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A Novel Method for Predicting Rockburst Intensity Based on an Improved Unascertained Measurement and an Improved Game Theory

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Abstract: A rockburst is a dynamic disaster that may result in considerable damage to mines and pose a threat to personnel safety. Accurately predicting rockburst intensity is critical for ensuring mine safety and reducing economic losses. First, based on the primary parameters that impact rockburst occurrence, the uniaxial compressive strength (σ_c), shear–compression ratio (σ_θ/σ_c), compression–tension ratio (σ_c/σ_t), elastic deformation coefficient (W_{et}), and integrity coefficient of the rock (K_V) were selected as the evaluation indicators. Second, an improved game theory weighting method was introduced to address the problem that the combination coefficients calculated using the traditional game theory weighting method may result in negative values. The combination of indicator weights obtained using the analytic hierarchy process, the entropy method, and the coefficient of variation method were also optimized using improved game theory. Third, to address the problem of subjectivity in the traditional unascertained measurement using the confidence identification criterion, the distance discrimination idea of the Minkowski distance was used to optimize the identification criteria of the attributes in an unascertained measurement and was applied to rockburst prediction, and the obtained results were compared with the original confidence identification criterion and the original distance discrimination. The results show that the improved game theory weighting method used in this model makes the weight distribution more reasonable and reliable, which can provide a feasible reference for the weight determination method of rockburst prediction. When the Minkowski distance formula was introduced into the unascertained measurement for distance discrimination, the same rockburst predictions were obtained when the distance parameter (p) was equal to 1, 2, 3, and 4. The improved model was used to predict and analyze 40 groups of rockburst data with an accuracy of 92.5% and could determine the rockburst intensity class intuitively, providing a new way to analyze the rockburst intensity class rationally and quickly.

Keywords: improving game theory; combination weights; improving unascertained measurement; distance discrimination; rockburst prediction

MSC: 28E99

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1. Introduction

It is well known that underground space engineering, such as mining and tunnel transportation, is constantly extending deeper into the earth [1–3]. However, with the deepening of underground engineering, the probability of engineering disasters also increases, especially that of rockbursts induced by high geo-stress [1]. Rockbursts, which are sudden releases of energy and rock ruptures caused by external disturbances under conditions of high ground stress, have been called a geological “cancer”. They are a relatively common engineering geohazard during the excavation and construction of deeply buried underground structures and are characterized by high risk, suddenness, and unpredictability [4–8]. For instance, a severe rockburst that happened on 28 November 2009 at the Jinping II hydropower facility in China caused seven fatalities, one major injury,

and the destruction of a tunnel-boring machine [9]. In November 2011, a catastrophic rockburst at the Qianqiu Mine in Henan Province killed 10 miners and injured 64 more [10]. On 31 May 2015, a rockburst at the Neelum–Jhelum Hydropower Project in Pakistan resulted in the deaths of three workers and the destruction of a TBM [11]. This type of disaster causes significant economic damage and casualties and poses a serious threat to the safety of construction personnel and equipment. In severe cases, it can even induce earthquakes. During construction, various techniques can be used to reduce the harm caused by rockbursts, such as improving the stress on the wall rock, improving the nature of the wall rock, and maintaining the integrity of the wall rock by using controlled blasting techniques, water spraying, water injection, enhanced support or advanced support, and other technical means [12]. However, due to the uncertainty of rockbursts, the prediction of rockburst probability and intensity classification has been a worldwide problem in the field of rock engineering, with positive implications for practical construction [13–16].

Rockburst criteria can typically be classified into two categories: single-indicator empirical criteria and multi-factor empirical evaluation criteria [1,4,17,18]. The commonly used single-indicator criteria include Turchaninov’s criterion [19], Russenes’ criterion [20], Barton’s criterion [21], Hoek’s criterion [22], and the rock elastic energy index [23], among others. However, these criteria usually only consider one or two influencing factors. Because the mechanism behind rockbursts is complex, multiple factors affect their occurrence. Therefore, these single-indicator criteria have limitations when predicting rockbursts [1]. Recognizing these limitations, some scholars have attempted to use key factors that influence rockburst occurrence as evaluation indicators [24]. Wang [25] was the first to propose a multi-factor rockburst prediction model through the lens of fuzzy mathematical theory, which offers a new comprehensive approach for predicting rockbursts. Many scholars have since begun to combine multi-factor indicators and mathematical methods to develop suitable mathematical models or empirical evaluation systems for integrated rockburst prediction in some underground engineering projects. The multi-factor rockburst prediction models are mainly divided into uncertainty evaluation models and intelligent optimization evaluation models. In the field of rockburst prediction uncertainty evaluation, there are several models available, including the distance discrimination method [26,27], the cloud model [28,29], extenics [30,31], the rough set theory [32], the efficacy coefficient method [33,34], set pair analysis [18,35], the attribute measure [36], the ideal point method [24,37], TOPSIS [38,39], fuzzy set theory [40,41], etc. All of these models consider a combination of rockburst indicators and their non-linear relationships with rockburst risk. However, there are still challenges in terms of selecting appropriate model functions, handling multi-source data with multiple indicators and indicator weights, and the critical issue of determining the weights of rockburst correlation indicators and their influencing factors while avoiding subjective decision making [1,24]. Intelligent optimization algorithms are novel methods that have been proposed to solve complex optimization problems. They were inspired by the principles of biological evolution and some physical phenomena. Among the mainstream intelligent optimization algorithms are PSO [16,42,43], BP neural networks [44,45], Bayesian networks [46,47], random forests [48,49], genetic algorithms [50], support vector machines [51], decision tree models [52,53], and so on. These algorithms have shown excellent performances in handling complex problems and exhibit high computational efficiency. However, the accuracy of their evaluation depends to some extent on the quality of the training sample. Moreover, they are also computationally expensive [54].

Unascertained measurement is a method that can effectively deal with fuzzy and uncertain information [55]. However, the traditional unascertained measurement approach uses a confidence criterion for calculations [56–61], which introduces some subjectivity. To ensure the objectivity of discrimination results, the idea of distance discrimination can be introduced to optimize an attribute recognition model. Additionally, the game theory method resolves the contradiction between subjective and objective empowerment methods, ensuring the accuracy of quantitative analyses and the scientificity of qualitative analyses. To avoid the unreasonable phenomenon of negative values for combined weight

coefficients that may arise from the traditional game theory calculation method, constraints were introduced to the existing formula, and an improved game theory weighting method was applied for the first time in the field of rockburst prediction. A flow chart of this paper is shown in Figure 1.

