, rock burst disasters can significantly impact underground civil engineering construction. For underground metal mines, rock burst evaluations and prevention during mining have become major research topics, and the prediction and prevention of rock burst must be based on the study of rocks and rock burst tendencies. To further prevent the risk of geological disasters and provide timely warnings, a finite-interval cloud model based on the CRITIC algorithm is proposed in this paper to address the uncertainty of rock burst evaluation, the complexity under multi-factor interactions, and the correlations between factors, and it then realizes a preliminary qualitative judgment of rock burst disasters. This paper selects the uniaxial compressive strength σ_c (l_1), ratio of the uniaxial compressive strength to the tensile strength σ_c/σ_t (brittleness coefficient, I_2), elastic deformation energy index W_{et} (l_3), ratio of the maximum tangential stress to the uniaxial compressive strength σ_θ/σ_c (stress coefficient, I_4) of the rock, depth of the roadway H (l_5), and integrity coefficient of the rock mass K_v (l_6) as indicators for rock burst propensity predictions. The CRITIC algorithm is used to consider the relationships between the evaluation indicators, and it is combined with an improved cloud model to verify 20 groups of learning samples. The calculation results obtained by the prediction method are basically consistent with the actual situation. The validity of the model is tested, and then the model is applied to the Dongguashan Copper Mine in Tongling, Anhui Province, China, for rock burst evaluation.

Keywords: cloud model, CRITIC algorithm, rock burst, uncertainty, prediction

INTRODUCTION

Rock burst is due to the impact of ground pressure on hard and brittle rock masses in high earth-stress states during the excavation of underground tunnels. Elastic strain energy is suddenly and rapidly released due to the stress concentration around the opening, and the dynamic instability of the energy leads to the sudden release of energy into the free space, thus destroying the equilibrium. This energy release is an earthquake induced by mining or tunnel excavation [1, 2]. As early as 1738, there were related reports of rock burst disasters [3]. Rock burst disasters are sudden and extremely destructive and will not only cause over-excavation, initiate support failure, and delay construction but may also cause earthquakes or destroy the entire tunnel or pit, thus causing casualties and serious economic losses. At the same time, rock burst disasters are often accompanied by the exfoliation and ejection of surrounding rock, the formation of a considerable amount of dust and the creation of air shock waves. Thus, these disasters can easily cause numerous casualties and determining a method of correctly predicting the risk of rock burst in underground engineering and geotechnical engineering practice has become a problem that must be solved.

Compared with other engineering fields, the occurrence of rock burst in underground metal mines is unique and mainly reflected in the following aspects: 1) Rock burst evaluation is an

important basis for determining the risk level and safety of mines; 2) In other metal mine production research fields, such as underground caverns, rock slopes and dam foundation stability, rock burst is a relatively important criterion; 3) Reasonable rock burst evaluations can provide effective theoretical criteria for process selection, disaster prevention and control during construction, which provides strong theoretical support for mining safety protection measures, such as safety support and safety shielding implementation; and 4) Underground engineering rock burst evaluations provide data for underground engineering surveys, designs and safe construction and represent an important research topic in rock mechanics and geotechnical engineering.

In recent decades, many scholars have performed a number of analyses and research based on the formation mechanism of rock burst and proposed many well-known theoretical criteria, such as the Russenes criterion, the Hoek criterion, the energy criterion, and the stress criterion. In recent years, rock burst criteria based on engineering experience have emerged. The above discrimination methods are based on the study of rock burst mechanisms and have been combined with qualitative or quantitative analysis methods to determine the rock burst tendency and hazard level. In general, current rock burst evaluation methods can be classified into three categories: theoretical analysis methods, field measurement methods and statistical evaluation methods. The specific contents and differences are as follows.

Theoretical Analysis

Theoretical analysis can be used in the process of rock burst evaluation. This method is inexpensive and can better simulate the influence of various on-site factors. The theoretical analysis method is based on different theories of rock burst mechanism, and the resulting criteria are used to form different prediction methods, including the following methods. 1) Rock burst tendency judgment method [4–6]: This method is mainly used in the engineering geological exploration stage after drilling rock samples on site and for conducting rock mechanics tests, and one indicator or a set of indicators (elastic deformation index, impact energy index, dynamic damage time, etc.) are used to analyze the possibility of rock burst. 2) Strength theory method [7, 8]: Strength theory suggests that rock burst may occur when the tensile stress or compressive strength of rock reaches a certain ratio, and the prediction criteria used in this method include the Norwegian Russenes criterion [9], elastic energy reserve criterion, brittleness coefficient criterion, and tangential stress criterion. 3) Energy release rate (ERR) index method [10–12]: The ERR value is the ratio of the energy release caused by the excavated ore to the volume of the mined rock, and it comprehensively reflects the influence of the geometry, depth, original rock stress field and rock mechanical properties of the excavation on rock burst. 4) Numerical prediction methods [13, 14]: These methods include the finite element method and finite difference method.

On-Site Measurement Method

The on-site measurement method uses the necessary instruments to determine whether a rock explosion occurs by investigating

and analyzing the mining site or testing the rock mass [15]. This approach mainly includes the following methods. 1) Drill cutting method [16]: This method is mainly used for drilling and sampling analysis of surrounding rock through the collection of dynamic response information, such as popping sounds, friction sounds and stuck drilling phenomena and auxiliary judgements. 2) Acoustic emission method [17]: This method is the most direct monitoring method for rock burst detection and most direct forecasting method, and the occurrence of rock burst is determined according to the shape and frequency spectrum of the acoustic emission signals emitted at different stages of rock deformation. 3) Electromagnetic radiation method [18–20]: This method can predict the possibility and development of rock burst. 4) Microgravity method: this method can predict rock burst early and over a wider prediction range, although its costs are higher than those of other methods.

Statistical Forecasting Methods

Uncertainty is the main feature of most engineering problems, mainly the randomness and ambiguity discussed in probability theory and fuzzy mathematics. Because of the randomness and complexity of the rock mass structure of underground mines, the severity, timing, form, and location of rock burst are uncertain. To resolve the uncertainty of the rock burst problem, domestic and foreign scholars have performed many studies on rock burst tendency predictions and proposed a variety of rock burst grading prediction methods [21–27]. For example, Zhou et al. [28] selected seven data parameters and 132 rock burst databases and combined multiple data models to carry out rock burst tendency prediction work. Xu [29] considered the basic theory of the ideal point method and selected several factors for the evaluation prediction index to construct a coupled ideal point prediction analysis model. Lu et al. [30] used the basic principles of Analytic Hierarchy Process and the entropy weight method to select prediction indexes from three aspects, namely, lithology conditions, stress conditions and surrounding rock conditions, to calculate the critical rock burst risk and the closeness of actual mine data. Wen et al. [31] proposed a rock burst propensity prediction model based on a support vector machine (SVM) with mixed particle swarm optimization (PSO) based on combination weighting, constructed a combination weighting criterion and established a H-PSO-SVM rock burst tendency prediction model based on the concept of the harmonic mean. Zhang et al. [32] established the rock burst cloud model with the distance index and uncertainty metric. Faradonbeh and Taheri [33, 34] used data mining technology to study rock burst tendencies and innovatively proposed the use of field experiments and data analysis methods to conduct research on the predicting deep rock mass and explosion tendencies, and they verified the feasibility of the method. However, some uncertainty analysis methods still have shortcomings. For example, when the AHP method is used to analyze the index weight and usually only measures the relative importance of the index, and it also presents subjectivity; the extension model takes a long time to analyze large-scale training samples and is dependent on the selection of the kernel function; the coupled neural network algorithm is complicated to calculate, the obtained samples are not

representative, and the fitting speed is difficult to control; and the distance discrimination weighting model is strongly dependent on the sample data.

