

Article

A Comprehensive Evaluation Method for Rockburst Potential of a Phosphate Mine Based on an Unascertained Measure Model

Weisheng Wang ^{1,2}, Yanlin Tang ^{1,2}, Wei Gao ^{1,2}, Peilei Zhang ³ and Jiangzhan Chen ^{3,*} 

¹ School of Minerals Processing and Bioengineering, Central South University, Changsha 410083, China; tlzdwsws2008@126.com (W.W.); 18605628869@163.com (Y.T.); 18805624110@163.com (W.G.)

² Tongling Nonferrous Metals Group Copper Crown Mine Construction Co., Ltd., Tongling 244000, China

³ School of Resources and Safety Engineering, Central South University, Changsha 410083, China; perry_zhangpeilei@163.com

* Correspondence: jiangzhanchen@csu.edu.cn

Abstract

Reliable assessment of rockburst tendency is essential for maintaining the stability and operational safety of deep underground excavations. However, the complex coupling among stress conditions, lithological characteristics, and structural features of rock masses introduces significant uncertainty into rockburst prediction. Conventional evaluation approaches relying on individual indices frequently produce inconsistent classifications and are often insufficient to represent actual rockburst behavior. To address this issue, a hybrid evaluation framework integrating unascertained measure theory, cloud-based uncertainty analysis, and a game-theoretic weighting strategy was developed in this study. Four representative parameters, including the strain energy storage index (W_{et}), geostress index (S), rock quality designation (RQD), and rock mass integrity factor (K_v), were adopted to characterize the energy-storage capability, stress environment, and structural condition of the surrounding rock mass. The conventional unascertained measure approach was further enhanced using the normal cloud model to describe the uncertain mapping relationship between quantitative measurements and qualitative rockburst classifications. In addition, a combination weighting scheme incorporating AHP, entropy weight (EW), and CRITIC methods was established to improve the stability and rationality of index weighting. The developed framework was subsequently applied to a deep phosphate mine in China. The calculated comprehensive weights of the four evaluation parameters were 0.1982, 0.3446, 0.2173, and 0.2399, respectively, demonstrating that the stress-related parameter has the greatest influence on rockburst evaluation. The results indicate that the investigated rock masses generally exhibit moderate-to-strong rockburst tendency. The shallow and moderately deep zones exhibited relatively high rockburst potential, while the ultra-deep dolomite formations mainly showed a moderate tendency due to the development of joints and fractures, which weakened the integrity of the deep rock mass. The proposed framework provides an effective and practical approach for preliminary hazard assessment, rockburst risk zoning, and prevention strategy design in deep mining engineering.



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1. Introduction

As underground engineering activities continue to extend to greater depths, the geological environment is increasingly characterized by extreme conditions, including elevated in-situ stress, high temperature, high pore pressure, and intense excavation disturbance [1–4]. Under these circumstances, rockburst has become one of the most significant dynamic hazards encountered in deep rock engineering [2,5,6]. Typically, rockburst refers to the sudden instability and violent failure of highly stressed brittle rock masses caused by rapid release of stored elastic strain energy, which is commonly associated with excavation, blasting, or stress unloading processes [6–9]. Due to its sudden occurrence, severe destructiveness, and limited predictability, rockburst poses substantial challenges to the safety and long-term stability of deep underground structures [10–13], as illustrated in Figure 1. Previous engineering practices have demonstrated that effective identification of rockburst tendency, combined with appropriate mitigation measures, can significantly reduce the risk and damage associated with rockburst events [14,15]. Therefore, a comprehensive evaluation framework that considers multiple geological and mechanical indices is necessary for reliable rockburst assessment.

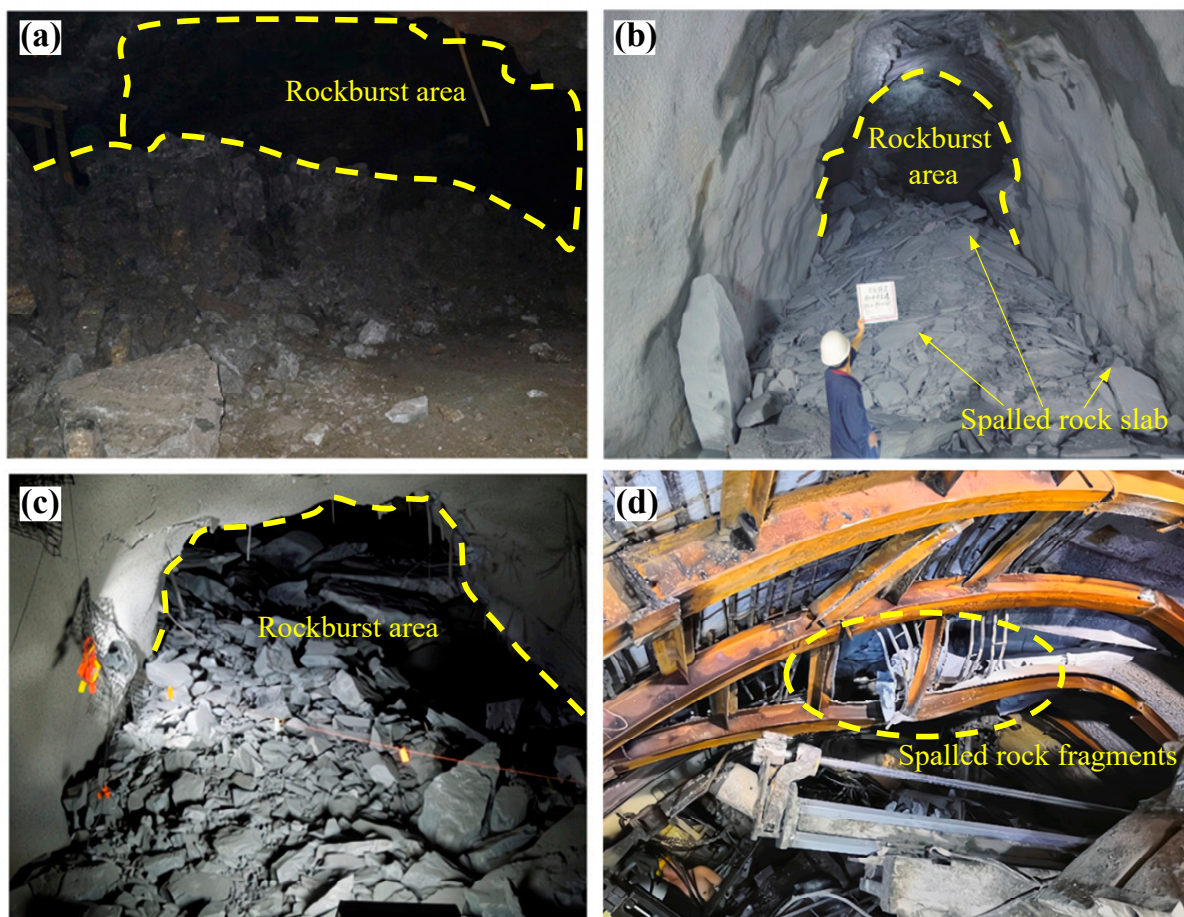


Figure 1. Scene images of rockburst areas of: (a) Hongtou mountain copper mine (revised after [10]); (b) Bayu tunnel (revised after [11]); (c) a deep metal mine in Norway (revised after [12]); and (d) Qinling tunnel (revised after [13]).

To accurately evaluate and predict rockburst potential, a variety of approaches have been proposed, including strength-based criteria [16], failure time criteria [17], brittleness indices [18,19], and energy-based methods [20,21]. Although these approaches provide valuable insights into rockburst behavior, most of them rely on individual or limited

indices, and their evaluation results may differ significantly depending on the selected parameters. This inconsistency can be attributed to the multi-factor nature of rockburst, which is jointly controlled by lithological characteristics, in-situ stress conditions, and the structural integrity of the surrounding rock mass [9,22]. Consequently, comprehensive evaluation methods have become a key focus in current research on rockburst prediction and assessment, as they provide a more systematic and reliable framework for capturing the complexity of rockburst mechanisms. For instance, Qiu et al. [23] proposed a Rockburst Vulnerability Index (RVI) for hard rock, which comprehensively incorporates in-situ stress, physical rock properties, excavation span, and geological structure. From a statistical perspective, Li and Jimenez [24] established a multi-factor relationship for rockburst classification using logistic regression, concluding that the probability of rockburst occurrence increases significantly with increasing burial depth. Recently, artificial intelligence has been widely adopted in this field. Li et al. [25] developed a grade evaluation framework based on a deep forest model. After incorporating seven rockburst assessment parameters and Bayesian optimization to tune the hyperparameters, the model achieved 100% recognition accuracy on the training set and 92.40% on the testing set (with an 80/20 data split) across 329 real-world rockburst cases. Furthermore, Pang et al. [26] trained various machine learning models on a massive dataset of 1114 rockburst cases to deduce an expert prediction system for rockburst intensity. Their system demonstrated that rock strength, elastic energy index, and in-situ stress are key controlling factors affecting rockburst classification accuracy.