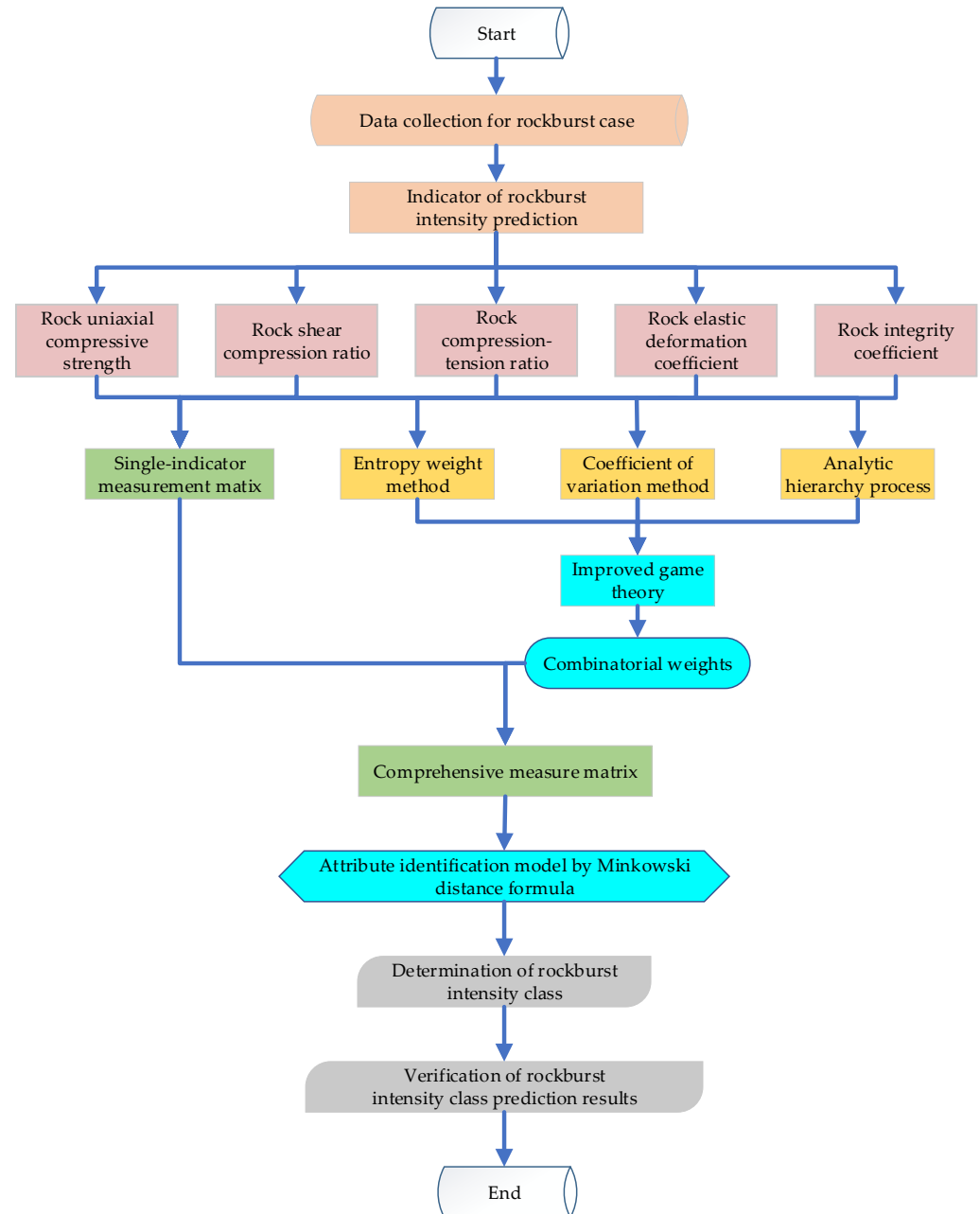


Figure 1. Model framework for predicting rockburst intensity.

2. Weighting Calculation Method

The indicator weights play a crucial role in rockburst prediction and evaluation, as they reflect the relative contribution of each indicator to the evaluated object, mainly including subjective and objective weighting methods [55]. The subjective weighting method mainly assesses the weight of each indicator in the decision-making process by evaluating the experience and attitude of the decision maker, thereby determining the level of importance of each indicator to the final decision, while the objective weighting method obtains relatively objective calculation results by using mathematical algorithms based on all the information contained in the raw data.

2.1. Subjective Weighting Method

The analytic hierarchical process (AHP) is a comprehensive evaluation method for system analysis and decision making that was proposed by T. L. Saaty [62]. AHP is a subjective assignment method based on a priority judgment matrix of pairwise comparisons of indicators. It organically integrates quantitative analysis and qualitative analysis to systematically and hierarchically analyze decision problems. In this study, a judgment matrix is constructed using the 9-level scale method to calculate the indicator's subjective weight coefficient, denoted as W_1 , and the matrix is tested for consistency.

The consistency index (CI) is calculated as follows:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (1)$$

where CI is the consistency index; $\lambda_{\max}$ denotes the maximum eigenvalue of the judgment matrix; and n is the order of the judgment matrix.

The value of the random consistency indicator RI of the matrix is judged, as shown in Table 1.

Table 1. Dimensions and corresponding RI values [36].

Dimensions	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49

The consistency ratio (CR) is calculated as follows:

$$CR = \frac{CI}{RI} \quad (2)$$

If $CR < 0.1$, it means that the judgment matrix meets the consistency requirement with the normalized feature vector as the weight vector; otherwise, the judgment matrix would need to be readjusted.

The factors involved in the rockburst prediction criterion can be broadly classified into three categories: rock mechanics properties, rock stress conditions, and surrounding rock conditions. To evaluate the rockburst risk, these key influencing factors are hierarchically divided, and the relevant target layer, guideline layer, and plan layer are determined, as shown in Figure 2.