Due to the complexity of rock burst, the above methods also have some limitations: 1) Many risk evaluation factors are derived from subjective experience, which may not make sense in theory; 2) The evaluation criteria standard is generally vague, and traditional evaluation models cannot handle the problem of index classification near the threshold; 3) When different evaluation indicators belong to different grades, the method of defining the actual evaluation indicators of the sample is also somewhat ambiguous; 4) The measured value of the evaluation factors will have some errors, which will lead to the unreasonable classification of factor levels near the threshold; and 5) The traditional method of determining the importance of the risk level factors of the object relies too much on subjective experience. When the production system is complex and there are many influencing factors, many redundant factors will interfere, thereby reducing the reliability of the evaluation results. The entropy weight method [35] determines the variability of the evaluation index based on the sample data to calculate the amount of information included in the index, thereby assigning the weight according to the amount of information included in the index, although it does not consider the correlation between the indicators. Therefore, it is necessary to introduce a relatively perfect rock burst evaluation model.

In this paper, based on the uncertainty of rock burst evaluations, the complexity under multi-factor interactions, and the correlations between factors, a cloud model of finite intervals based on the CRITIC algorithm is proposed. When using the traditional normal cloud model to address the parameter distribution of the single interval boundary, the deviation between the actual situation and the model distribution will not be considered. The calculation result obtained in this case often differs from the actual engineering, and this difference affects the accuracy of the prediction result. When classifying rock burst grades, the determination of index weights is the key to object evaluation. Although the traditional method of objective weights is based on objective data, the results may be poorly interpreted. This paper uses the improved CRITIC method-normal cloud model for rock burst propensity prediction to determine the weight of the index. The model is applied to the rock burst examples of underground engineering worldwide, the validity of the model is tested, and the model is finally applied to the Dongguashan Copper Mine in Tongling, Anhui Province, for rock burst evaluation.

THEORETICAL BASIS

Identification Framework and BPA

For a fuzzy evaluation problem, the answers can be composed of a set, and the internal elements of the set are mutually exclusive. Under certain conditions, the answer to the question can be the only element in the set. For this reason, Shafer [36] refers to this mutually exclusive set Θ as the recognition framework according to the set theory:

$$\Theta = \{A_1, A_2 \ldots A_m\} \quad (1)$$

where Am indicates the evaluation level of the evaluation question and Θ indicates the evaluation standard in the evaluation question.

The evidence set is the basis for judging whether the identification framework of a problem Θ is a subset, which is equivalent to the index factor in the evaluation and is recorded as follows:

$$\Phi = \{E_1, E_2 \ldots E_k\} \quad (2)$$

where En represents the index factor in the evaluation question, which is usually used to express the sample and judge its subordinate level. In the recognition framework Θ, the basic probability distribution function f is a mapping of the set 2^{Θ} to $[0, 1]$ and satisfies the following:

$$\sum_{A \in \Theta} f(A) = 1 \quad (3)$$

where A denotes any subset of the recognition frame Θ, which is denoted as $A \in \Theta$; and $f(A)$ is the basic probability distribution function of A, which indicates the degree of evidence support for A. In the evaluation question, $f(A)$ indicates the degree of membership, which is characterized by the fact that the measured values of the indicators of the evaluation factors belong to the degree of membership of different evaluation levels.

Definition of the Cloud Model

The essence of the membership function concept, which is the most basic of fuzzy mathematics, did not have good theoretical support before the cloud model was produced. In particular, it is basically impossible to use accurate membership functions to define fuzzy thinking activities. For this reason, Li Deyi et al. proposed the concept of a cloud model [37, 38]. From the perspective of membership degree, they analyzed the data randomness and ambiguity problems in engineering practice. Randomness means that there is a certain basic definition, although the events may not occur. The characteristic of this problem is randomness. In the evaluation model, the concept and distribution of each evaluation factor index are deterministic but for different evaluation subjects; however, the specific data distribution is uncertain. Therefore, the mine risk assessment problem shows randomness; moreover, the basic concept of ambiguity can be characterized as the uncertainty contained in the event that has occurred but is difficult to accurately define. The method has been applied in many fields [39–48] and achieved good evaluation results.

The "cloud" is a two-way cognitive model between a qualitative concept and its quantitative representation expressed by linguistic values to reflect the uncertainty of random and ambiguous concepts in natural language. The relevant definitions are as follows [39].

There is an exact numerical representation of the quantitative set $U = \{x\}$, where U is the domain (1D, 2D or multidimensional), the A_k inter-cell is the fuzzy interval in the domain U, K is the number of grade intervals in the domain segmentation, and C is the qualitative concept of A_k. An arbitrary element x is observed

in A_k, and each corresponding $x \in A_k$ has a stable random number in the mapping $\mu: x \to \mu_A(x)$, which is randomly implemented in the qualitative concept $C\mu_A(x)$ is called the degree of certainty of x for concept C and can also be called the membership degree. The distribution of $\mu_A(x)$ on the domain U is called the cloud model, $\mu_A(x) \in (0, 1)$:

$$\mu: U \to \left(C_{\min}^{kl}, C_{\max}^{kr} \right), A_k \subseteq U, \forall x \in A_k, x \to \mu_A(x) \qquad (4)$$

The distribution of $\mu_A(x)$ on each fuzzy set A_k is called a cloud, and each point $[x, \mu(x)]$ is called a cloud drop, where $C_{\min}^{kl}$ represents the smallest value in the smallest fuzzy level interval that is segmented, which is usually 0; and $C_{\max}^{kr}$ indicates the maximum corresponding maximum value of the segmented fuzzy level interval. For the one-sided interval $(C_{\min}^{kr}, +\infty)$, the expected value of the k-1 interval may be taken as E_x^{kr-1}, and then the expected value of the interval may be obtained. Alternatively, we can determine the default boundary parameters by considering the upper and lower limits of the data. When the rock burst risk is positively correlated with the evaluation index, kl and kr represent the minimum and maximum fuzzy level intervals, respectively; otherwise, they represent the maximum and minimum fuzzy level intervals, respectively. The traditional normal cloud model is shown in **Figure 1**, in which the abscissa X ($x_1, x_2, \ldots x_n$) represents the value corresponding to the qualitative concept in the domain at this time, the width of the domain represents the value of a certain fuzzy level interval A_k, while the ordinate represents the degree of certainty μ (x_i) ($x_{1i}, x_{2i}, \ldots x_{ni}$), which ranges from 0 to 1 and is a measure of the language value. Each point in the figure corresponds to one cloud drop, which is a specific implementation of the quantified language value.

Digital Characteristics of the Cloud

Usually, the support of the cloud model concept is mainly expressed by three numerical eigenvalues [49]: expectation E_x, entropy E_n, and super entropy H_e. The specific meaning of the expression is shown in **Figure 2**, where three lines are selected in the cloud drop graph and E_x is expected to represent the central value of the data parameter in the Universe. In the geometric sense, a random value corresponding to the highest point of the graph is selected. The location of the cloud drop distributions suggests that $E_{x3} > E_{x2} > E_{x1}$. Entropy E_n indicates the range of values of the cloud drop expressed in the qualitative domain of the Universe, thus reflecting the ambiguity and randomness of the basic concept, which also determines the cloud drop. The greater the confusion is, the greater the width of a cloud map, the larger the value range of the cloud droplet, the more blurred the qualitative concept, and the greater the dispersion of the cloud droplet; thus, $E_{n2} > E_{n1} = E_{n3}$. The super entropy H_e, which is the entropy of entropy and indicates the uncertainty of entropy, is the thickness of the cloud in the cloud drop diagram. The larger the super entropy is, the thicker the cloud, which is characterized as $H_{e1} = H_{e2} > H_{e3}$ in the cloud drop diagram.