Rockburst development is controlled by the combined influence of multiple geological and mechanical factors [2,5,27]. During the transformation from quantitative laboratory data to qualitative rockburst grades, considerable fuzziness and randomness exist. This inherent uncertainty often renders deterministic evaluation models inadequate for comprehensive engineering decision-making. In recent years, unascertained measure theory (UMT) and fuzzy mathematics have provided effective solutions for handling incomplete and uncertain information in multi-index decision-making problems and have been widely applied to engineering assessment [28,29]. Based on these theories, Xiong et al. [30] integrated the Analytic Hierarchy Process (AHP) with fuzzy comprehensive evaluation to establish a cloud model encompassing 4 criteria and 17 factors for assessing roof accident risks. Similarly, Zhou et al. [31] utilized information entropy to determine the index weights within the unascertained measure framework, thereby developing an evaluation model for rock mass excavability. They further analyzed the influence of different membership functions on coal burst assessment and established a burst classification model based on different index-weighting schemes [32]. Wu et al. [33] established a rockburst assessment model integrating UMT and evidence theory, yielding evaluation results that closely aligned with actual field observations. However, in conventional unascertained measure models, the distribution of index values within the evaluation grade space is usually represented by simple linear functions. This approach fails to adequately characterize the intrinsic randomness and fuzziness of rockburst phenomena, thereby limiting the accuracy and physical interpretability of the evaluation results. From the perspective of statistical distribution, the normal distribution is widely applicable to engineering failure analysis [30,34]. Therefore, the introduction of the normal cloud model (NCM) offers an effective framework for describing the uncertain transition between qualitative classifications and quantitative data. It can more reasonably characterize the membership contribution of individual rockburst evaluation indices to the comprehensive assessment results.

To overcome these limitations, this study proposes a comprehensive rockburst evaluation framework by integrating UMT, the NCM, and a game theory-based combination weighting method. This framework is subsequently applied to a deep phosphate mine to

evaluate rockburst potential across various burial depths. Compared with previous studies, this framework incorporates a combination weighting strategy, thereby avoiding the potential bias associated with reliance on a single weighting scheme. In addition, the introduction of the NCM improves the treatment of boundary fuzziness by mapping quantitative index values to rockburst grades through cloud-based membership distributions. The results indicate that the integrated model improves the robustness and reliability of rockburst potential assessment and provides useful support for risk evaluation and prevention in deep mining engineering.

2. Improved Unascertained Measure Model for Rockburst Evaluation

2.1. Unascertained Measure Theory

Compared with traditional multi-criteria assessment frameworks, the UMT has advantages in handling complex geological systems where data ambiguity and epistemic uncertainty prevail. Specifically, unlike classical fuzzy sets that may suffer from subjective bias during membership function construction, UMT utilizes measure functions to more accurately map the nonlinear relationships between rockburst indices and their corresponding risk levels, thereby yielding more reliable evaluation outcomes. In 1990, Wang [35] pioneered the mathematical theory of unascertained information to mitigate subjective uncertainty stemming from incomplete knowledge. In complex engineering scenarios, decision-making must account for such unascertained data, which can be quantified using subjective probability and membership degrees to capture both randomness and fuzziness.

The computational framework is described as follows:

Assume that the assessment system contains n evaluation samples, denoted as: $R = \{R_1, R_2, \dots, R_n\}$. Each sample is described by m evaluation indices, forming the index set: $I = \{I_1, I_2, \dots, I_m\}$. For each index, the evaluation results are divided into η hazard grades, which constitute the grade set $C = \{C_1, C_2, \dots, C_\eta\}$. These grades follow an ordered risk relationship, where the hazard intensity increases progressively from C_1 to C_η , i.e., $C_\eta > C_{\eta-1} > \dots > C_2 > C_1$. Accordingly, C can be regarded as an ordered partition of the evaluation grade space.

After establishing the evaluation framework, the main computational procedure of UMT can be summarized in three steps.

(1) Construction of the single-index measure matrix

Based on the single-index measure function, the membership degree of each index value with respect to different hazard grades is calculated, thereby forming the single-index measure matrix. For an evaluation sample R_i , the measure value I_{ij} is calculated as μ_{ijk} ($I_{ij} \in C_k$). Specifically, μ_{ijk} denotes the measure of I_{ij} to grade k , and the variable μ is subjected to the following constraints:

Non-negativity and boundedness:

$$0 \leq \mu_{ijk}(I_{ij} \in C_k) \leq 1 \quad (1)$$

Normalization:

$$\mu_{ij}(I_{ij} \in C) = 1 \quad (2)$$

Additivity:

$$\mu_{ij}\left(I_{ij} \in \bigcup_{k=1}^{\eta} C_k\right) = \sum_{k=1}^{\eta} \mu_{ijk}(I_{ij} \in C_k) \quad (k = 1, 2, \dots, \eta) \quad (3)$$

When these constraints are satisfied simultaneously, the single-index measure matrix can be established as:

$$\left(\mu_{ijk}\right)_{m \times \eta} = \begin{bmatrix} \mu_{i11} & \mu_{i12} & \cdots & \mu_{i1\eta} \\ \mu_{i21} & \mu_{i22} & \cdots & \mu_{i2\eta} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{im1} & \mu_{im2} & \cdots & \mu_{im\eta} \end{bmatrix} \quad (4)$$

(2) Determination of the multi-index comprehensive measure vector v_i :

$$v_{ij} = \sum_{k=1}^{\eta} w_j \mu_{ijk} \quad (i = 1, 2, \dots, n; k = 1, 2, \dots, \eta) \quad (5)$$

$$v_i = [v_1, v_2, \dots, v_n] \quad (6)$$

(3) Application of the confidence recognition criterion:

$$C = \min \left[k : \sum_{i=1}^k v_i \geq \lambda, k = 1, 2, \dots, p \right] \quad (7)$$

The risk classification is executed by iterating k upwards from 1; once the above mathematical condition is met, the evaluation object is officially assigned to the risk grade C_k .

In this study, the confidence level is an important threshold parameter in the grade recognition process. In general, λ is effective within the range of 0.5~1.0. A lower value may lead to a more permissive classification, whereas an excessively high value may result in an empty confidence set or the loss of valid classification information when the membership degrees of adjacent grades are close. Therefore, the selection of λ should consider both the risk-grade characteristics and the distribution of evaluation data. Following the previous study [36], $\lambda = 0.6$ is also adopted in this study as a balanced threshold between classification sensitivity and engineering conservatism.

2.2. Normal Cloud-Based Improved Unascertained Measure Model

The process of rockburst evaluation is inherently uncertain, as it involves determining the grades through a comprehensive assessment of multiple quantitative evaluation indices [9,26,36–38]. In the conventional UMT framework, the single-index measure matrix is commonly constructed using piecewise linear measure functions. This treatment provides a simple and intuitive way to describe the relationship between quantitative index values and qualitative risk grades. However, rockburst classification involves the transformation from measured quantitative data to qualitative evaluation concepts, and this process is affected by both randomness and fuzziness. Therefore, a purely linear measure function may not fully represent the uncertain transition near grade boundaries. In particular, when the measured value of an evaluation index is close to the boundary between two adjacent rockburst grades, the conventional linear UMT may produce relatively rigid membership assignments. This limitation motivates the induction of the NCM to improve the uncertainty representation of the UMT framework.

The NCM is composed of numerous cloud droplets, and a larger number of cloud droplets generally leads to a more stable and accurate representation of the underlying qualitative concept. Let U denote the discourse domain and C represent a qualitative concept defined on U . For a quantitative variable $x \in U$, if x is regarded as a random instantiation of the qualitative concept C , then it satisfies the following normal distribution:

$$x \sim N\left(Ex, En'^2\right), En'^2 \sim \left(Ex, He^2\right) \quad (8)$$

where Ex is the expectation, En is the entropy, He is the hyper-entropy.