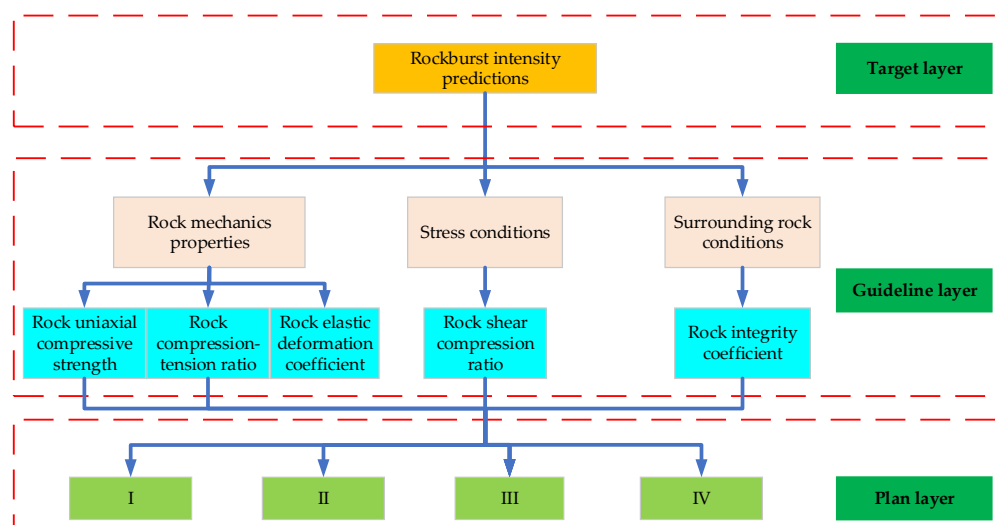


Figure 2. A diagram of the evaluation indicator hierarchy.

2.2. Objective Weighting Method

2.2.1. Entropy Weight Method

The mathematician Shannon introduced the concept of thermodynamic entropy into information theory in 1948 to measure the uncertainty of a system [63]. The “entropy” approach calculates indicator weights based on the information utility provided by each indicator, making it an objective weighting method. Indicators with smaller entropy values contain more information and contribute less uncertainty to the system [64]. The weight (W_2) calculated by the entropy weighting method can effectively avoid the subjective influence of weighting decisions with more objective results.

Suppose there are m objects to be evaluated and each has t evaluation indicators. Let the j th index of the i th objects take the value x_{ij} , forming the original evaluation index data matrix as

$$X = (x_{ij})_{m \times t} \quad (3)$$

Step 1: normalization process:

For benefit-based indicators:

$$b_{ij} = \frac{x_{ij} - \min_j(x_{ij})}{\max_j(x_{ij}) - \min_j(x_{ij})} \quad (4)$$

For cost-based indicators:

$$b_{ij} = \frac{\max_j(x_{ij}) - x_{ij}}{\max_j(x_{ij}) - \min_j(x_{ij})} \quad (5)$$

where $\max_j(x_{ij})$ and $\min_j(x_{ij})$ denote the maximum and minimum values of the j th column of matrix X , respectively.

Step 2: calculate the entropy value of each indicator:

$$E_j = \frac{-\sum_{i=1}^m F_{ij} \ln F_{ij}}{\ln m} \quad (6)$$

where

$$F_{ij} = \frac{1 + b_{ij}}{\sum_{i=1}^m (1 + b_{ij})} \quad (7)$$

when $f_{ij} = 0$, E_i is 0. where b_{ij} is the value of the indicator normalized according to Equations (4) and (5).

Step 3: determine the indicator weight:

$$\lambda_i = \frac{1 - E_i}{t - \sum_{j=1}^t E_j} \quad (i = 1, 2, \dots, t) \quad (8)$$

Therefore, the weights $W_2 = (\lambda_1, \lambda_2, \dots, \lambda_m)$ are calculated using the entropy weight method.

2.2.2. Coefficient of Variation Method

The coefficient of variation method (CV) is utilized to measure the degree of variation in the values taken by each indicator through the coefficient of variation of each indicator. The higher the degree of variation, the greater the degree of importance of an indicator, and the higher the weight of an indicator [65]. The weights calculated using this method can

eliminate the influence of the evaluation indicator system on the calculation process caused by the different quantitative units and orders of magnitude of each indicator, providing an objective and dynamic weighting method [31]. The steps involved in this method are as follows:

$$\delta_j = \sigma_j / h_j \quad (9)$$

$$v_j = \frac{\delta_j}{\sum_{j=1}^t \delta_j} \quad (10)$$

where σ_j is the coefficient of variation of the indicator; σ_j is the standard deviation; h_j is the mean of the indicator; and v_j is the weight of the indicator.

Therefore, the weights $W_3 = (v_1, v_2, \dots, v_t)$ are calculated using the coefficient of variation method.

2.3. Improved Game Theory Combination Weighting Method

The fundamental principle of the game theory weighting method is to seek linear combination coefficients so that the deviation between the combination weights and the weights calculated using different methods is minimized. However, the combination coefficients calculated using the traditional game theory weighting method may have negative values, which is inconsistent with the actual situation [66]. Therefore, some scholars [67] have proposed improvements to the game theory weighting method by introducing a constraint function to ensure that the combination coefficients are non-negative. The improved game theory can be used to calculate the combined weight (W_C). The specific steps for calculating the combined weights using the improved game theory are as follows:

Let the weights of the evaluation indicators be calculated by K methods and then establish the linear combination of the integrated weight (W_C) for the K weights, as shown in Equation (11):

$$W_C = \sum_{i=1}^K \alpha_i w_i^T \quad (11)$$

where α_i is the linear combination coefficient, $\alpha_i > 0$, and w_i^T is the transpose of the weight row vector calculated using the i th method.

The countermeasure model of the optimal solution of W_C is established to minimize the deviation of the integrated weight from all w_i values, as shown in Equation (12):

$$\text{Min} \left\| \sum_{i=1}^K \alpha_i w_i^T - w_r \right\|_2, r = 1, 2, \dots, K \quad (12)$$

The optimal condition of Equation (12) can be derived from the differential properties of the matrix, as shown in Equation (13):

$$\text{Min}_{\alpha_1, \alpha_2, \dots, \alpha_l} g = \sum_{i=1}^K \left| \left(\sum_{j=1}^K \alpha_j w_i w_j^T \right) - w_i w_i^T \right| \quad (13)$$

To ensure that the calculated combination coefficients are greater than 0, an optimization model is established with the addition of constraints, as shown in Equation (14):

$$\begin{cases} \text{Min}_{\alpha_1, \alpha_2, \dots, \alpha_l} g = \sum_{i=1}^K \left| \left(\sum_{j=1}^K \alpha_j w_i w_j^T \right) - w_i w_i^T \right| \\ \text{s.t. } \sum_{j=1}^n \alpha_j^2 = 1, \alpha_j > 0, j = 1, 2, \dots, K \end{cases} \quad (14)$$

To solve the model, the following Lagrangian function (Equation (15)) is established:

$$L(a_j, \lambda) = \sum_{i=1}^K \left| \left(\sum_{j=1}^K a_j w_i w_j^T \right) - w_i w_i^T \right| + \frac{\lambda}{2} \left(\sum_{j=1}^K a_j^2 - 1 \right) \quad (15)$$