In the cloud model, each cloud drop satisfies $x \sim N(E_x, E_n'^2)$, where $E_n' \sim N(E_n, H_e^2)$; then, the degree of certainty of x to C is as follows:
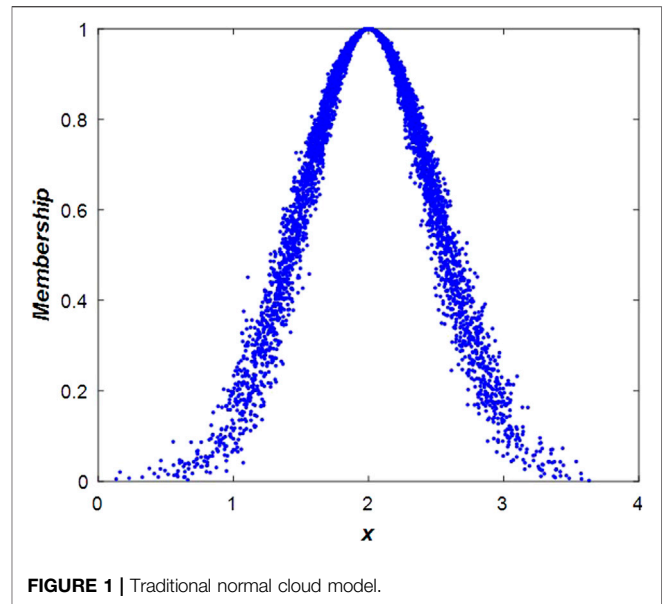

FIGURE 1 | Traditional normal cloud model.

$$\mu(x) = \exp\left[\frac{-(x - E_x)^2}{2 * E_n'^2} \right] \qquad (5)$$

The boundary value C_k is a transition value of two levels, and the membership degrees belonging to the two fuzzy intervals are equal:

$$\exp\left[-\frac{\left(C_{\max}^k - C_{\min}^k \right)^2}{8 E_n^2} \right] = 0.5 \qquad (6)$$

For the rock burst hazard grading interval, there are fuzzy edge intervals of magnitude $A_{Kr} = (0, C_{\max}^{Kl})$ and $A_{Kl} = (C_{\min}^{Kr}, +\infty)$, and the index variables at this time no longer obey the traditional cloud model distribution. Therefore, $\mu_A(x)$ should be transformed into a uniform distribution with a degree of certainty of 1 on the edge blur intervals A_{kr} and A_{kl}, and it is usually described by a half-lift trapezoidal cloud and a half-fall trapezoidal cloud. The calculation equations of the cloud characteristic parameters are as follows:

$$\begin{aligned} E_x^k &= \frac{C_{\max}^k + C_{\min}^k}{2} \\ E_n^k &= \frac{C_{\max}^k - C_{\min}^k}{2.355} \\ H_e^k &= \lambda E_n^k \end{aligned} \qquad (7)$$

where C^k is the half-length of the k-level; $C_{\max}^k$ and $C_{\min}^k$ are the upper and lower bounds of the level interval, respectively; and λ is the empirical value, which can be appropriately adjusted according to the fuzzy value of the index variable and is temporarily set to 0.01 in this article. It should be clear that the empirical value λ cannot affect the final result. A change of its value will only affect the value of He, and it does not affect the upper and lower thresholds of the fuzzy interval as shown in **Figure 2** and is mainly used to characterize the thickness of the "cloud."
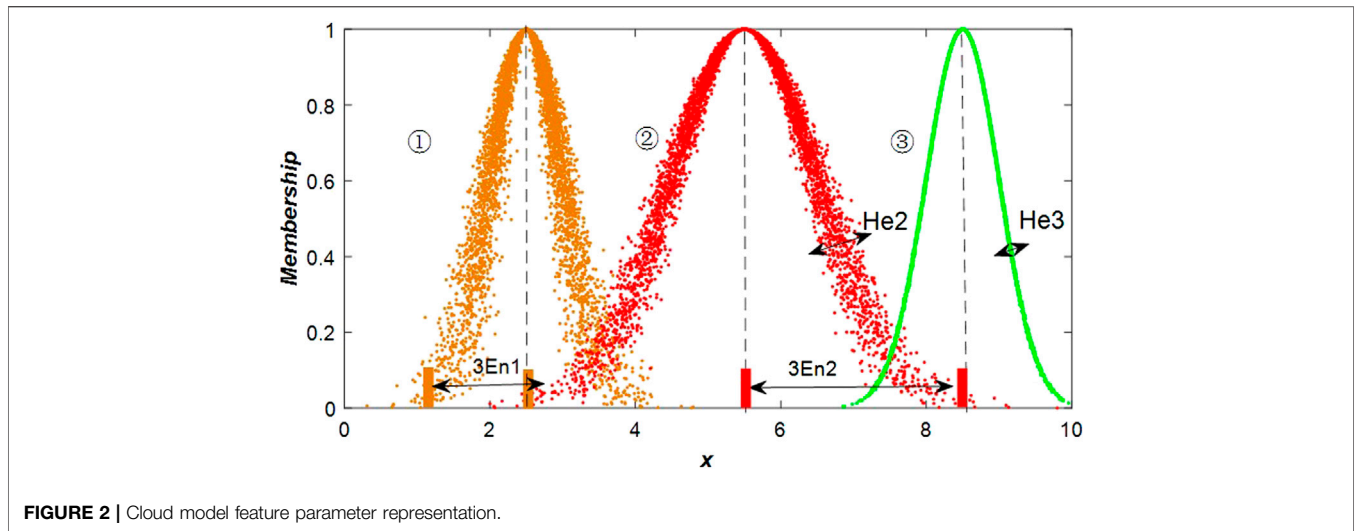
FIGURE 2 | Cloud model feature parameter representation.

Forward Cloud Generator

Cloud generators, including forward cloud generators and reverse cloud generators, are an important medium to transform qualitative concepts into quantitative data. This paper uses a forward cloud generator as a means of qualitative and quantitative conversion. According to the cloud characteristic parameter N (E_x, E_n, H_e), a cloud drop map is generated in the blur interval A_k by the forward cloud generator. For each cloud drop P $[x_i, \mu_A(x)]$ $(i = 1, 2, . . ., n)$, n is the number of cloud droplets to be generated in the fuzzy interval A_k and $N = n_1 + n_2 + n_k$ represents the total number of clouds generated in the entire Universe U ($N = 5,000$ in this paper). When the indicator is in the mean interval of the non-edge level cloud, the degree of certainty of x to C is $\mu(x) = \exp[-(x - E_x)^2/2E_{n,2}]$. When the indicator is in the edge level interval, x no longer has a normal distribution but has a uniform distribution with a degree of certainty of 1. Combining these two distributions, we have

$$\begin{cases} \mu_A(x) = 1 & x \in \left(0, E_x^{k1}\right) \cup \left(E_x^{kn}, C_{\max}^{kn}\right) \\ \mu_A(x) = \exp\left[\dfrac{-(x - Ex)^2}{2En'^2}\right] & x \in otherrval \end{cases} \quad (8)$$

The generated edge interval is a uniformly distributed cloud model as shown in **Figure 3**, where curve one and curve three represent a finite-interval cloud model and indicate hazard levels one and three, respectively, and the left and right edges of the two curves obey a uniform distribution with a degree of certainty of one.

The positive normal cloud model is applied to rock burst evaluation based on the following four reasons:

(1) Rock burst risk assessment is a problem of uncertainty, and the cloud model expresses and reflects the uncertainty of concepts in the process of human cognition through the three characteristic parameters of N (Ex, En, He);
(2) The cloud model with the edge obeys the normal distribution, and its main body still obeys the normal distribution, which has certain universality and extensiveness;
(3) In the natural sciences, the characteristic curves of many qualitative concepts approximately obey a normal distribution;
(4) The cloud model can convert qualitative concepts and quantitative values, and the rock burst risk assessment selected in this article is also a research process from qualitative to quantitative.