Then, the membership degree of x with respect to the qualitative concept C , denoted by $u \in [0, 1]$, can be calculated by the following expression:

$$u(x) = \exp \left[-(x - Ex)^2 / 2En'^2 \right] \quad (9)$$

The characteristic parameters are calculated as follows:

$$Ex_{ij} = (B_{\min} + B_{\max}) / 2 \quad (10)$$

$$En_{ij} = (B_{\max} - B_{\min}) / 6 \quad (11)$$

$$He = k \quad (12)$$

where $i = 1, 2, \dots, m$; $j = 1, 2, \dots, \eta$; and $B_{\max}$ and $B_{\min}$ represent the upper and lower boundary values of the rockburst grade standard, respectively.

Notably, He represents the dispersion degree of entropy and controls the uncertainty range of cloud droplets in the NCM. Since different evaluation indices have different numerical ranges and dimensions, He is defined within a normalized domain of discourse in this study. A larger normalized value indicates a more dispersed cloud droplet distribution, a lower degree of conceptual consensus, and stronger uncertainty near the classification boundary.

The forward normal cloud generator enables the transformation of qualitative concepts into quantitative representations. Based on the predefined digital characteristics of the cloud model, a series of cloud droplets can be generated to characterize the attribute distribution of the evaluation object and its corresponding membership information. As illustrated in Figure 2, the implementation procedure of the forward cloud generator for rockburst classification can be summarized as follows:

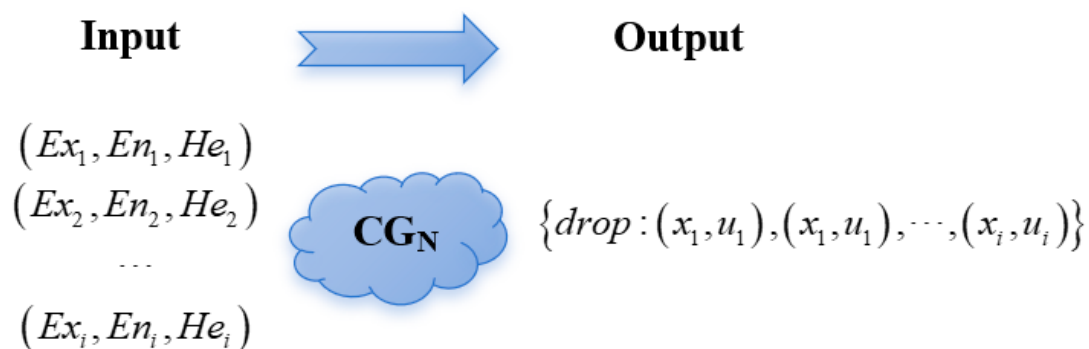


Figure 2. Forward cloud generator.

(1) Determine the digital characteristics of the cloud model:

$$Ex = (Ex_1, Ex_2, \dots, Ex_m), En = (En_1, En_2, \dots, En_m), He = (He_1, He_2, \dots, He_m) \quad (13)$$

(2) Generate a normally distributed random variable with mean En and standard deviation He , expressed as:

$$En' = (En'_1, En'_2, \dots, En'_m) \quad (14)$$

(3) Generate the normal random variable x_1 using Ex as the expectation and En' as the standard deviation;

(4) Compute the membership degree $u(x_i)$ of the quantitative variable x_i with respect to the qualitative concept C.

3. Engineering Application and Rockburst Proneness

3.1. Engineering Background

In a deep phosphate mine in China, the phosphate orebody is buried at considerable depth, and the overlying Dengying Formation mainly consists of competent hard rock strata. As the mining depth increases, the in-situ stress increases markedly. This elevated stress condition is expected to induce severe deformation and failure in the roadway, including floor heave, spalling, and roof caving. It may even trigger rockburst events, thereby posing a severe threat to future underground mining operations.

To assess the rockburst tendency and hazard intensity of the surrounding rock mass in the mining area, the geological characteristics and spatial distribution features of the exploration zones associated with orebodies VI and VII in the phosphate mine were systematically investigated. Starting from a burial depth of 400 m, four geological sampling levels are established at intervals of 400 m for borehole coring. According to burial depth, the boreholes are divided into four sections: the shallow section (approximately at the 400 m level), the moderately deep section (approximately at the 800 m level), the deep section (approximately at the 1200 m level), and the ultra-deep section located 100 m above the borehole bottom.

3.2. Rockburst Evaluation Indices

Accurate determination of rockburst-related indices is fundamental to reliable rockburst classification [2,5,9]. For this purpose, drilling cores were processed into standard specimens for laboratory experiments. Considering the practical testing conditions and the accessibility of parameter acquisition, four representative evaluation indices were selected to characterize the lithological properties, stress conditions, and structural integrity of the surrounding rock mass. These indices were then experimentally determined and employed as the basis for subsequent rockburst classification.

(1) Lithological property (strain energy storage index, (W_{et}) [27,39]):

This parameter characterizes the ability of the rock mass to accumulate elastic strain energy, and, to a certain extent, comprehensively reflects the energy release potential during rock failure. In general, a higher W_{et} value inherently indicates a stronger energy storage capacity and greater rockburst proneness.

(2) In-situ stress condition (geostress index, (S) [40]):

The geostress index is defined as the ratio of the maximum principal stress to the uniaxial compressive strength (UCS) of the rock, which reflects the stress concentration level and external energy input within the deep rock mass. Higher in-situ stress conditions promote the accumulation of elastic strain energy. When the stored energy before peak failure exceeds the critical threshold for instability, the intensity of the resulting rockburst may be significantly enhanced.

(3) Rock mass integrity (rock quality designation, (RQD) [40,41], and rock mass integrity factor, (K_v) [42]):

The abundance and distribution of internal fractures profoundly govern the overall integrity of the rock mass. A highly fractured rock mass exhibits diminished structural integrity, thereby displaying a reduced rockburst potential due to its inability to effectively store elastic energy. Thus, RQD and K_v can be utilized as effective indices to characterize this structural state.

Based on the comprehensive integration of these four evaluation indices, the rockburst classification criteria are detailed in Table 1.

Table 1. Rockburst classification criteria (reference from [27,39–42]).

Evaluation Index	Calculation Method	Rockburst Potential			
		No	Slight	Moderate	Strong
W_{et}	$W_{et} = \frac{\phi_{sp}}{\phi_{st}}$ where ϕ_{sp} is the elastic strain energy, ϕ_{st} is the dissipated strain energy.	<2.0	2.0–3.5	3.5–5.0	>5.0
S	$S = \frac{\sigma_1}{\sigma_c}$ where σ_1 is the maximum principal stress of rock, σ_c is the UCS of rock.	<0.15	0.15–0.20	0.20–0.25	>0.25
RQD	$RQD = \frac{\sum h_{10}}{h_b - h_a} 100[\%]$ where $\sum h_{10}$ is the total length of the pieces longer than 10 cm, h_b is the upper depth of boreholes, h_a is the lower depth of the boreholes.	<25	25–50	50–70	>70
K_v	$K_v = \left(\frac{V_{pm}}{V_{pr}} \right)^2$ where V_{pm} is the P-wave velocity of rock mass, V_{pr} is the P-wave velocity of intact rock.	<0.55	0.55–0.65	0.65–0.75	>0.75

3.3. Evaluation Framework

By incorporating the forward NCM, the conventional UMT is improved and applied to rockburst potential evaluation. After determining the rockburst evaluation indices and the corresponding classification system, the proposed computational framework can be interpreted as a three-stage procedure, as follows:

First, the NCM is used to transform the predefined rockburst classification intervals into cloud-based membership distributions. In this step, the quantitative values of each evaluation index are mapped to different qualitative rockburst grades, and the corresponding membership degrees are obtained. Specifically, Equations (10)–(12) are used to calculate the digital characteristics of the cloud model for each evaluation index under different rockburst grades. These digital characteristics are then used as input for the forward cloud generator to generate normal clouds for each evaluation index. Each cloud represents the membership relationship between the measured index value and the corresponding rockburst grade, and the membership degree of each evaluation index with respect to different rockburst grades is calculated using Equation (9).

Second, these membership degrees are introduced into the UMT framework to construct the single-index measure matrix, which describes the relationship among each sample, each evaluation index, and each rockburst grade.

Third, an appropriate weighting method is adopted to determine the relative importance of the selected evaluation indices. By combining the single-index measure matrix with the obtained index weights, the comprehensive measure vector of each sample is calculated, and the final rockburst grade is identified according to the confidence criterion.

The overall assessment framework is illustrated in Figure 3.