The optimal solution of the combination coefficient $\alpha_j (\alpha_j > 0)$ is calculated by solving Equation (16), as shown in Equation (17):

$$\alpha_j = \frac{\sum_{i=1}^K w_i w_j^T}{\sqrt{\sum_{j=1}^K \left(\sum_{i=1}^K w_i w_j^T \right)^2}} \quad (16)$$

$$\alpha_j^* = \frac{\sum_{i=1}^K w_i w_j^T}{\sum_{j=1}^K \sum_{i=1}^K w_i w_j^T} \quad (17)$$

This value can be substituted into Equation (11), which can be solved to obtain the combined weight (W_C), followed by normalization, as shown in Equation (18):

$$W = \sum_{j=1}^K \alpha_j^* w_j^T \quad (18)$$

3. Evaluation Method

3.1. Multi-Indicator Comprehensive Measurement

Unascertained measurement, a mathematical method for dealing with uncertain information, was first proposed by Professor Wang [68]. Based on this study, Liu [69] proposed a mathematical theory of unascertained measurement and first applied it to the evaluation problem. After years of unremitting research by many experts and scholars, its theoretical system has gradually matured and has been applied in many fields [57,70,71].

There are m samples of object X to be evaluated, and for each evaluated object ($X = \{X_1, X_2, \dots, X_m\}$) there are k single evaluation index spaces, denoted as $R = \{R_1, R_2, \dots, R_t\}$. Let X_i be denoted as a t -dimensional vector ($X_i = \{x_{i1}, x_{i2}, \dots, x_{it}\}$), where x_{ij} denotes the measurement of the evaluation object (X_i) with respect to the evaluation index (R_j). For each subtest (x_{ij}) with k evaluation levels, assume that the evaluation space (P) has k evaluation levels, denoted as $P = \{P_1, P_2, \dots, P_k\}$. The t th evaluation class (P_t) is the class value of x_{ij} . Let class P_{i+1} be "higher" or "lower" than class P_i , denoted as $P_{i+1} > P_i$. If $P_k > P_{k-1} > \dots > P_2 > P_1$ is satisfied, then $\{P_1, P_2, \dots, P_k\}$ is called an ordered partition class of the evaluation class space (P).

$\mu_{ijt} = \mu(x_{ij} \in P_t)$ denotes the degree to which observation x_{ij} belongs to the t th assessment class (P_t), with μ being satisfied as follows:

$$0 \leq \mu(x_{ij} \in P_l) \leq 1 \quad (i = 1, 2, \dots, m; j = 1, 2, \dots, t; l = 1, 2, \dots, k) \quad (19)$$

$$\mu(x_{ij} \in P) = 1 \quad (20)$$

$$\mu \left| x_{ij} \in \bigcup_{l=1}^k P_l \right| = \sum_{i=1}^k \mu(x_{ij} \in P_i) \quad (21)$$

where Equation (19) is called non-negative boundedness, Equation (20) is called normalizability, Equation (21) is called additivity, and μ satisfied by Equations (19)–(21) at the same time is called an unascertained measurement.

There are many ways to construct single-indicator measure functions, but linear measure functions are considered to be the simplest and most widespread in application [58,60].

$$(\mu_{ijl})_{t \times k} = \begin{bmatrix} \mu_{i11} & \mu_{i12} & \cdots & \mu_{i1k} \\ \mu_{i21} & \mu_{i22} & \cdots & \mu_{i2k} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{it1} & \mu_{it2} & \cdots & \mu_{itk} \end{bmatrix} \quad (22)$$

The weighted comprehensive measure matrix (C) of multiple indicators can be calculated using Equations (18) and (22).

$$C = W \cdot \begin{bmatrix} \mu_{i11} & \mu_{i12} & \cdots & \mu_{i1k} \\ \mu_{i21} & \mu_{i22} & \cdots & \mu_{i2k} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{it1} & \mu_{it2} & \cdots & \mu_{itk} \end{bmatrix} \quad (23)$$

3.2. Improving the Attribute Recognition Model Using Distance Discrimination

The characteristics of things are divided into k categories: $F_1, F_2, \dots, F_k$. Correspondingly, the m factors are also classified into k categories. Then, the sample mean of each category is determined as the classification center of k classification patterns ($F_1, F_2, \dots, F_k$), so the unascertained measurements are $f_1 = [1, 0, 0, \dots, 0]$, $f_2 = [0, 1, 0, \dots, 0]$, ..., $f_k = [0, 0, 0, \dots, 1]$, respectively.

The distance discrimination method is used as the attribute identification criterion so that the distance ($L_{p,k}$) calculated using Minkowski's distance formula is the distance from the comprehensive multi-indicator measure (μ_{ijk}) to the classification class (v_k). The formula is shown below.

$$L_{p,k} = \left(\sum_{i=1}^n |x_{ijk} - f_k|^p \right)^{\frac{1}{p}} \quad (24)$$

When $p = 1$, the Minkowski distance formula is the Manhattan distance.

$$L_{1,k} = \sum_{i=1}^n |x_{ijk} - f_k| \quad (25)$$

When $p = 2$, the Minkowski distance formula is the Euclidean distance.

$$L_{2,k} = \sqrt{\sum_{i=1}^n (x_{ijk} - f_k)^2} \quad (26)$$

For convenience of calculation in engineering applications, this paper compares the magnitude of each unascertained measurement distance ($L_{p,j} (j = 1, 2, \dots, k)$) by taking $p = 1, 2, 3$, and 4, as shown in Equation (27):

$$d_{p,\min} = \text{Min}(L_{p,1}, L_{p,2}, \dots, L_{p,k}) \quad (27)$$

If $d_{p,\min} = L_{p,k}$, it indicates that the sample (p) to be predicted is closest to class k and thus could be classified into class k .

4. Rockburst Intensity Class Prediction

From the study of most of the discrimination indicators of rockburst prediction [25,31,36,55], the five indicators of rock uniaxial compressive strength (σ_c), the ratio of rock uniaxial compressive strength to tensile strength (σ_θ/σ_c), the ratio of rock uniaxial compressive strength to tensile strength (σ_c/σ_t), rock elastic deformation indicator (W_{et}), and the rock integrity coefficient (K_V) contain the main information for predicting rockbursts. By classifying rocks, it is possible to gain more valuable insights into them [72]. Take {no rockburst,

low rockburst, medium rockburst, heavy rockburst} = {I,II,III,IV}. Each evaluation indicator classification was established, as shown in Table 2, and a single-indicator measurement chart is shown in Figure 3.