CLOUD MODEL BASED ON THE CRITIC ALGORITHM FOR ROCK BURST EVALUATION

To use the CRITIC algorithm-based cloud model for rock burst evaluation, the appropriate evaluation index system and its
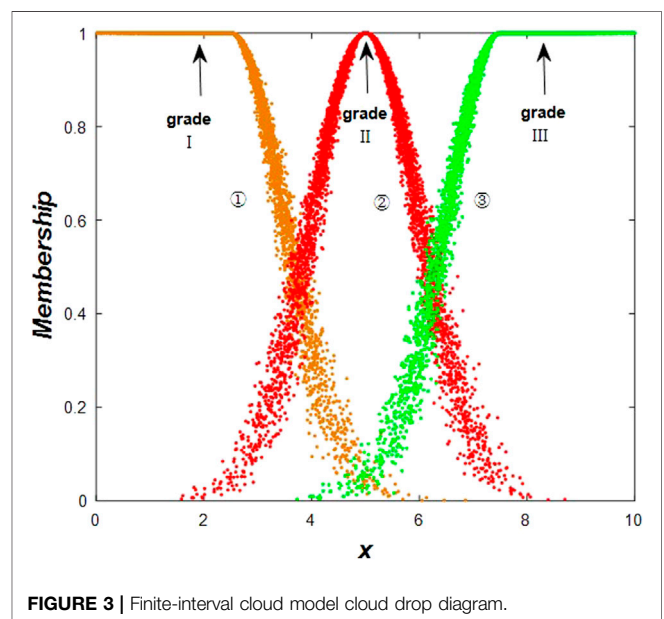

FIGURE 3 | Finite-interval cloud model cloud drop diagram.

corresponding evaluation criteria must be selected and the index weights are then calculated by the CRITIC algorithm; then, the corresponding evaluation index criteria are used to calculate the cloud characteristic parameters of each level. The cloud model is generated using the cloud generator, and the degree of certainty corresponding to each index is calculated according to the measured data of the sample. Finally, the comprehensive weight value is calculated, and the rock burst risk level is determined according to the principle of maximum membership degree. The evaluation flow chart is shown in **Figure 4**.

Selection of Rock Burst Evaluation Classification Indicators and Intensity Grading Standards

The mechanism of rock burst is complicated, and there are many influencing factors. The selection of indicators is a key step in the prediction process. The impact of rock burst is two-fold: internal and external. In a high-stress environment, excavation of a cavern will lead to stress redistribution and stress concentration in the surrounding rock mass. The environment in which the rock mass is located undergoes a certain change, which is the external factor of rock burst. The mechanical properties of the rock mass itself are internal factors, and hard rock and brittle rock are prone to rock burst. Therefore, it is necessary not only to carry out mechanical experiments on the rock but also to obtain the rock burst tendency index and consider external conditions in

rock burst evaluation. Based on related research on rock burst [50, 51], the theory of rock burst tendency, and intrinsic rock burst conditions, lithological factors, energy factors and geological factors, this paper selects the uniaxial compressive strength σ_c (I_1), ratio of the uniaxial compressive strength to the tensile strength σ_c/σ_t (brittleness coefficient, I_2), elastic deformation energy index W_{et} (I_3), ratio of the maximum tangential stress to the uniaxial compressive strength σ_θ/σ_c (stress coefficient, I_4) of the rock, depth of the roadway H (I_5), and integrity coefficient of the rock mass K_v (I_6) as indicators for rock burst propensity prediction. According to the characteristics of rock burst occurrence during underground mining of metal mines, the selection of evaluation indicators should be scientific, independent and representative. The main factors should be included in the evaluation as much as possible. The stronger the independence of the indicators, the more accurate the prediction results will be.

According to the relevant research and classification criteria, the rock burst intensity can be divided into four grades. Grade I (no rock burst) is mainly manifested as a lack of rock wall tearing, rock fragmentation, sound emission phenomenon, etc., and there is no need to take any safety measures. Grade II (weak rock burst) is characterized by a loose rock wall surface and block spalling occurs, and safety and safety monitoring measures are required. Grade III (moderate rock burst) is characterized by block spalling of the rock in the diverticulum and roadway wall accompanied by occasional projectiles that often emit sharp ejecting sounds and may cause casualties and property losses; thus, it is necessary to implement
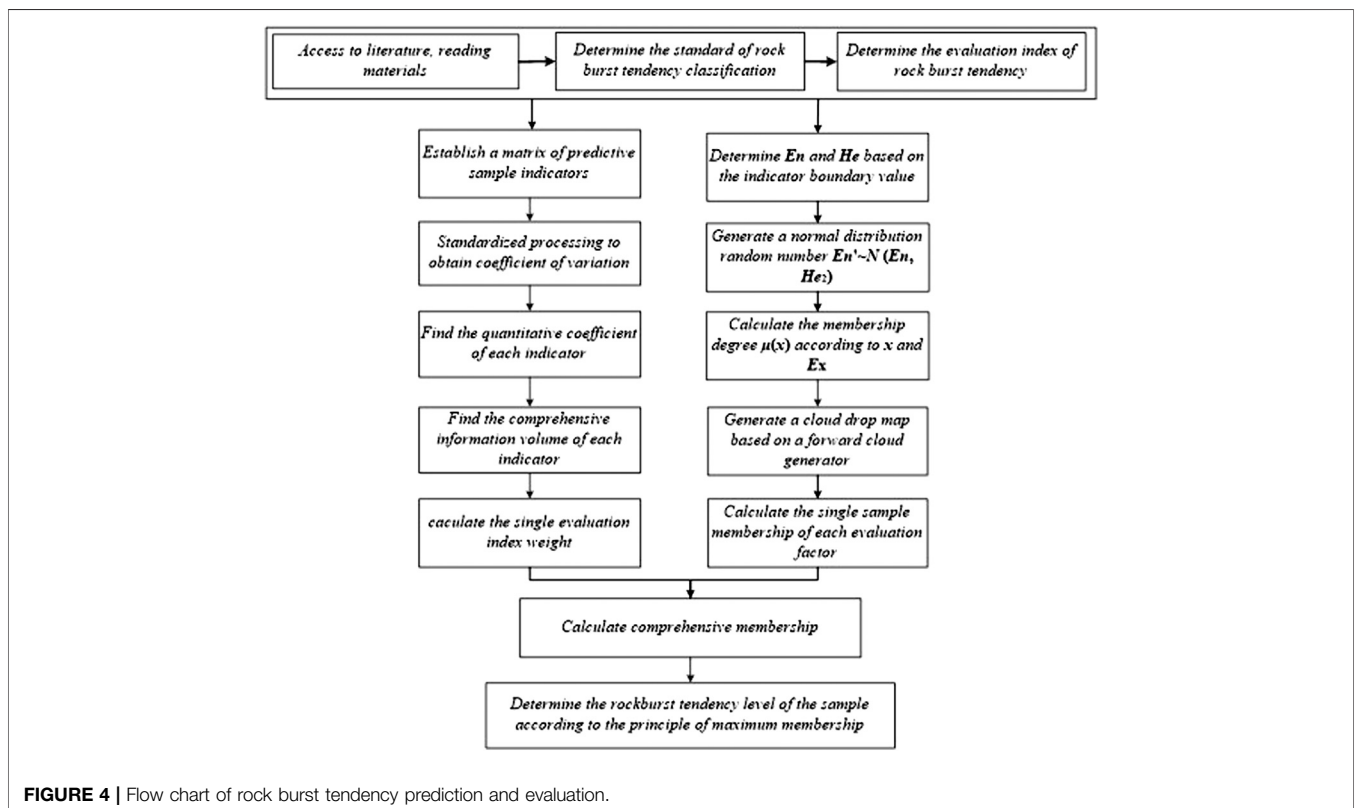

FIGURE 4 | Flow chart of rock burst tendency prediction and evaluation.

monitoring measures to perform isolation and protection work. Grade IV (violent rock burst) is characterized by large rock mass spalling, rapidly deformed surrounding rock, and a large number of blast pits; this type of rock burst is prone to causing numerous casualties and injuries, and relevant safety protection measures must be taken. The specific classification criteria are shown in **Table 1** [52–54]. Multiple studies at home and abroad indicate that the classification standards for rock burst tendencies are different. The classification standards selected in this article indicate a trend and only show the uncertainty of the rock burst problem.