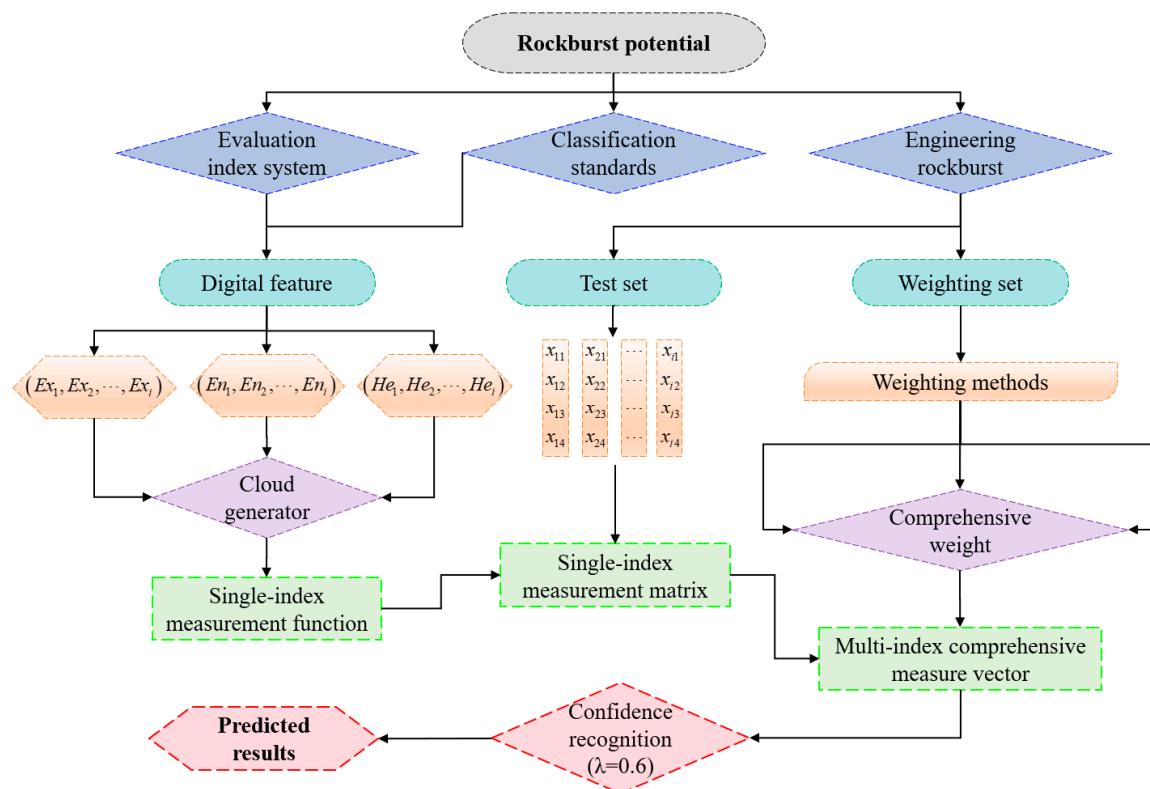


Figure 3. Comprehensive evaluation framework for rockburst potential.

4. Model Analysis

4.1. Experimental Results

To accurately determine the evaluation indices, in-situ rock cores were obtained through drilling, during which each core sample was systematically labelled to record its detailed information. Subsequently, the rock mass integrity index and P-wave velocity were determined based on the collected core samples. After the evaluation parameters were determined, the collected rock cores were processed into standard cylindrical specimens with a height-to-diameter ratio of 2:1 in accordance with relevant testing specifications. Specimens measuring $\varnothing 20 \text{ mm} \times 40 \text{ mm}$ were prepared for acoustic emission (AE) tests to infer the in-situ stress state, whereas $\varnothing 50 \text{ mm} \times 100 \text{ mm}$ specimens were used for uniaxial compression and loading–unloading tests associated with strain-energy analysis. It should be noted that the maximum principal stress used to calculate the geostress index (S) was obtained through AE-based stress inversion tests on drilled core samples. This method provides an indirect but effective laboratory approach for estimating the in-situ stress state, particularly in deep mining areas where the orebody has not yet been extensively excavated and direct field stress measurement is difficult to conduct. The complete experimental workflow is presented in Figure 4.

Based on the experimental results, the rockburst potential of the rock mass at different borehole depths in the phosphate mine is summarized in Table 2. Notably, distinct discrepancies exist among the evaluation results derived from different single indices at the same depth. For example, for the sample obtained from a burial depth of 1350 m in borehole SZK0803#, the different indices suggest inconsistent rockburst grades. This discrepancy primarily arises because a single index typically reflects the rock mass characteristics from merely one specific aspect, such as rock strength, elastic energy storage capacity, or in-situ stress state. Consequently, a single index is inadequate for comprehensively capturing the complex mechanisms underlying rockburst occurrences. In practice, rockburst is a

multi-factor coupled phenomenon controlled by lithological conditions, stress state, and the structural integrity of the surrounding rock mass. Therefore, relying exclusively on a single index may fail to accurately assess rockburst potential and may lead to partial or even biased evaluation outcomes. Accordingly, it is necessary to introduce a multi-index comprehensive evaluation methodology to systematically integrate and analyze all relevant factors, thereby significantly enhancing the reliability and accuracy of the rockburst prediction.

Table 2. Results of rockburst potential under a single-index.

Borehole No.	Depth/m	Classification			
		W_{et}	S	RQD	K_v
SZK1107#	400	5.87 (Strong)	0.20 (Moderate)	54.77 (Moderate)	0.54 (No)
	800	7.30 (Strong)	0.22 (Moderate)	81.56 (Strong)	0.83 (Strong)
	1200	5.50 (Strong)	0.16 (Slight)	66.61 (Moderate)	0.89 (Strong)
	1450	7.82 (Strong)	0.25 (Moderate)	74.11 (Strong)	0.67 (Moderate)
SZK0803#	400	10.46 (Strong)	0.14 (No)	82.78 (Strong)	0.55 (Slight)
	800	7.93 (Strong)	0.14 (No)	81.90 (Strong)	0.66 (Moderate)
	1200	5.27 (Strong)	0.23 (Moderate)	66.63 (Moderate)	0.64 (Slight)
	1350	6.08 (Strong)	0.23 (Moderate)	36.67 (Slight)	0.48 (No)
SZK0503#	500	4.26 (Moderate)	0.33 (Strong)	66.08 (Moderate)	0.91 (Strong)
	800	2.77 (Slight)	0.35 (Strong)	83.28 (Strong)	0.89 (Strong)
	1200	6.16 (Strong)	0.25 (Strong)	72.65 (Strong)	0.51 (No)
	1350	6.31 (Strong)	0.30 (Strong)	55.87 (Moderate)	0.33 (No)
SZK0301#	500	7.88 (Strong)	0.14 (No)	33.40 (Slight)	0.70 (Moderate)
	800	7.71 (Strong)	0.22 (Moderate)	76.91 (Strong)	0.58 (Slight)
	1200	4.68 (Moderate)	0.29 (Strong)	89.29 (Strong)	0.80 (Strong)
	1500	5.96 (Strong)	0.34 (Strong)	57.71 (Moderate)	0.52 (No)
NZK0801#	500	5.53 (Strong)	0.18 (Slight)	75.43 (Strong)	0.57 (Slight)
	900	4.06 (Moderate)	0.31 (Strong)	32.41 (Slight)	0.79 (Strong)
	1200	5.64 (Strong)	0.41 (Strong)	82.64 (Strong)	0.85 (Strong)
	1400	4.67 (Moderate)	0.79 (Strong)	50.70 (Moderate)	0.39 (No)

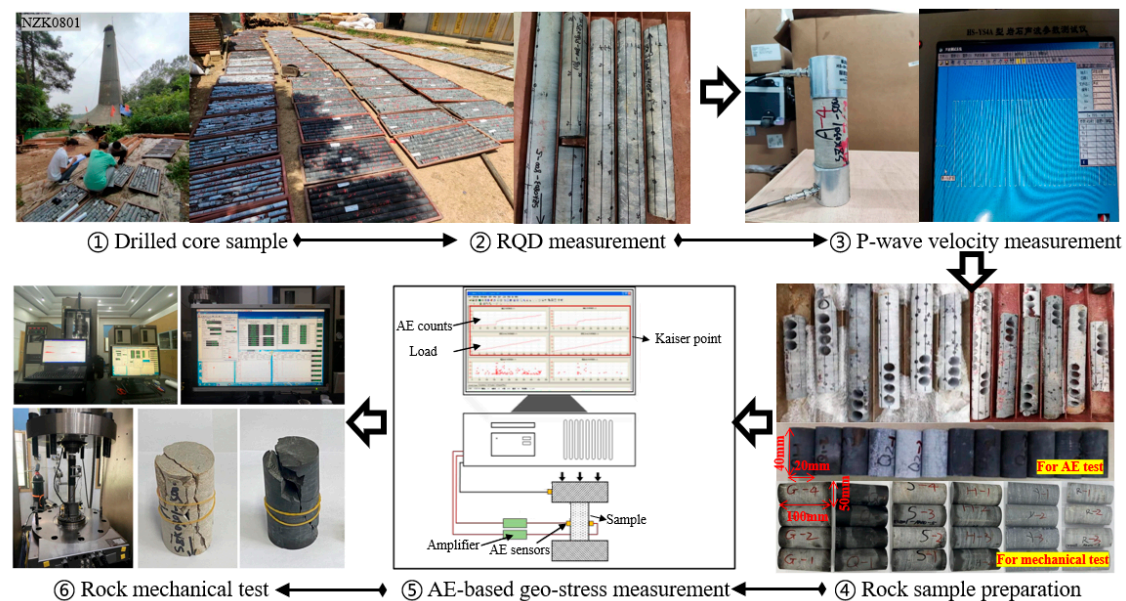


Figure 4. Mechanics tests and parameter measurements for rockburst potential.