Table 2. Single-indicator classification standards for rockburst intensity.

Evaluation Indicators	σ_c (MPa)	σ_θ/σ_c	σ_c/σ_t	W_{et}	K_V
No rockburst (I)	0–80	0–0.3	40–53	0–2.0	0–0.55
Low rockburst (II)	80–120	0.3–0.5	26.7–40	2.0–3.5	0.55–0.65
Medium rockburst (III)	120–180	0.5–0.7	14.5–26.7	3.5–5.0	0.65–0.75
Heavy rockburst (IV)	180–320	0.7–1.0	0–14.5	5.0–10.0	0.75–1.0

To verify the reasonableness and validity of the improved rockburst intensity prediction model, 40 sets of typical rockburst example data from the literature [25,32,36,55,73–76] were counted, and detailed indicators of the measured values and actual rockburst classes are shown in Table 3.

The weights $W_1 = [0.1429, 0.1429, 0.1429, 0.2857, 0.2857]$ were calculated according to the AHP evaluation method, the weights $W_2 = [0.2403, 0.2560, 0.1019, 0.2323, 0.1695]$ of the entropy weight method were calculated according to Equations (3)–(8), and the weights $W_3 = [0.2255, 0.2283, 0.1404, 0.2220, 0.1839]$ of the coefficient of variation method were calculated according to Equations (9) and (10). Then, the combination weights of each indicator were calculated using the improved game theory method (Equations (17) and (18)) to be Equation (28), as shown in Table 4 and Figure 4.

$$W = [0.2028, 0.2090, 0.1283, 0.2467, 0.2132] \quad (28)$$

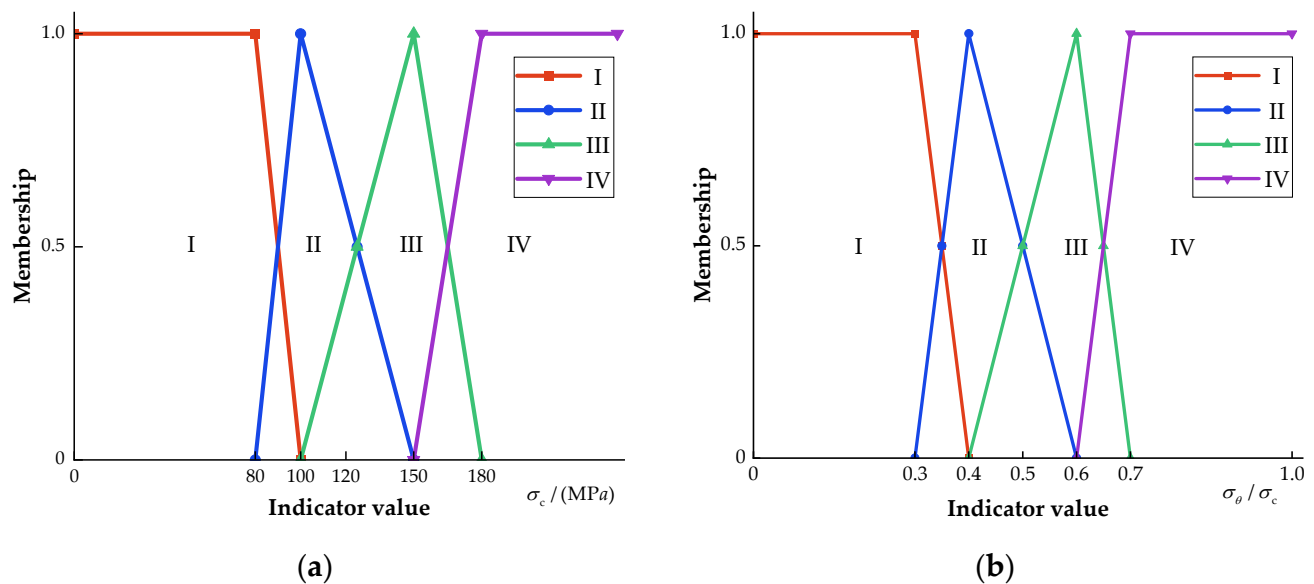


Figure 3. Cont.