Rock Burst Propensity Prediction CRITIC Algorithm

The so-called weight refers to the importance of the risk indicators that affect the problem in the evaluation process. The methods of determining weight mainly include subjective weighting methods and objective weighting methods. According to the engineering characteristics of the rock burst problem, this paper adopts the CRITIC objective weighting algorithm to determine the index weight. The CRITIC method was proposed by Diakoulaki et al. [55] in 1995, and it focuses on using the information and correlation of risk indicators to determine risk weights. The improved CRITIC algorithm is based on the original calculation steps, adding the concept of coefficient of variation (**Formula 12**), thereby reducing the shortcomings of using standard deviation to measure the variability of indicators [56], the main steps are as follows:

STEP 1: Using the initial data, establish a matrix of predicted sample indicator values:

$$X = \left(x_{ij}\right)_{m \times n} \tag{9}$$

where x_{ij} is the original value corresponding to the jth indicator of the ith evaluation object.

STEP 2: According to the Z-score method, standardize the index values in matrix X of the above formula:

$$x_{ij}^* = \frac{x_{ij} - \overline{x}_j}{s_j} \ (i = 1, 2, \ldots, m; j = 1, 2, \ldots, n) \tag{10}$$

According to the algorithm, the two parameters in the above formula are defined as follows:

$$\overline{x}_j = \frac{1}{m}\sum_{i=1}^{m} x_{ij}, \ \ s_j = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}\left(x_{ij} - \overline{x}_j\right)^2} \tag{11}$$

where $\overline{x}_j$ is the average of the jth indicator and s_j is the standard deviation of the jth indicator.

STEP 3: Find the coefficient of variation in the indicator:

$$v_j = \frac{s_j}{\overline{x}_j} \ (j = 1, 2, \ldots, n) \tag{12}$$

where v_j is the coefficient of variation in the jth indicator.

STEP 4: Use STEP 2 to obtain the normalized matrix X^* and use the statistical concept to calculate the correlation coefficient:

$$r = \frac{\sum_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \overline{x})^2 \cdot \sum_{i=1}^{n} (y_i - \overline{y})^2}} \tag{13}$$

Obtain the Correlation Coefficient Matrix

$$R = (r_{kl})_{n \times n} \ (k = 1, 2, \ldots, n \ ; \ l = 1, 2, \ldots) \tag{14}$$

where r_{kl} is the correlation coefficient between the kth indicator and the 1st indicator.

STEP 5: Identify the degree of independence—quantization coefficient—of each indicator:

$$\eta_j = \sum_{k=1}^{n} \left(1 - r_{kj}\right)(j = 1, 2, 3, \ldots n) \tag{15}$$

STEP 6: Calculate the total volume of information for each indicator:

$$D_j = v_j \sum_{k=1}^{n} \left(1 - r_{kj}\right), j = 1, 2, 3 \ldots n \tag{16}$$

STEP 7: Determine the weight of each evaluation index:

$$\omega_j = \frac{D_j}{\sum_{j=1}^{n} D_j} \ (j = 1, 2, 3, \ldots, n) \tag{17}$$

According to the cloud model theory and the improved CRITIC algorithm, the coupling process is as follows.

(1) With reference to the rock burst risk level classification standard and cloud model concept, determine the number and interval of the divided states.
(2) According to the numerical characteristics of the cloud model (**Eq. 7**) and the grading standard of the rock burst intensity level, the numerical eigenvalues of different hazard levels of different evaluation factors can be obtained. The specific values are shown in **Table 2**. When the edge interval is treated as $(C_k, +\infty)$, the expected value of the k-1 interval can be assumed, and then the expected value of the entire interval can be obtained.

TABLE 1 | Rock burst classification criteria.

Rock burst grade	$\sigma_{c/Mpa}$	σ_c/σ_t	W_{et}	σ_θ/σ_c	H/m	K_v
I (no rock burst)	(0, 80)	(40, +∞)	(0, 2)	(0, 0.3)	(0, 50)	(0, 0.55)
II (weak rock burst)	(80, 120)	(26.7, 40)	(2, 3.5)	(0.3, 0.5)	(50, 200)	(0.55, 0.65)
III (moderate rock burst)	(120, 180)	(14.5, 26.7)	(3.5, 5)	(0.5, 0.7)	(200, 700)	(0.65, 0.75)
IV (violent rock burst)	(180, +∞)	(0, 14.5)	(5, +∞)	(0.7, +∞)	(700, +∞)	(0.75, 1]

TABLE 2 | Characteristic parameters of the rock burst cloud model.

Rock burst grade	Model feature	Evaluation factor					
		I1	I2	I3	I4	I5	I6
I	Ex	40	46.65	1	0.15	25	0.275
	En	33.97	5.65	0.64	0.13	21.23	0.23
	He	0.34	0.057	0.0064	0.0013	0.21	0.0023
II	Ex	100	33.35	2.75	0.4	125	0.6
	En	16.98	5.65	0.64	0.085	63.69	0.042
	He	0.17	0.057	0.0064	0.00085	0.64	0.00042
III	Ex	150	20.6	4.25	0.6	450	0.7
	En	25.48	5.18	0.64	0.085	212.31	0.042
	He	0.25	0.052	0.0064	0.00085	2.12	0.00042
IV	Ex	210	7.25	5.75	0.8	950	0.875
	En	25.48	6.16	0.64	0.085	212.31	0.11
	He	0.25	0.062	0.0064	0.00085	2.12	0.0011

(3) Based on the evaluation criteria in this table and the characteristics of the cloud model, the MATLAB simulator is used to generate a cloud drop graph of each evaluation index by a forward cloud generator, and then the specific generation graph can be determined as shown in **Figure 5**. Let drop $(x_{1i}, x_{2i}, \ldots x_{ni}, \mu_i)$ be a cloud drop, which is a specific implementation of the number of linguistic values represented by the cloud, where X $(x_{1i}, x_{2i}, \ldots x_{ni})$ is the value of the qualitative concept in this field and $\mu(x_i)$ is the degree to which the x value (the measured value of the sample) belongs to different levels.

(4) Use the improved CRITIC weighting algorithm (**Eqs 9–17**) to calculate the importance of a single evaluation factor, i.e., the weight value.

(5) Combine the weights determined by the improved CRITIC algorithm with the cloud model feature parameters to obtain the final degree of certainty.

(6) After the expansion and calculation of the above steps, we can obtain the uncertainty in the different evaluation indicators x subordinate to a certain cloud $\mu(x)$ and then utilize the CRITIC algorithm to calculate the weight of different evaluation indicators. Then, the final comprehensive determination formula is as follows:

$$\mu_k = \sum_{i=1}^{m} \omega(E_i) \bullet \mu_{k,j} \qquad (18)$$

where k is the degree of determination of the measured value of the jth indicator of the $\mu_{k,j}$ sample; and $\omega(E_j)$ represents the weight of the jth evaluation index of the sample.

(7) According to the final comprehensive determination and the principle of maximum membership, the membership level of the sample is determined:

$$L = \max(\mu_1, \mu_2, \ldots \mu_k) \qquad (19)$$

ROCK BURST EVALUATION ANALYSIS OF LEARNING SAMPLES

To verify the rationality and effectiveness of the rock burst propensity prediction model used in this paper, referring to 20 sets of typical rockburst example data in literature [50]. The details of the measured index values and actual rock burst grades are listed in **Table 3**.