4.2. Rockburst Potential Based on the Comprehensive Evaluation Method

Rockburst potential evaluation is essentially a multi-objective and multi-attribute decision-making problem. Determining the relative importance of various evaluation indices through appropriate weight allocation is crucial for achieving accurate assessment results. Initially, a comprehensive sample set for rockburst evaluation was established based on the index values acquired at different borehole depths. In multi-index evaluation systems based on fuzzy mathematical approaches, the assignment of index weights is a key issue affecting the reliability of the assessment results.

Previous studies have demonstrated that the selection of weighting schemes has a significant influence on the predictive performance of evaluation models [36,43]. In practical rockburst assessment, a single weighting method may introduce bias because it usually reflects only one aspect of index importance. For example, subjective weighting methods emphasize expert knowledge and engineering experience, whereas objective weighting methods mainly depend on the statistical characteristics of measured data. Therefore, relying on only one weighting strategy may reduce the stability and consistency of the evaluation results. To overcome this limitation, a game-theory-based combination weighting strategy is employed to integrate three representative weighting approaches, including the analytic hierarchy process (AHP), entropy weight (EW), and CRITIC methods, thereby obtaining a more balanced and robust weight vector.

The optimal weights of the four evaluation indices are determined through a stepwise combination procedure. First, three different weighting methods are used to generate three independent basic weight vectors. Specifically, AHP reflects expert judgment and engineering experience, EW determines index importance according to the information variability of measured data, and CRITIC considers both the contrast intensity of each index and the conflict among different indices. Then, the game theory-based method is used to construct the final comprehensive weight vector as a combination of these basic weight vectors. The combination coefficients are optimized by minimizing the deviation between the comprehensive weight vector and each basic weight vector. After normalization, the final combined weights of the four evaluation indices are obtained. The main principles and procedures can be described as follows:

(1) Assume that the weights of evaluation indices are determined by ξ different methods, denoted as w_i ($i = 1, 2, 3, \dots, \xi$). Accordingly, ξ weight vectors can be obtained as follows:

$$w(l) = [w_{l1}, w_{l2}, \dots, w_{lm}] \quad (l = 1, 2, \dots, \xi) \quad (15)$$

$$w = \sum_{l=1}^{\xi} \alpha_l w_l^T \quad (16)$$

(2) To minimize the discrepancy between the comprehensive weight vector w and the individual weighting vectors, the linear combination coefficients α are optimized. Accordingly, the optimal combined weight vector can be expressed as follows:

$$\min \left\| \sum_{l=1}^{\xi} \alpha_l w_l^T - w_p \right\|_2 \quad (p = 1, 2, \dots, \xi) \quad (17)$$

The corresponding optimal solution can be expressed as follows:

$$\sum_{l=1}^{\xi} \alpha_l w_p w_l^T = w_p w_p^T \quad (18)$$

After determining the combination coefficients $\alpha_1, \alpha_2, \dots, \alpha_{\xi}$, a normalization procedure is applied to calculate the comprehensive weight of evaluation indices, as follows:

$$\alpha_l^* = \frac{|\alpha_l|}{|\alpha_1| + |\alpha_2| + \dots + |\alpha_l|} \quad (l = 1, 2, \dots, \xi) \quad (19)$$

$$w^* = \sum_{l=1}^{\xi} \alpha_l^* w_l^T \quad (20)$$

Using the game-theory-based combination weighting method, the AHP, EW, and CRITIC weighting results are integrated to determine the optimal combined weights. The AHP-derived weights of the four evaluation indices (W_{et} , S , RQD , and K_v) are 0.22, 0.33, 0.18, and 0.27, respectively. The corresponding weights obtained using the EW method are 0.1841, 0.2375, 0.2978, and 0.2806, respectively, whereas those calculated by the CRITIC method are 0.1896, 0.3952, 0.2102, and 0.2050, respectively. Finally, the optimal combined weights of the four indices obtained through the game-theory-based combination weighting method are 0.1982, 0.3446, 0.2173, and 0.2399, respectively.

The comparison among the three basic weighting methods and the final combined weights indicates that the game-theory-based combination weighting method can effectively balance subjective judgment and objective data characteristics. Among the four indices, the geostress index has the highest comprehensive weight, indicating that the in-situ stress condition is the most influential factor in the rockburst potential evaluation of the phosphate mine. This finding is consistent with the mechanical mechanism of rockburst, in which high in-situ stress promotes the accumulation and sudden release of elastic strain energy.

The characteristic parameters of the NCM are then calculated according to the method described in Section 2.2, with the results listed in Table 3. Based on these parameters, the corresponding normal clouds are generated (Figure 5), where each cloud represents the membership distribution of index values with respect to different rockburst grades. The comprehensive measure vector v_i (C_1, C_2, C_3, C_4) for each test sample is subsequently obtained by incorporating the index weights. According to the confidence criterion, the rockburst grade can then be identified. When the confidence level $\lambda = 0.6$, the proposed

method can be applied to evaluate the rockburst potential of rock masses at different borehole depths in the phosphate mine.

Table 3. Digital feature of NCM.

Rockburst Potential	Digital Feature	Rockburst Evaluation Index			
		W_{et}	S	RQD	K_v
No	Ex	2.38	0.145	28.7	0.44
	En	0.128	0.002	1.23	0.037
	He	0.1	0.001	0.1	0.01
Slight	Ex	2.75	0.175	37.5	0.60
	En	0.25	0.008	4.17	0.017
	He	0.1	0.001	0.1	0.01
Moderate	Ex	4.25	0.225	60.0	0.70
	En	0.25	0.008	3.33	0.017
	He	0.1	0.001	0.1	0.01
Strong	Ex	7.7	0.520	79.6	0.83
	En	0.91	0.108	3.22	0.027
	He	0.1	0.001	0.1	0.01