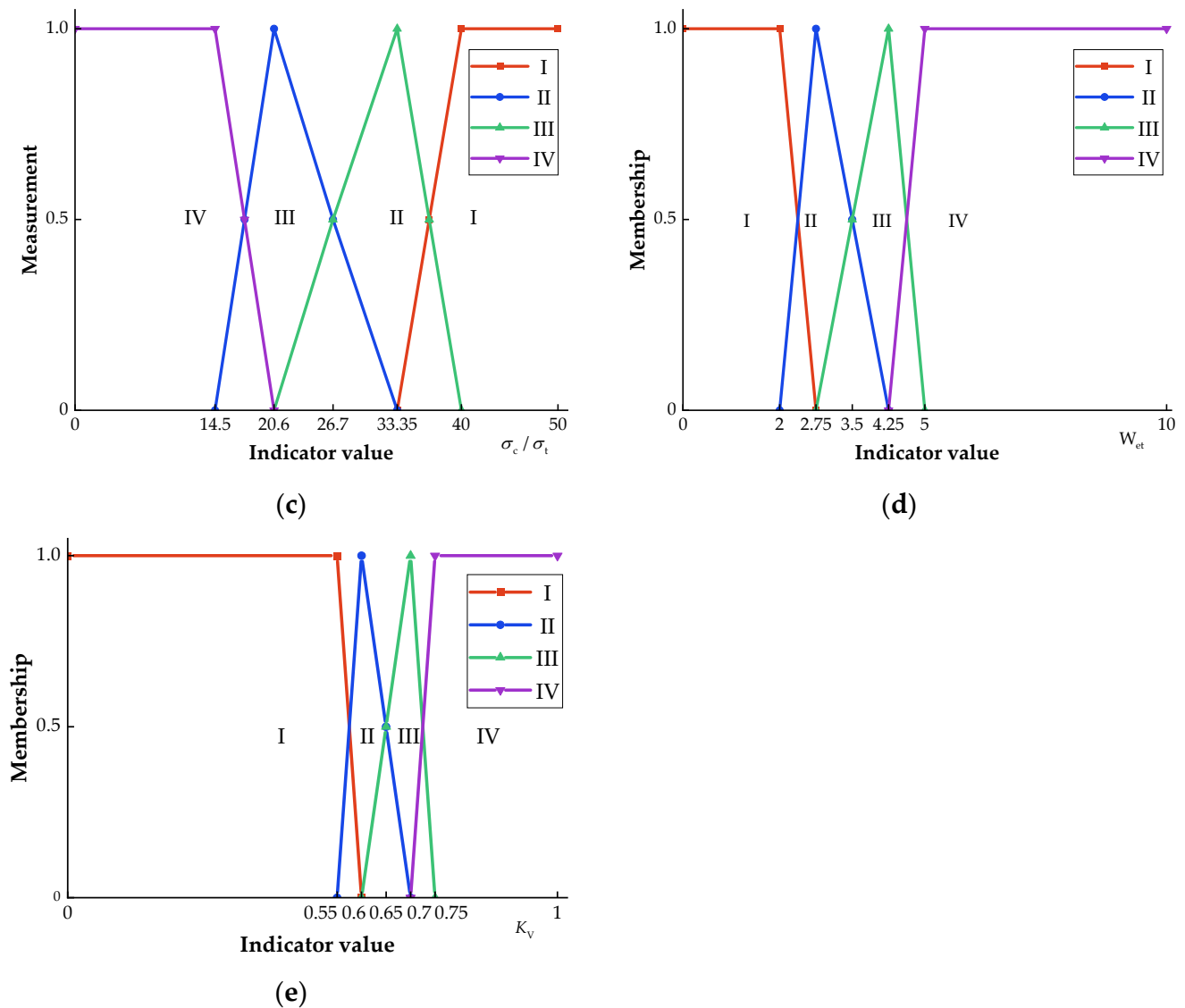


Figure 3. Single-indicator measurement functions for rockbursts. (a) Measurement function of rock uniaxial compressive strength. (b) Measurement function of rock shear to compressive strength ratio. (c) Measurement function of rock compressive strength–tensile strength ratio. (d) Measurement function of rock elastic deformation coefficient. (e) Measurement function of rock integrity coefficient.

Table 3. Indicators and classes of actual rockburst intensity.

Sample	Actual Data for Rockburst Indicators					Classification
	σ_c (MPa)	σ_θ / σ_c	σ_c / σ_t	W_{et}	K_v	
1	148.40	0.45	17.46	5.10	0.68	III
2	157.60	0.58	13.24	6.30	0.79	IV
3	107.50	0.20	41.35	1.70	0.50	I
4	167.20	0.66	13.17	6.80	0.82	IV
5	170.00	0.53	15.04	6.50	0.70	III
6	181.00	0.42	21.81	4.50	0.67	III
7	130.00	0.38	19.70	5.00	0.69	III
8	215.00	0.30	24.00	6.60	0.73	III
9	153.00	0.38	22.10	5.10	0.72	III
10	173.00	0.42	21.70	5.20	0.74	III

Table 3. Cont.

Sample	Actual Data for Rockburst Indicators					Classification
	σ_c (MPa)	σ_θ/σ_c	σ_c/σ_t	W_{et}	K_V	
11	156.00	0.20	11.20	3.60	0.44	I
12	172.00	0.77	17.50	5.50	0.82	IV
13	121.00	0.72	13.90	9.05	0.91	IV
14	124.00	0.64	14.40	7.74	0.96	IV
15	120.00	0.52	18.60	4.16	0.87	III
16	157.63	0.58	13.18	6.27	0.79	IV
17	132.05	0.39	20.86	4.63	0.65	III
18	127.93	0.28	28.90	3.67	0.60	II
19	96.41	0.19	47.93	1.87	0.43	I
20	167.19	0.66	13.20	6.83	0.82	IV
21	118.46	0.22	33.75	2.89	0.54	II
22	148.52	0.66	22.30	3.23	0.88	III
23	162.33	0.72	13.20	5.23	0.71	IV
24	116.78	0.37	29.73	3.52	0.68	II
25	109.33	0.42	32.77	2.97	0.71	II
26	98.56	0.28	42.73	2.17	0.49	I
27	156.73	0.49	20.13	3.82	0.91	III
28	100.32	0.38	28.77	3.02	0.70	II
29	142.20	0.72	27.52	4.30	0.73	III
30	160.32	0.69	16.55	5.72	0.90	IV
31	97.60	0.42	15.50	3.20	0.62	II
32	106.32	0.22	36.42	1.75	0.46	I
33	146.75	0.62	19.35	4.50	0.88	III
34	160.75	0.65	12.36	5.41	0.91	IV
35	146.72	0.59	18.75	4.20	0.84	III
36	162.70	0.73	29.70	3.82	0.70	III
37	157.60	0.58	13.20	6.30	0.79	IV
38	132.10	0.39	20.90	4.60	0.65	III
39	107.50	0.20	41.00	1.70	0.50	I
40	167.20	0.66	13.20	6.80	0.82	IV

Table 4. The weights of each indicator of rockburst intensity.

Methods	σ_c (MPa)	σ_θ/σ_c	σ_c/σ_t	W_{et}	K_V
AHP	0.1429	0.1429	0.1429	0.2857	0.2857
EWM	0.2403	0.2560	0.1019	0.2323	0.1695
CV	0.2255	0.2283	0.1404	0.2220	0.1839
GT	0.2028	0.2090	0.1283	0.2467	0.2132

Sample 1 is used as an example in this paper, while the computational process of the remaining 39 groups of samples was the same as that of sample 1. Therefore, only the computational results are listed (see Table 5), and the detailed computational process is not repeated.

Table 5. Statistics of the predicted results of the case samples.

Sample	I-1	I-2	I-3	I-4	C-0.6	C-0.7	MD-1	MD-2	Actual Class
1	III	III	III	III	III	IV●	III	III	III
2	IV	IV	IV	IV	IV	IV	III●	III●	IV
3	I	I	I	I	I	I	II●	II●	I
4	IV	IV	IV	IV	IV	IV	III●	IV	IV
5	IV●	IV●	IV●	IV●	IV●	IV●	III	III	III

Table 5. Cont.