Indicator Weight Determination

In this paper, the CRITIC method is used to calculate the index weight and the information volume of the indicator and the correlation between the indicators are comprehensively considered. According to the steps outlined in **Formulas 10**
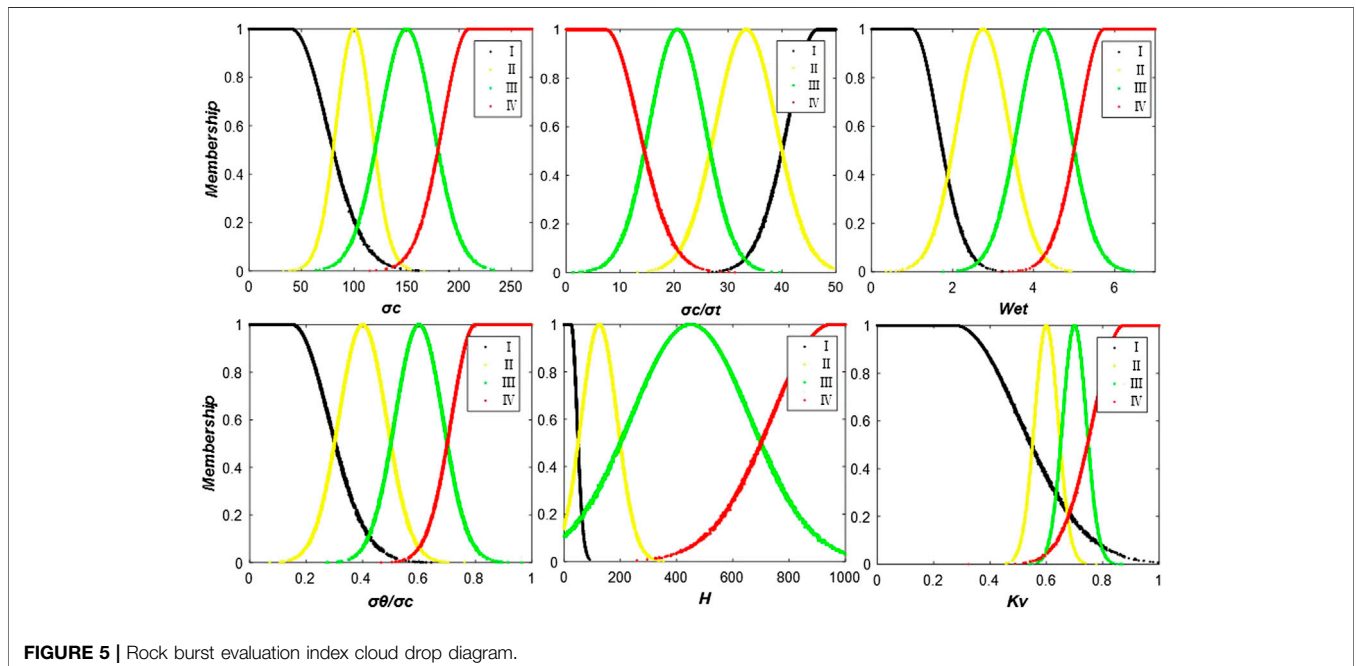

FIGURE 5 | Rock burst evaluation index cloud drop diagram.

Sample number	Evaluation factor						Actual rock burst grades
	I_1	I_2	I_3	I_4	I_5	I_6	
1	148.52	22.3	3.23	0.66	166	0.88	III
2	162.33	13.2	5.23	0.72	317	0.71	IV
3	116.78	29.73	3.52	0.37	177	0.68	II
4	109.33	32.77	2.97	0.42	148	0.71	II
5	98.56	42.73	2.17	0.28	171	0.49	I
6	156.73	20.13	3.82	0.49	289	0.91	III
7	100.32	28.77	3.02	0.38	182	0.70	II
8	142.20	27.52	4.30	0.72	308	0.73	III
9	160.32	16.55	5.72	0.69	265	0.90	IV
10	97.60	15.50	3.20	0.42	162	0.62	II
11	100.20	30.12	4.50	0.58	274	0.64	II
12	106.32	36.42	1.75	0.22	289	0.46	I
13	125.77	10.36	5.75	0.65	277	0.92	III
14	146.75	19.35	4.50	0.62	318	0.88	III
15	107.75	31.20	3.15	0.57	276	0.58	II
16	160.75	12.36	5.41	0.65	294	0.91	IV
17	146.72	18.75	4.20	0.59	342	0.84	III
18	162.70	29.70	3.82	0.73	278	0.70	III
19	95.50	42.30	2.75	0.37	215	0.36	I
20	105.70	37.35	3.08	0.37	155	0.66	II

and **11**, the Z-score method is used to standardize the index values in **Table 3** and then the mean and variance of each index are calculated. The coefficient of variation in each index is obtained by using **Eq. 12**. These results are shown in **Table 4**.

According to the basic concept of the Pearson correlation coefficient, the correlation coefficients of the standardized calculated indexes are obtained by referring to **Formula 13** as shown in **Table 5**.

The coefficient of independence of each index is obtained by using **Eq. 15**, and the coefficient of variation and the coefficient of independence of each index are multiplied by **Eq. 16**. Finally, using **Eq. 17**, we can obtain the weight values of each prediction index I_1 (σ_c), I_2 (σ_c/σ_t), I_3 (*Wet*), I_4 (σ_θ/σ_c), I_5 (*H*), and I_6 (K_v): 0.022, 0.142, 0.135, 0.340, 0.019, and 0.342, respectively.

Prediction Results and Analysis

According to the cloud model characteristic parameters obtained from the table, by substituting them into **Formula 8**, the degree of certainty of the selected test samples are calculated to categorize their hazard levels, and the corresponding weights are calculated according to **Formula 18**. According to the principle of maximum membership degree, the degrees of membership of the samples to be tested are shown in **Table 6**.

In order to further verify the accuracy of the calculation method proposed in this manuscript, we selected the calculation of F1 score for discussion and analysis. F1 Score is an indicator used in statistics to measure the accuracy of a binary classification model. It takes into account the accuracy and recall of the classification model. F1 score can be regarded as a weighted average of model accuracy and recall. Its maximum value is 1 and its minimum value is 0. The F1 score analysis includes the following four basic concepts, namely Tue Positive (*TP*:

prediction is positive, actual is positive); False Positive (*FP*: prediction is positive, actual is negative); False Negative (*FN*: prediction is negative, actually positive); True Negative (*TN*: predicted negative, actual negative). The so-called positive means that the predicted result is correct; the negative concept means that the predicted result is wrong. Therefore, for the rockburst grading of level 1, the *TP* value is 3, and similarly corresponding to the 2, 3, and 4 levels, the *TP* values are 6, 6, and 3 respectively. In terms of *FP* value and *FN* value, the situation is shown in **Table 8**:

The calculation formula for the precision rate *P* and the recall rate *R* are:

$$Precision\ P = \frac{TP}{TP + FP} \tag{20}$$

$$Recall\ R = \frac{TP}{TP + FN} \tag{21}$$

The formula for calculating F1 score is:

$$F1 = 2 \bullet \frac{Precision \bullet Recall}{Precision + Recall} \tag{22}$$

The calculation shows that the *p* value, *R* value, and F1 score are all 0.9, which also verifies that the model is reasonable and feasible in the exploration of rockburst tendency classification.

The calculation results of the proposed rock burst cloud model based on the CRITIC algorithm are consistent with the actual data, indicating that the proposed model is reasonable and effective for rock burst grading. The generation of sample error is due to the gray features of the rock burst problem itself, causing its prediction to have some ambiguity, and the factors affecting the rock burst tendency are multi-faceted and include other external environmental factors, such as the installation of artificial support and the humidity of the internal environment, all of which complicate the accuracy of rock burst tendency.

In the CRITIC method, the correlation between the information volume and the indicator index is comprehensively considered and the reliability of the weight calculation result is improved. As a cognitive model that realizes the qualitative concept and the bidirectional transformation of quantitative data, the cloud model can transform the ambiguity and randomness of the rock burst evaluation process into quantitative data of certainty, which accurately reflects the uncertainty of rock burst grading. This approach is superior to other methods.