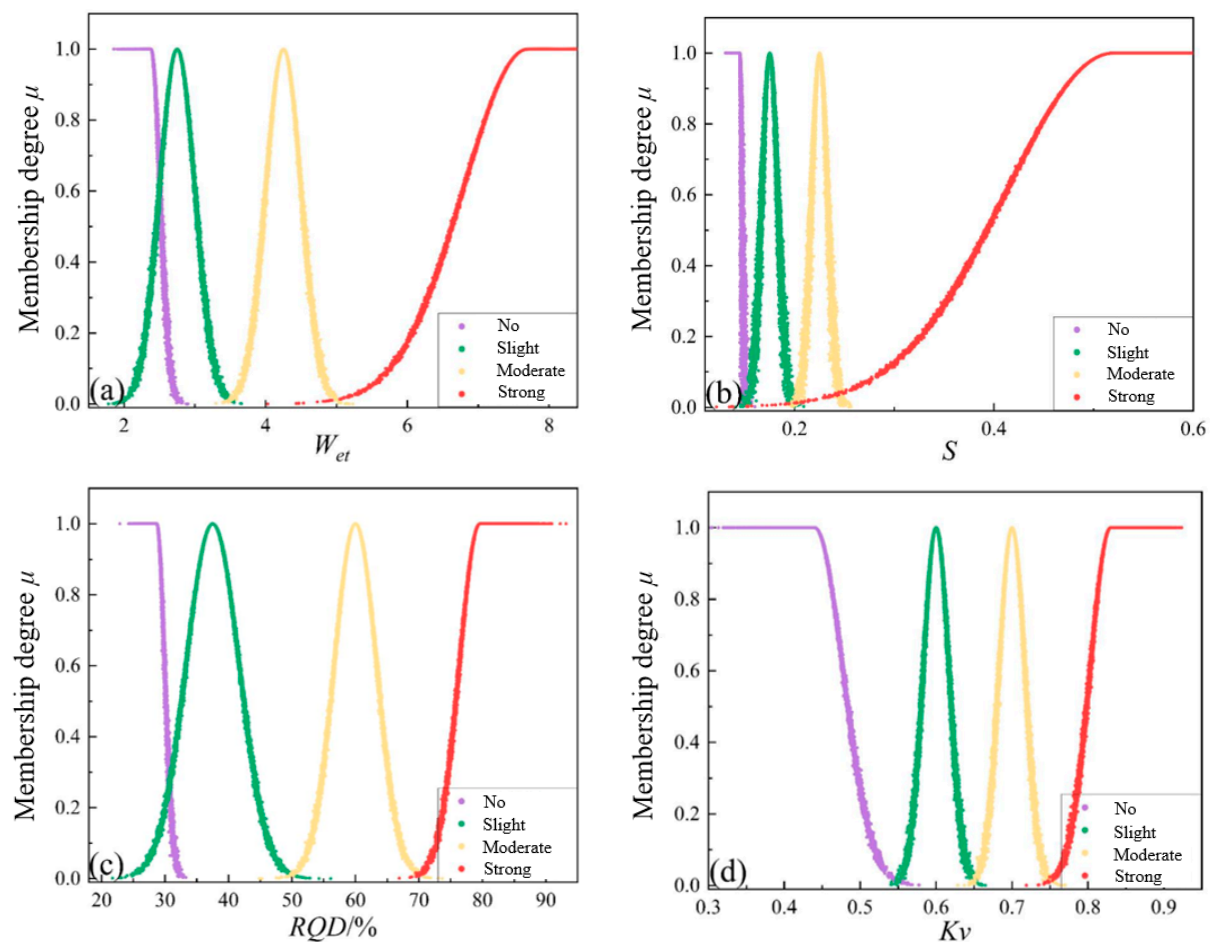


Figure 5. Nonlinear measurement function: (a) W_{et} ; (b) S ; (c) RQD; (d) K_v .

As shown in Figure 6 and Table 4, the rock mass in the phosphate mine predominantly exhibits moderate-to-strong rockburst potential. However, the variation in rockburst grade with burial depth is not strictly monotonic for all boreholes, and the evaluation results are also affected by the borehole-specific lithology, in-situ stress conditions, geological

structures, and rock mass integrity. Overall, the results indicate that moderate-to-strong rockburst potential is dominant in the shallow-to-moderately deep zones, although the variation with depth differs among boreholes. For example, at the SZK0503–500 m borehole location, the rock mass is characterized by extremely high integrity ($K_v = 0.91$) and relatively strong elastic energy capacity, resulting in a strong rockburst classification. In the moderately deep zone, the rockburst potential remains high, with localized intensification. Notably, at the SZK0803–800 m borehole location, certain rock samples exhibit high strength and pronounced brittleness, thereby indicating a strong rockburst potential. In the deep zone at 1200 m, the rockburst potential is mainly classified as moderate-to-strong, whereas in the ultra-deep region around 1400 m, it decreases to a predominantly moderate level in the comprehensive evaluation. At this depth, the rock mass is mainly composed of dolomite. Although the tested samples exhibit relatively high compressive strength, joints and fractures are relatively developed in rock cores, resulting in a lower rock mass integrity coefficient. This factor affects the overall evaluation of rockburst potential. Moreover, the stress–strain curves of the ultra-deep samples show a more progressive post-failure behaviour, indicating that the stored energy is released gradually and that the rockburst tendency is relatively weakened. Therefore, the comprehensive assessment suggests that the rockburst potential in the ultra-deep zone of the phosphate mine is slightly reduced, but it should still be carefully considered during subsequent mining activities.

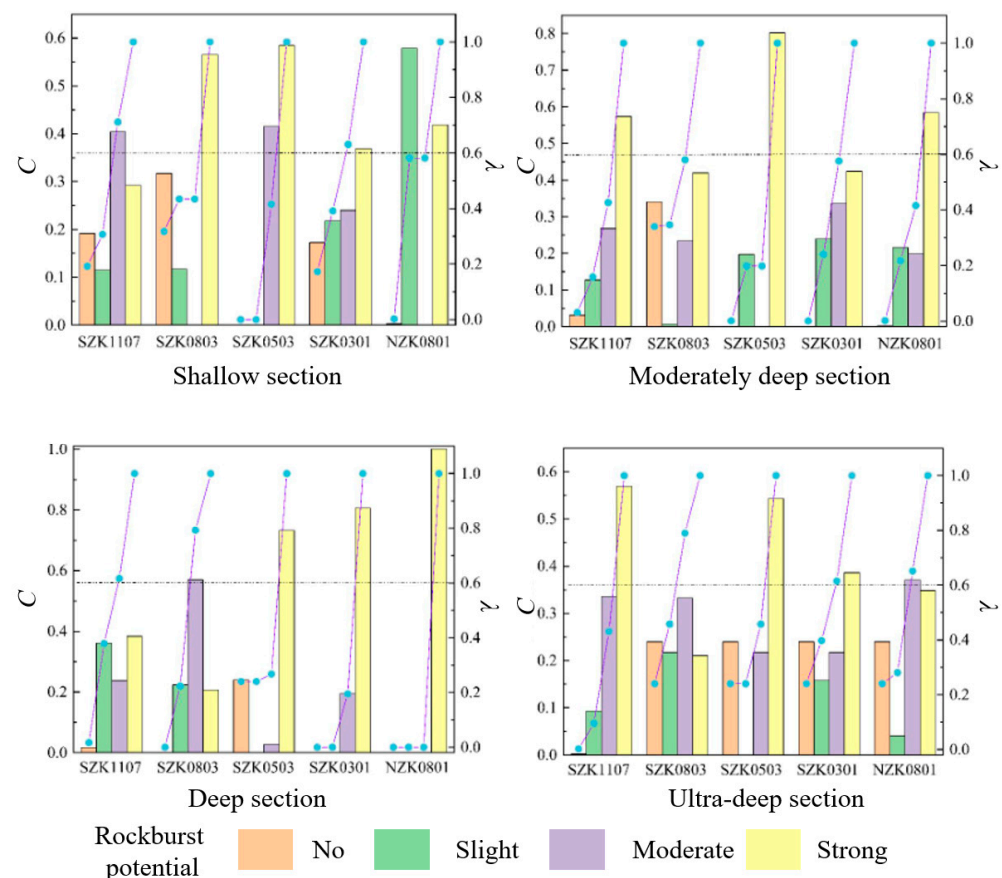


Figure 6. Evaluation results of rock burst in phosphate mine.

The validity of the proposed comprehensive evaluation framework can be supported from both methodological and engineering perspectives. Methodologically, the framework integrates key factors related to energy storage capacity, stress condition, fracture development, and rock mass integrity, thereby reducing the bias associated with single-index evaluation. The weighting result also shows good physical consistency, as the stress-related

index (S) receives the greatest contribution, reflecting the important role of stress accumulation in rockburst development. From an engineering perspective, the predicted grades are generally consistent with the observed depth-dependent geological and mechanical characteristics of the studied mining area. Therefore, the proposed comprehensive framework provides a reasonable and applicable tool for rockburst assessment in the studied mining area.

Table 4. Comprehensive measure and the evaluation results.

Borehole	Depth/m	Comprehensive Measure				Evaluation Results by NCM-UMT	Evaluation Results by Traditional Linear-UMT
		C_1	C_2	C_3	C_4		
SZK1107	400	0.1920	0.1151	0.4041	0.2918	Moderate	Moderate
	800	0.0310	0.1275	0.2679	0.5736	Strong	Strong
	1200	0.0172	0.3618	0.2378	0.3832	Moderate	Strong
	1450	0.0021	0.0933	0.3357	0.5689	Strong	Strong
SZK0803	400	0.3172	0.1171	0.0000	0.5657	Strong	No
	800	0.3401	0.0065	0.2334	0.4200	Strong	Moderate
	1200	0.0000	0.2237	0.5694	0.2069	Moderate	Moderate
	1350	0.2399	0.2173	0.3323	0.2105	Moderate	Moderate
SZK0503	500	0.0000	0.0000	0.4152	0.5848	Strong	Strong
	800	0.0008	0.1974	0.0000	0.8018	Strong	Strong
	1200	0.2399	0.0000	0.0276	0.7325	Strong	Strong
	1350	0.2399	0.0000	0.2173	0.5428	Strong	Strong
SZK0301	500	0.1727	0.2183	0.2399	0.3690	Moderate	Slight
	800	0.0005	0.2394	0.3359	0.4242	Strong	Moderate
	1200	0.0000	0.0000	0.1949	0.8051	Strong	Strong
	1500	0.2399	0.1577	0.2173	0.3861	Moderate	Strong
NZK0801	500	0.0026	0.5791	0.0000	0.4183	Strong	Moderate
	900	0.0019	0.2154	0.1981	0.5846	Strong	Strong
	1200	0.0000	0.0000	0.0000	1.0000	Strong	Strong
	1400	0.2399	0.0406	0.3710	0.3485	Moderate	Moderate

Furthermore, the comparison between the conventional linear UMT and the NCM-UMT method shows that the conventional linear UMT constructs the single-index measure matrix using piecewise linear measure functions, whereas the NCM-UMT method uses cloud-based membership distributions to describe the randomness and fuzziness involved in the transformation from quantitative index values to qualitative rockburst grades. According to the comparison results, although the two methods provide consistent classifications for most samples, differences are observed in several cases (also shown in Table 4). These discrepancies mainly occur in samples with inconsistent single-index evaluation results or ambiguous grade boundaries. This indicates that the NCM-UMT method provides a more flexible representation of uncertainty and is more suitable for comprehensive rockburst potential assessment in the studied phosphate mine.