Sample	I-1	I-2	I-3	I-4	C-0.6	C-0.7	MD-1	MD-2	Actual Class
6	III	III	III	III	III	III	III	III	III
7	III	III	III	III	III	III	III	III	III
8	IV•	IV•	IV•	IV•	IV•	IV•	III	III	III
9	III	III	III	III	III	IV•	III	III	III
10	IV•	IV•	IV•	IV•	IV•	IV•	III	III	III
11	I	I	I	I	III•	III•	II•	II•	I
12	IV	IV	IV	IV	IV	IV	IV	III•	IV
13	IV	IV	IV	IV	IV	IV	IV	IV	IV
14	IV	IV	IV	IV	IV	IV	IV	IV	IV
15	III	III	III	III	III	III	III	III	III
16	IV	IV	IV	IV	IV	IV	III•	III•	IV
17	III	III	III	III	III	III	III	III	III
18	II	II	II	II	II	III•	II	II	II
19	I	I	I	I	I	I	II•	I	I
20	IV	IV	IV	IV	IV	IV	III•	IV	IV
21	II	II	II	II	II	II	II	II	II
22	III	III	III	III	III	IV•	III	III	III
23	IV	IV	IV	IV	IV	IV	III•	III•	IV
24	II	II	II	II	III•	III•	II	II	II
25	II	II	II	II	II	III•	II	II	II
26	I	I	I	I	I	I	II•	II•	I
27	III	III	III	III	III	III	III	III	III
28	II	II	II	II	II	III•	II	II	II
29	III	III	III	III	III	IV•	III	III	III
30	IV	IV	IV	IV	IV	IV	IV	IV	IV
31	II	II	II	II	II	II	II	II	II
32	I	I	I	I	I	I	I	II•	I
33	III	III	III	III	III	IV•	III	III	III
34	IV	IV	IV	IV	IV	IV	III•	IV	IV
35	III	III	III	III	III	III	III	III	III
36	III	III	III	III	III	III	III	III	III
37	IV	IV	IV	IV	IV	IV	III•	III•	IV
38	III	III	III	III	III	III	III	III	III
39	I	I	I	I	I	I	II•	II•	I
40	IV	IV	IV	IV	IV	IV	III•	IV	IV

In the table, I-1 indicates an improved unascertained measurement with $p = 1$; C-0.6 indicates an unascertained measurement with a credibility degree of 0.6; MD-1 and MD-2 denote the distance discriminants of the Manhattan distance and Euclidean distance, respectively; and • indicates a misjudgment.

According to Equations (19)–(21), the single-indicator measure matrix was:

$$\mu = \begin{bmatrix} 0 & 0.032 & 0.968 & 0 \\ 0 & 0.750 & 0.250 & 0 \\ 0 & 0 & 0.485 & 0.515 \\ 0 & 0 & 0 & 1 \\ 0 & 0.200 & 0.800 & 0 \end{bmatrix} \quad (29)$$

According to Equations (23), (28), and (39), the comprehensive weight was:

$$C = [0 \quad 0.206 \quad 0.481 \quad 0.313] \quad (30)$$

According to Equation (25), when $p = 1$, unascertained measurement distance L can be calculated:

$$\begin{aligned}
L_{1,1} &= |0 - 1| + |0.206 - 0| + |0.481 - 0| + |0.313 - 0| = 2.000 \\
L_{1,2} &= |0 - 0| + |0.206 - 1| + |0.481 - 0| + |0.313 - 0| = 1.588 \\
L_{1,3} &= |0 - 0| + |0.206 - 0| + |0.481 - 1| + |0.313 - 0| = 1.038 \\
L_{1,4} &= |0 - 0| + |0.206 - 0| + |0.481 - 0| + |0.313 - 1| = 1.374
\end{aligned} \tag{31}$$

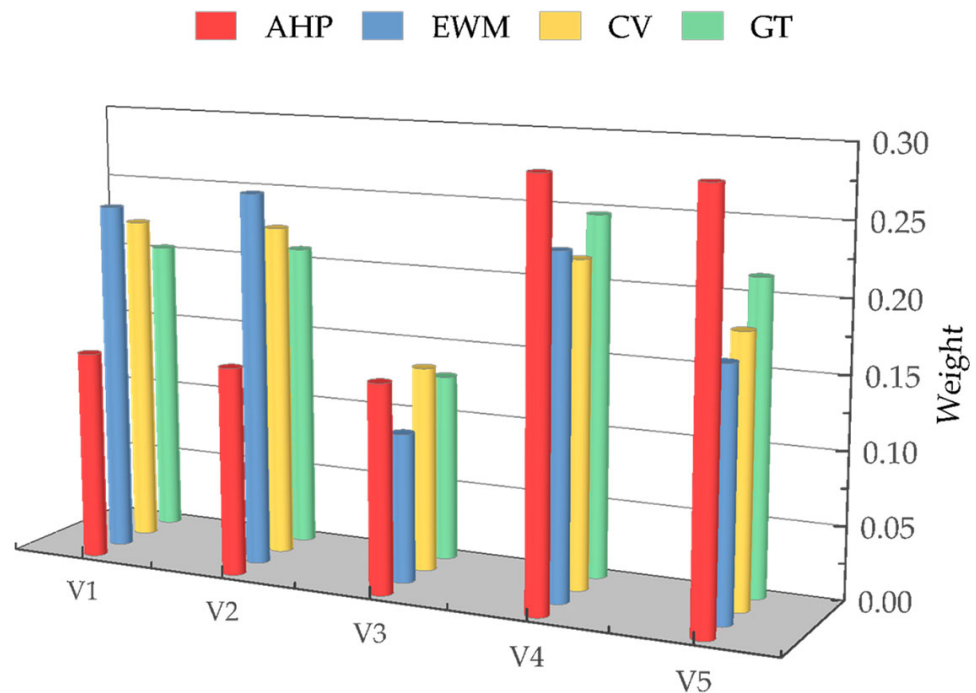


Figure 4. Visual comparison of indicator weights. In the figure, V1, V2, V3, V4, and V5 represent σ_c , σ_θ/σ_c , σ_c/σ_t , W_{et} , and K_V and AHP, EWM, CV, and GT represent the analytic hierarchy process, the entropy method, the coefficient of variation method, and the improved game theory, respectively.

The shortest distance $d_{\min}^1$ was determined:

$$d_{1,\min} = \text{Min}\{L_{1,1}, L_{1,2}, L_{1,3}, L_{1,4}\} = L_{1,3} = 1.038 \tag{32}$$

According to Equation (26), when $p = 1$, sample 1 could be calculated using the distance discriminant method to predict rockburst class III, which belongs to the medium rockburst classification.

$$\begin{aligned}
L_{2,1} &= \sqrt{(0 - 1)^2 + (0.206 - 0)^2 + (0.481 - 0)^2 + (0.313 - 0)^2} = 1.171 \\
L_{2,2} &= \sqrt{(0 - 0)^2 + (0.206 - 1)^2 + (0.481 - 0)^2 + (0.313 - 0)^2} = 0.980 \\
L_{2,3} &= \sqrt{(0 - 0)^2 + (0.206 - 0)^2 + (0.481 - 1)^2 + (0.313 - 0)^2} = 0.640 \\
L_{2,4} &= \sqrt{(0 - 0)^2 + (0.206 - 0)^2 + (0.481 - 0)^2 + (0.313 - 1)^2} = 0.864
\end{aligned} \tag{33}$$

The shortest distance $d_{2,\min}$ was determined:

$$d_{2,\min} = \text{Min}\{L_{2,1}, L_{2,2}, L_{2,3}, L_{2,4}\} = L_{2,3} = 0.640 \tag{34}$$

When $p = 2$, sample 1 could be calculated using the distance discriminant method to predict rockburst class III, which belongs to the medium rockburst classification. Likewise, for $p = 3$ and 4, it was possible to calculate rockburst intensity class III according to the same method.