Since rock burst tendency is a qualitative concept, the classification of its hazard level will be affected and controlled by many uncertain factors. Although the application of the cloud model has certain predictability for the occurrence of rock burst, the finite-interval cloud model cannot completely eliminate the gray features of its existence by transforming its ambiguity and randomness into certainty. The current cloud model used for evaluation does not reflect the characteristics of rock burst affected by multiple factors and does not reflect the correlation of factors in the process. The form of the actual distribution of the rock burst tendency evaluation index will have an impact on the

TABLE 4 | Sample-normalized index values and CRITIC algorithm index parameters.

Sample number			Sample standardization			
1	1.857	–0.699	–0.295	0.186	–5.055	0.196
2	3.080	–2.489	0.731	0.269	4.589	–0.005
3	–0.953	0.762	–0.146	–0.214	–4.353	–0.040
4	–1.613	1.360	–0.428	–0.145	–6.205	–0.005
5	–2.566	3.319	–0.838	–0.338	–4.736	–0.265
6	2.584	–1.126	0.008	–0.048	2.801	0.232
7	–2.410	0.573	–0.402	–0.200	–4.033	–0.017
8	1.298	0.327	0.254	0.269	4.014	0.019
9	2.902	–1.830	0.982	0.228	1.268	0.220
10	–2.651	–2.037	–0.310	–0.145	–5.311	–0.111
11	–2.421	0.839	0.357	0.076	1.843	–0.088
12	–1.879	2.078	–1.053	–0.421	2.801	–0.301
13	–0.157	–3.047	0.997	0.173	2.034	0.244
14	1.701	–1.279	0.357	0.131	4.653	0.196
15	–1.753	1.051	–0.336	0.062	1.970	–0.159
16	2.940	–2.654	0.823	0.173	3.120	0.232
17	1.698	–1.397	0.203	0.090	6.186	0.149
18	3.113	0.756	0.008	0.283	2.098	–0.017
19	–2.837	3.234	–0.541	–0.214	–1.926	–0.419
20	–1.934	2.261	–0.371	–0.214	–5.758	–0.064
Mean value of the sample						
	127.54	25.86	3.80	0.53	245.15	0.71
Sample variance						
	11.29	5.08	1.95	0.72	15.66	0.84
Coefficient of variation						
	0.09	0.20	0.51	1.38	0.06	1.18

evaluation results. The cloud model generated by the combination of uniform and normal distributions reflects the actual situation more reasonably, the parameter method must be further improved to generate more accurate results. In addition, the selection of the evaluation index should also be performed according to the actual project conditions and cannot be rushed. Because of the location of the rock burst, the external environment and human factors will affect the occurrence of rock burst.

ENGINEERING APPLICATION

The Dongguashan copper deposit is located in the Shizishan orefield of Tongling City, Anhui Province, on the polymetallic metallogenic belt along the Yangtze River. The surface is a hilly area with a ground elevation of 15–182 m. The ore body is inclined to 35° and dips to the northwest and southeast with the surrounding rock. The inclination angle is generally approximately 20°, and the maximum inclination angle is 30–35°. The ore body is mainly composed of copper-bearing skarns, copper-bearing pyrite, copper-bearing pyrrhotite and copper-bearing serpentinite. The direct surrounding rock of the ore body is the Carboniferous Lower Gorilla Formation of quartz diorite, which is dominated by horny siltstone. Dongguashan Copper Mine is the main mine of Tongling Nonferrous Metals Group Holdings Co., Ltd. The deposit is a layer-controlled skarn-type deeply buried deposit, with a burial depth of more than 700 m. Therefore, the original rock stress and ore strength of the mining area are relatively high. In the

process of mining, the prediction and prevention of rock burst has become a major issue and must be based on the study of rock burst tendency. Because the Dongguashan Copper Mine has a deep burial depth, a high initial rock stress, a favourable ore body structure and hard rock properties, rock burst is possible in this mine according to the experience of deep mine mining outside of China. Under the action of high stress, a destructive rock burst event with rock ejection as the main feature occurred during the construction of the tunnel during the construction and production of the Winter Melon Mountain Mine. Therefore, rock burst tendency predictions have become a focus of mine earthquake prevention and disaster reduction and important technical mean. In this paper, the physico-mechanical properties of the core of seven kinds of typical ore from the ore-bearing rock mass and the surrounding rock of the upper and lower layers are selected as the criterion for the 730 m middle section of the Dongguashan copper deposit (the geological map of this section is shown in

TABLE 5 | Normalized index Pearson correlation coefficients.

Forecast indicator	Pearson correlation coefficient					
	$I1$	$I2$	$I3$	$I4$	$I5$	$I6$
$I1$	1	–0.6473	0.6616	0.7770	0.5956	0.7381
$I2$	–0.6473	1	–0.8017	–0.6612	–0.4469	–0.8009
$I3$	0.6616	–0.8017	1	0.8066	0.5542	0.7315
$I4$	0.7770	–0.6612	0.8066	1	0.5719	0.6564
$I5$	0.5956	–0.4469	0.5542	0.5719	1	0.3291
$I6$	0.7381	–0.8009	0.7315	0.6564	0.3291	1

TABLE 6 | Rock burst propensity prediction results.

Sample number	Comprehensive certainty				Prediction results in this paper	Actual grade
	μ_1	μ_2	μ_3	μ_4		
1	0.011	0.134	0.442	0.414	III	III
2	0.049	0.010	0.442	0.499	IV	IV
3	0.126	0.469	0.347	0.058	II	II
4	0.084	0.508	0.321	0.087	II	II
5	0.647	0.339	0.013	0.001	I	I
6	0.018	0.230	0.418	0.334	III	III
7	0.109	0.479	0.336	0.076	II	II
8	0.043	0.084	0.545	0.329	III	III
9	0.008	0.004	0.335	0.652	IV	IV
10	0.126	0.628	0.181	0.065	II	II
11	0.088	0.335	0.521	0.056	IIIa	II
12	0.726	0.250	0.023	0.000	I	I
13	0.008	0.012	0.339	0.641	IV[a]	III
14	0.011	0.021	0.582	0.387	III	III
15	0.128	0.523	0.334	0.016	II	II
16	0.008	0.005	0.380	0.607	IV	IV
17	0.017	0.041	0.597	0.346	III	III
18	0.053	0.142	0.517	0.288	III	III
19	0.490	0.482	0.028	0.000	I~II	I
20	0.168	0.576	0.215	0.041	II	II

[a]Indicates misjudgement.

Figure 6). The core data of wells zk504 and zk504 are shown in Table 8 [57].

In this paper, six rock burst propensity prediction indexes are selected: the uniaxial compressive strength σ_c (I_1), ratio of the uniaxial compressive strength to the tensile strength σ_c/σ_t (brittleness coefficient, I_2), elastic deformation energy index Wet (I_3), and ratio of the maximum tangential stress to the uniaxial compressive strength σ_θ/σ_c (stress coefficient, I_4) of the rock, depth of the roadway H (I_5), and integrity coefficient of the rock mass K_v (I_6). A comparison of σ_c/σ_t and Wet is easy to obtain, and σ_θ/σ_c is determined by the formula of the maximum shear stress around the circular roadway:

$$\sigma_\theta = \xi(3 - \lambda)p_y \qquad (23)$$

where ξ is the laneway shape correction coefficient and λ is the side stress coefficient, which is equal to the ratio of the horizontal stress p_x to the vertical stress p_y.