4.3. Application Insights and Limitations

The proposed framework, which integrates UMT with the NCM and a game theory-based combination weighting approach, demonstrates good applicability for rockburst evaluation in deep underground engineering. By simultaneously considering multiple influencing factors, including lithological characteristics, stress conditions, and rock mass integrity, the model effectively addresses the limitations of traditional single-index methods and provides a more comprehensive and reliable assessment of rockburst potential. From an engineering perspective, the incorporation of the NCM enables a unified representation of randomness and fuzziness, thereby capturing the inherent uncertainty in the mapping

between quantitative index values and qualitative rockburst grades. Meanwhile, the game-theory-based combination weighting method improves the objectivity and robustness of index weighting by integrating both subjective and objective weighting schemes. These advantages make the proposed approach well suited for practical applications, including preliminary rockburst risk zoning, support design optimization, and pre-mining risk assessment in deep underground excavations. The proposed model also has potential transferability to other mines. Its mathematical framework is not limited to the specific phosphate mine investigated in this research, because the evaluation process is based on general uncertainty modeling and multi-index decision-making theory. Therefore, it can be extended to other underground mines facing rockburst hazards. However, when the model is applied to other mining areas, site-specific calibration is necessary. The grading standards, cloud model parameters, and index weights may vary with lithology, in-situ stress environment, mining depth, geological structures, and excavation disturbance conditions. Therefore, reliable geological, mechanical, and monitoring data should be used to calibrate the grading standards, cloud model parameters, and index weights before the framework is applied to other mining areas.

In this study, four representative indices, including W_{et} , S , RQD , and K_v , are selected to construct the rockburst evaluation system. These representative indices characterize the energy capacity and geological environments of the rock mass, and can be obtained from available borehole sampling and laboratory tests. Therefore, this method provides a practical and measurable index system for evaluating rockburst potential in the deep phosphate mine.

However, several limitations should be noted. First, the effectiveness of the proposed model depends on the quality and representativeness of the input data. The evaluation indices are primarily derived from laboratory tests and a limited number of borehole samples. Although these data can reflect the rockburst potential to a certain extent, they may not fully capture the dynamic evolution of rockburst risk induced by mining disturbances in in-situ rock masses. Second, the model relies on predefined rockburst classification criteria and corresponding cloud model parameters, which may introduce uncertainty when geological conditions change significantly. Third, as mentioned above, the current framework mainly uses static geological and mechanical parameters and does not explicitly incorporate real-time monitoring information, such as micro-seismic activity, AE responses, or stress monitoring data. In addition, the nonlinear interactions among the evaluation indices should also be further investigated. The proposed method has been preliminarily applied to a case study from the phosphate mine. Although the evaluation results are generally consistent with the geological and mechanical characteristics of the studied area, systematic validation using field rockburst records and continuous monitoring data is still limited at this stage. Future studies should further integrate field rockburst records, continuous monitoring data, and numerical simulation results to establish a dynamically updated rockburst assessment framework and improve its engineering reliability under excavation disturbance conditions.

5. Conclusions

An integrated evaluation framework combining UMT, the NCM, and game-theoretic combination weighting was established and implemented for rockburst assessment in a deep phosphate mine. The major conclusions obtained from this study are presented as follows:

(1) A comprehensive evaluation framework incorporating W_{et} , S , RQD and K_v is established. The results demonstrate that single-index methods may lead to inconsistent or biased assessments, whereas the proposed approach significantly improves the relia-

bility and consistency of rockburst evaluation by comprehensively considering multiple influencing factors.

(2) The introduction of the NCM enables effective characterization of the uncertainty mapping between quantitative index values and qualitative rockburst grades. By simultaneously capturing randomness and fuzziness, the proposed method provides a more realistic and robust description of rockburst classification uncertainty.

(3) The game-theory-based combination weighting method successfully integrates subjective weighting (AHP) and objective weighting (EW and CRITIC) schemes, enhancing the objectivity and robustness of index weighting. The results show that the geostress index S has the highest comprehensive weight, indicating its important contribution to rockburst potential evaluation.

(4) Application to a deep phosphate mine reveals that the investigated rock masses generally exhibit moderate-to-strong rockburst potential. The rockburst grade does not vary strictly monotonically with burial depth for all boreholes, but a moderate-to-strong tendency is dominant in the shallow-to-moderately deep zones. In the ultra-deep dolomite zone, the comprehensive evaluation indicates a predominantly moderate tendency, which is mainly associated with developed joints and fractures and reduced rock mass integrity. The proposed framework demonstrates good applicability for preliminary rockburst potential assessment when the confidence level is set to $\lambda = 0.6$.

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References

1. He, M.C.; Xia, H.M.; Jia, X.N.; Gong, W.L.; Zhao, F.; Liang, K.Y. Studies on classification, criteria and control of rockbursts. *J. Rock. Mech. Geotech. Eng.* **2012**, *4*, 97–114. [[CrossRef](#)]
2. Xu, Z.H.; Yu, T.F.; Li, S.C.; Lin, P.; Ma, W.; Han, T.; Li, S. Intelligent identification of lithology and adverse geology: A state-of-the-art review. *Smart Undergr. Eng.* **2025**, *1*, 3–25. [[CrossRef](#)]
3. Ortlepp, W.D. The behaviour of tunnels at great depth under large static and dynamic pressures. *Tunn. Undergr. Space Technol.* **2001**, *16*, 41–48. [[CrossRef](#)]
4. Naji, A.M.; Emad, M.Z.; Rehman, H.; Yoo, H. Geological and geomechanical heterogeneity in deep hydropower tunnels: A rock burst failure case study. *Tunn. Undergr. Space Technol.* **2019**, *84*, 507–521. [[CrossRef](#)]
5. Gong, F.Q.; Dai, J.H.; Xu, L. A strength-stress coupling criterion for rockburst: Inspirations from 1114 rockburst cases in 197 underground rock projects. *Tunn. Undergr. Space Technol.* **2023**, *142*, 105396. [[CrossRef](#)]