The credibility degree was set at 0.6 and 0.7 when calculated using the confidence criterion [57,60]. It was compared with the attribute identification model optimized using

the Minkowski distance discrimination criterion. Then, the accurate judgments and misjudgments of the predicted rockburst intensity were calculated for each model (see Table 5).

As shown in Table 6 and Figure 5, the accuracy of the prediction results using the improved unascertained measurement was 92.5%, and the prediction evaluation results were the same when $p = 1, 2, 3$, and 4. Accordingly, on one hand, the accuracy values of the prediction results when calculated using the confidence criterion with the credibility degree set at 0.6 and 0.7 were 87.5% and 67.5%, respectively. On the other hand, the accuracy values calculated solely using the Manhattan distance and Euclidean distance methods were 67.5% and 75.0%, respectively. Compared to the other models, the improved unascertained measurement proposed in this paper had higher accuracy, with more accurately judged cases than the other models and a smaller number of misjudged cases. Therefore, it was demonstrated that the model is more accurate and reliable in practical engineering applications. Furthermore, the predicted rockburst results of the model were higher than the actual classes, even in the case of misjudgment, which means that the use of the model's predictions to prevent the occurrence of rockburst hazards provides a greater assurance of safety.

Table 6. Rockburst prediction results of each model.

Sample	I-1	I-2	I-3	I-4	C-0.6	C-0.7	MD-1	MD-2
Accurate	37	37	37	37	35	27	27	30
Lower than reality	0	0	0	0	0	0	8	5
Misjudged	3	3	3	3	5	13	13	10
Accuracy	92.5%	92.5%	92.5%	92.5%	87.5%	67.5%	67.5%	75.0%

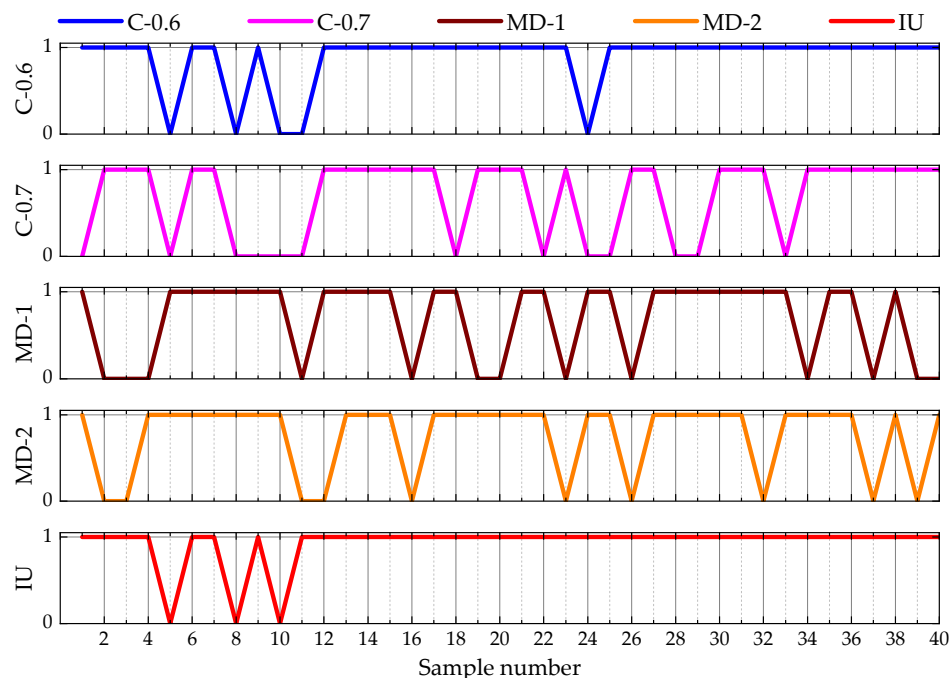


Figure 5. Comparison of prediction results of different models, where IU stands for the improved unascertained measurement obtained using the Minkowski distance formula in this paper, while 0 and 1 represent misjudgments and correct judgments, respectively.

5. Conclusions

In this work, considering the mechanism of rockbursts and the influencing factors, the five factors of the uniaxial compressive strength, the shear to compression ratio, the compression to tension ratio, the elastic deformation coefficient, and the integrity coefficient

of the rock were selected as evaluation indexes. A new model for rockburst prediction was proposed by comprehensively analyzing the shortcomings of the existing rockburst criteria. The main conclusions are as follows:

1. By introducing constraints to improve the game theory combination weighting method and then combining the analytic hierarchy process, the entropy method, and the coefficient of variation method, the combination weights of each indicator affecting rockbursts were calculated. This methodology effectively addresses the inadequacies of a singular weighting method by overcoming the one-sidedness of indicator weights and resolving the potential for negative combination coefficients.
2. Based on the unascertained measurement, the Minkowski distance formula was introduced for attribute identification, eliminating the error of discrimination results caused by different credibility degrees, which not only reduced the effect of high subjectivity due to the confidence criterion but also improved the discriminatory accuracy of the model.
3. A novel model for rockburst prediction based on improved game theory and improved unascertained measurement was proposed. Forty sets of typical rockburst cases were selected from around the world, and the improved model was compared to the unimproved model. The accuracy rate of the improved model was 92.5%, which was higher than the other methods, indicating that this method is effective and reliable.

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Abbreviations

σ_c	uniaxial compressive strength
σ_θ/σ_c	shear–compression ratio
σ_c/σ_t	compression–tension ratio
W_{et}	elastic deformation coefficient
K_V	integrity coefficient of the rock
CI	the consistency index
RI	the random consistency indicator of the matrix
CR	the consistency ratio
AHP	the analytic hierarchical process
CV	the coefficient of variation method
EWM	the entropy weight method
GT	the improved game theory

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