The rock mass integrity coefficient K_v is the square of the longitudinal wave velocity of the rock mass. The longitudinal wave velocity V_p of the rock is easy to determine (as shown in Formula 23). Therefore, the value of K_v is determined according to V_p. The higher the elastic wave velocity is, the better the rock integrity. The rock sample test data of the Dongguashan Copper Mine are shown in Table 8 [58].

$$K_v = \left(\frac{V_{pm}}{V_{pr}}\right)^2 \qquad (24)$$

where K_v is the rock mass integrity coefficient, and V_{pm} is the longitudinal wave velocity of rock mass, and V_{pr} is the longitudinal wave velocity of indoor rock (block).

For the roadway height, since the height span is not very large, this paper takes the average measured height; based on these data, the value of the prediction index can be calculated. The calculation results are shown in Table 9.

Referring to the calculation method of the learning sample, the calculation and analysis of the actual engineering data can be comprehensively determined. The prediction results shown in Table 10 show that the rock burst tendencies of the diorite and siltstone are the strongest while those of the garnet skarn are the

TABLE 7 | Analysis of prediction results (TP, FP, FN values of different rockburst prediction grades).

	I	II	III	IV	Total
TP	3	6	6	3	18
FP	0	0	1	1	2
FN	0	1	1	0	2

TABLE 8 | Rock sample test data of seven typical ore rocks from Donggua Mountain.

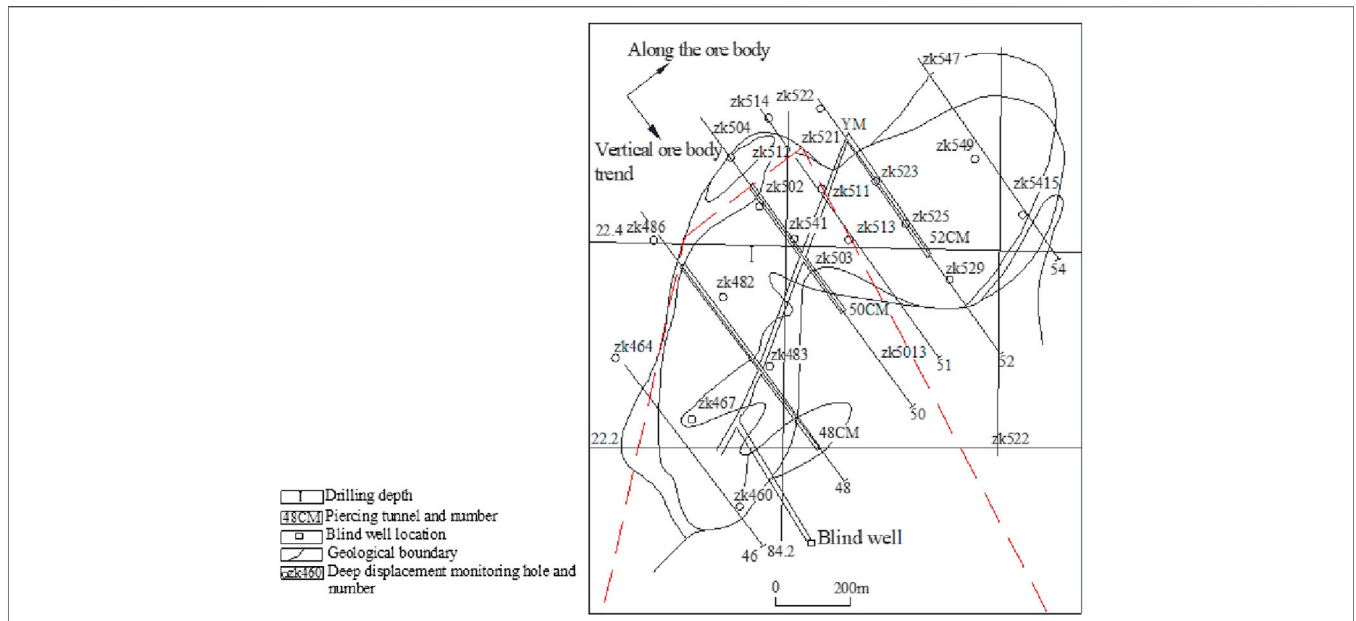| Rock type	Sampling depth	Stress level (p_x, p_y)	σ_c	σ_t	V_p	W_{et}
Skarn	631–637	(30.0, 25.4)	132.2	16.4	6,430	3.97
Diorite	720–735	(32.9, 28.0)	304.2	20.9	6,108	10.57
Garnet skarn	761–764	(33.9, 29.0)	128.6	13	7,025	5.76
Qixia formation marble	792–798	(34.9, 29.9)	78.3	6.8	4,709	3.11
Siltstone	837–849	(36.4, 31.2)	171.3	22.6	5,804	7.27
Quartz sandstone	850–853	(36.6, 31.5)	237.2	17.66	5,735	6.38

FIGURE 6 | Geological map of the 730 m middle section of the Dongguashan Copper Mine.

TABLE 9 | Rock burst tendency prediction value for the Dongguashan Copper Mine.

Rock type	Evaluation index					
	σ_c	σ_c/σ_t	W_{et}	σ_θ/σ_c	H	K_v
Skarn	132.2	8.06	3.97	0.55	634	0.75
Diorite	304.2	14.56	10.57	0.37	727.5	0.71
Garnet skarn	128.6	9.89	5.76	0.61	762.5	0.82
Qixia formation marble	78.3	11.51	3.11	0.82	795	0.55
Siltstone	171.3	7.58	7.27	0.53	843	0.68
Quartz sandstone	237.2	13.43	6.38	0.44	851.5	0.67

TABLE 10 | Rock burst tendency prediction results for the Dongguashan Copper Mine.

Rock type	Comprehensive certainty				Prediction results in this paper
	μ_1	μ_2	μ_3	μ_4	
Skarn	0.040	0.090	0.564	0.306	III
Diorite	0.128	0.306	0.178	0.389	IV
Garnet skarn	0.021	0.021	0.375	0.583	III~IV
Qixia formation marble	0.178	0.290	0.457	0.075	III
Siltstone	0.073	0.152	0.233	0.541	IV
Quartz sandstone	0.094	0.335	0.343	0.228	III

next strongest. The skarn grade is between III and IV, while the quartz sandstone and skarn are of grade III. The grade III predictions are the most certain, but the degree of membership for IV is not small. Finally, the Qixia Formation is predicted to be III (moderate rock burst).

Through the analysis of loading and unloading tests and the sum of the brittleness coefficient, impact energy index and

elastic deformation energy index, the rock burst tendency of each rock sample type is ranked from the largest to the smallest: siltstone, quartz sandstone, garnet skarn, skarn, and Qixia group marble. The prediction results of this paper are basically consistent with this strong-to-weak ranking.

CONCLUSION

(1) To further evaluate the rock burst tendency and provide corresponding engineering technical guidance, this article selects the membership function cloud model that considers randomness and ambiguity and comprehensively accounts for the complexity of multi-factors and the correlation between factors in the rock burst evaluation problem. The CRITIC weighting algorithm is selected for the comprehensive evaluation, the rationality of the evaluation method is verified by selecting 20 groups of underground engineering rock burst example data, and the method is finally applied to the Dongguashan copper mine. The explosion tendency evaluation obtained good results.

(2) Although the edge of the cloud model with uniform distribution reduces the actual error to a certain extent, deviations may occur between the actual production situation and the analysis result, such as the calculation of some parameters for Dongguashan. Therefore, the risk assessment result can only be used as a reference and the actual situation needs to be analyzed in detail. Capturing the risk factors that affect the occurrence of the disaster by the theoretical analysis process is indeed difficult because regardless of the

influencing factor selected for modeling, analysis and calculation, other objective factors may be ignored.

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.

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AUTHOR CONTRIBUTIONS

The first author JW drafted the content of the manuscript, there are related contents about on-site practice in this manuscript, MH is a member of Hongda Blasting Engineering Group Co., Ltd had in China and he is a Doctor of Engineering in Central South University who made relevant contributions and, the corresponding author JG was responsible for the guidance of the manuscript and put forward relevant revision opinions.

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