6. Li, Z.H.; Ren, H.; Wang, W.Q.; Feng, D.; Huang, Y.F.; Cao, Z.Z.; Wang, L.J. Multi-factor coupled numerical simulation and sensitivity analysis of hysteresis water inundation induced by the activation of small faults in the bottom plate under the influence of mining. *Appl. Sci.* **2026**, *16*, 1051. [[CrossRef](#)]
7. Li, G.S.; Zhang, H.; Li, M.Z.; Shen, Z.H.; Tian, A.F.; Wang, L.J. Study on coal wall spalling mechanism of large mining height working face based on folding mutation theory. *Sci. Rep.* **2026**, *16*, 15277. [[CrossRef](#)] [[PubMed](#)]
8. Jiang, Q.; Feng, X.T.; Xiang, T.B.; Su, G.S. Rockburst characteristics and numerical simulation based on a new energy index: A case study of a tunnel at 2,500 m depth. *Bull. Eng. Geol. Environ.* **2010**, *69*, 381–388. [[CrossRef](#)]
9. Cao, R.L.; Xiao, H.H.; Li, J.P.; Chen, Z.Y.; Chen, S.Y.; Wang, X.N. Rockburst prediction using machine learning: Comparative study of algorithms and features. *Smart Undergr. Eng.* **2025**, *1*, 77–91. [[CrossRef](#)]
10. Feng, X.T. *Rockburst: Mechanism, Monitoring, Warning and Mitigation*; Elsevier Health Sciences Division: London, UK, 2018.
11. Zhao, Y.; Shi, S.S.; Tian, S.M.; Li, G.L.; Tao, W.M.; Guo, W.D. Technical difficulties and countermeasure suggestions in tunnel construction of Ya'an-Linzhi section of Sichuan-Tibet railway. *Tunn. Constr.* **2021**, *41*, 1079–1090. [[CrossRef](#)]
12. Li, C.C. Principles and methods of rock support for rockburst control. *J. Rock. Mech. Geotech. Eng.* **2021**, *13*, 46–59. [[CrossRef](#)]
13. Du, L.J.; Hong, K.R.; Wang, J.X.; Li, Q.W.; Yang, Y.L.; Li, W.W.; Huang, J.G. Rockburst characteristics and prevention and control technologies for tunnel boring machine construction of deep-buried tunnels. *Tunn. Constr.* **2021**, *41*, 1–15. [[CrossRef](#)]
14. Zhou, J.; Li, X.B.; Mitri, H.S. Evaluation method of rockburst: State-of-the-art literature review. *Tunn. Undergr. Space Technol.* **2018**, *81*, 632–659. [[CrossRef](#)]
15. Dong, L.J.; Li, X.B.; Peng, K. Prediction of rockburst classification using random forest. *Trans. Nonferrous Met. Soc. China* **2013**, *23*, 472–477. [[CrossRef](#)]
16. Qi, Q.X.; Peng, Y.W.; Li, H.Y.; Li, J.Q.; Wang, Y.G.; Li, C.R. Study of bursting liability of coal and rock. *Chin. J. Rock. Mech. Eng.* **2011**, *30*, 2736–2742.
17. Li, S.L.; Feng, X.T.; Wang, Y.J.; Yang, N.G. Evaluation of rockburst proneness in a deep hard rock mine. *J. Northeast Univ. (Nat. Sci.)* **2001**, *22*, 60–63. [[CrossRef](#)]
18. Feng, T.; Pan, C.L. Lamination spallation buckling model for formation mechanism of rockburst. *Chin. J. Nonferrous Met.* **2000**, *10*, 287–290. [[CrossRef](#)]
19. Qiao, C.S.; Tian, Z.Y. Possibility of rockburst occurrence in dongguashan copper deposit. *Chin. J. Rock. Mech. Eng.* **1998**, *17*, 917–921.
20. Singh, S.P. Burst energy release index. *Rock. Mech. Rock. Eng.* **1988**, *21*, 149–155. [[CrossRef](#)]
21. Wang, J.A.; Park, H.D. Comprehensive prediction of rockburst based on analysis of strain energy in rocks. *Tunn. Undergr. Space Technol.* **2001**, *16*, 49–57. [[CrossRef](#)]
22. Askaripour, M.; Saeidi, A.; Rouleau, A.; Mercier-Langevin, P. Rockburst in underground excavations: A review of mechanism, classification, and prediction methods. *Undergr. Space* **2022**, *7*, 577–607. [[CrossRef](#)]
23. Qiu, S.L.; Feng, X.T.; Zhang, C.Q.; Wu, W.P. Development and validation of rockburst vulnerability index (RVI) in deep hard rock tunnels. *Chin. J. Rock. Mech. Eng.* **2011**, *30*, 1126–1141.
24. Li, N.; Jimenez, R. A logistic regression classifier for long-term probabilistic prediction of rock burst hazard. *Nat. Hazards* **2018**, *90*, 197–215. [[CrossRef](#)]
25. Li, D.Y.; Liu, Z.D.; Armaghani, D.J.; Xiao, P.; Zhou, J. Novel ensemble tree solution for rockburst prediction using deep forest. *Mathematics* **2022**, *10*, 787. [[CrossRef](#)]
26. Pang, H.L.; Gong, F.Q.; Gao, M.Z.; Dai, J.H. Improved expert system of rockburst intensity level prediction based on machine learning and data-driven: Supported by 1114 rockburst cases in 197 rock underground projects. *J. Cent. South Univ.* **2026**, *33*, 335–356. [[CrossRef](#)]
27. He, M.C.; Cheng, T.; Qiao, Y.F.; Li, H.R. A review of rockburst: Experiments, theories, and simulations. *J. Rock. Mech. Geotech. Eng.* **2023**, *15*, 1312–1353. [[CrossRef](#)]
28. Harrison, J.P.; Hudson, J.A. Incorporating parameter variability in rock mechanics analyses: Fuzzy mathematics applied to underground rock spalling. *Rock. Mech. Rock. Eng.* **2010**, *43*, 219–224. [[CrossRef](#)]
29. Xiang, G.; Zhang, X.H.; Wang, S.N.; Wu, Z.J.; Pan, X.M.; Xu, D.H. Unloading damage evolution and rockburst risk assessment of Xuefengshan No.1 tunnel by combining multiple approaches. *Sci. Rep.* **2025**, *15*, 2016. [[CrossRef](#)] [[PubMed](#)]
30. Xiong, Y.; Kong, D.Z.; Cheng, Z.B.; Wu, G.Y.; Zhang, Q. The comprehensive identification of roof risk in a fully mechanized working face using the cloud model. *Mathematics* **2021**, *17*, 2072. [[CrossRef](#)]
31. Zhou, J.; Chen, C.; Armaghani, D.J.; Ma, S.Y. Developing a hybrid model of information entropy and unascertained measurement theory for evaluation of the excavability in rock mass. *Eng. Comput.* **2022**, *38*, 247–270. [[CrossRef](#)]
32. Zhou, J.; Chen, C.; Wang, M.Z.; Khandelwal, M. Proposing a novel comprehensive evaluation model for the coal burst liability in underground coal mines considering uncertainty factors. *Int. J. Min. Sci. Technol.* **2021**, *31*, 799–812. [[CrossRef](#)]
33. Wu, S.L.; Dong, C.; Zhang, T.; Huo, L. Research on rockburst intensity evaluation based on unascertained measure-evidence theory. *Geosci. J.* **2025**, *29*, 802–812. [[CrossRef](#)]

34. Guan, J.F.; Yuan, P.; Li, L.; Yao, X.H.; Zhang, Y.L.; Meng, W. Rock fracture with statistical determination of fictitious crack growth. *Theor. Appl. Fract. Mech.* **2021**, *112*, 102895. [[CrossRef](#)]
35. Wang, G.Y. Uncertainty information and its mathematical treatment. *J. Harbin Archit. Eng. Insit* **1990**, *23*, 52–58.
36. Hu, X.M.; Huang, L.Q.; Chen, J.Z.; Li, X.B.; Zhang, H.Z. Rockburst prediction based on optimization of unascertained measure theory with normal cloud. *Complex Intell. Syst.* **2023**, *9*, 7321–7336. [[CrossRef](#)]
37. Zhang, L.W.; Zhang, X.Y.; Wu, J.; Zhao, D.K.; Fu, H. Rockburst prediction model based on comprehensive weight and extension methods and its engineering application. *Bull. Eng. Geol. Environ.* **2020**, *79*, 4891–4903. [[CrossRef](#)]
38. Wang, M.W.; Liu, Q.Y.; Wang, X.; Shen, F.Q.; Jin, J.L. Prediction of rockburst based on multidimensional connection cloud model and set pair analysis. *Int. J. Geomech.* **2020**, *20*, 04019147. [[CrossRef](#)]
39. Kidybinski, A.Q. Bursting liability indices of coal. *Int. J. Rock. Mech. Min. Geomech. Abstr.* **1981**, *18*, 295–304. [[CrossRef](#)]
40. Liu, Z.J.; Li, J.L. Comprehensive prediction method for rock burst based on fuzzy probability theory. *J. Yangt River Sci. Res. Inst.* **2007**, *24*, 42–45+49. [[CrossRef](#)]
41. Li, T.B.; Xiao, X.P. Comprehensively integrated methods of rockburst prediction in underground engineering. *Adv. Earth Sci.* **2008**, *23*, 533–540. [[CrossRef](#)]
42. Shang, Y.J.; Zhang, J.J.; Fu, B.J. Analyses of three parameters for strain mode rockburst and expression of rockburst potential. *Chin. J. Rock. Mech. Eng.* **2013**, *32*, 1520–1527.
43. Zhou, H.; Liao, X.; Chen, S.K.; Feng, T.; Wang, Z.M. Rockburst risk assessment of deep lying tunnels based on the combination weight and unascertained measure theory: A case study of Sangzhuling Tunnel on the Sichuan-Tibet Railway. *Earth Sci.* **2022**, *47*, 2130–2148. [[CrossRef](#)]

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