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*Research Article*

# Evaluating the Risk of Roof Fall in Phosphate Mines: Case Study of the Shanshuya Phosphate Mine in China

**Guangliang Feng**,[1] **Lanai Cen**,[2,3] **Manqing Lin**,[2,3] **Gang Yang**,[4] **Xianfu Li**,[2,3] **Jingang Ma**,[2,3] **and Guofeng Liu**[5]

[1]*State Key Laboratory of Geomechanics and Geotechnical Engineering, Institute of Rock and Soil Mechanics, Chinese Academy of Sciences, Wuhan 430071, China*
[2]*School of Resource and Safety Engineering, Wuhan Institute of Technology, Wuhan 430073, China*
[3]*Engineering Research Center of Ministry of Education for Phosphorus Resources Development and Utilization, Wuhan Institute of Technology, Wuhan 430073, China*
[4]*Key Laboratory of Geological Hazards on Three Gorges Reservoir Area, Ministry of Education, China Three Gorges University, Yichang, Hubei 443002, China*
[5]*Guangxi Key Laboratory of Disaster Prevention and Engineering Safety, Guangxi University, Nanning 530004, China*

Correspondence should be addressed to Guangliang Feng; glfeng@whrsm.ac.cn and Manqing Lin; linmanqing831206@163.com

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Roof fall in phosphate mines seriously endangers the safety of the mining activity. In this paper, the risk of roof fall occurring in phosphate mines is evaluated using the underground phosphate mine in Shanshuya, China, as an engineering background. The factors affecting roof fall in phosphate mines are analyzed, and an index system for evaluating the risk of roof fall in phosphate mine is established. Four evaluation models are employed to evaluate the risk of roof fall occurring: a set pair analysis model based on combination weights, a comprehensive fuzzy model based on hierarchical analysis, an approximately ideal ranking model based on entropy weight, and a gray relational analysis model. The evaluation results of the first two models are moderate risk with a bias toward intense risk. And the evaluation results of the last two models are slight risk with a bias toward moderate risk and moderate risk with a bias toward slight risk, respectively. The suitability of each of the evaluation models is analyzed which reveals that the evaluation results obtained using the different models are inconsistent. A combined evaluation method based on the four original evaluation models is subsequently proposed. Application of the combined evaluation method to the Shanshuya phosphate mine produces results that the roof fall risk is moderate with a bias toward slight risk. It is consistent with the actual situation in this phosphate mine. The results of the study can be used to provide technical support to engineers evaluating the risk of roof fall occurring in similar phosphate mines.

## 1. Introduction

The demand for phosphorus products is increasing due to the rapid rate of development of society [1]. As a result, phosphate mining is gradually moving deeper underground. The geological environment encountered in deep mines is complex and the ground stress is high, and this can frequently lead to disasters occurring, e.g., roof fall and rockburst [2–5]. Roof fall occurs when a rock body that has poor stability undergoes deformation and failure. As the mining face advances during the mining process, the roof area that is unsupported increases, and the stress in the top slab becomes redistributed. In this case, the integrity of the roof of the rock body is likely to fail. In particular, if no remedial measures are taken, the roof of the mine will collapse [6].

Roof fall is one of the most common hazards in mines and will, of course, seriously endanger the safety of the mining process and personnel in the mine. Many scholars have analyzed mining hazards from different perspectives. As a result, different technical methods and engineering theories have been applied to evaluating and predicting

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hazards in mines. For coal mines, for example, Xiong et al. [7] selected 17 risk factors affecting the roof disaster in Yushen coal mining area. They thus constructed a comprehensive standard cloud model to comprehensively evaluate the risk of roof hazards occurring. Zhang et al. [8] selected 9 factors relating to coal and gas protrusion accidents. An improved assessment method based on integrated weights and cloud computing theory was then used to assess the risk of coal and gas protrusion accidents occurring in a coal mine in Shanxi, China. Zhang et al. [9] selected the main factors affecting the damage suffered by the floor of a coal seam. Gray correlation degree analysis theory was then used to study the relative importance of the main influencing factors. In terms of metal mines, Małkowski et al. [10] used artificial neural networks to evaluate the risk of roof fall occurring in Polish copper mines based on various aspects (geological, mining, technical, and monitoring). Feng and Webber [11] selected many risk factors associated with rockburst hazards, e.g., excavation depth, excavation width, and support measures. They also used artificial neural networks to predict the risk of rockburst occurring (in deep gold mines located in South Africa). Liu et al. [12] used an established normal cloud model to assess the risk of damage occurring in deep tunnels in copper mines from the point of view of three aspects: geological conditions, degree of mining disturbance, and microseismic activity. Gong et al. [13] selected evaluation indices related to rockburst occurrence and used an analytical hierarchy process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS) evaluation method to predict the intensity of rockbursts in the Gemma copper polymetallic ore mine in Tibet. Dong et al. [14] analyzed 33 risk factors related to the safety of lead–zinc mines. They then proposed an evaluation model based on fuzzy-gray correlation analysis and applied it to risk evaluation in a lead–zinc mine.

System engineering theory has also been widely used to evaluate and predict other engineering hazards. For example, Peng et al. [15] proposed 9 factors based on engineering geology, hydrogeology, and construction factors. An AHP-TOPSIS evaluation model was then used to predict the risk of water and mud bursts occurring in the Longjinxi tunnel in China. Wang et al. [16] selected 7 factors as indices to evaluate water inrush (formation lithology, favorability of the geological conditions, etc.). They thus established a normal cloud theory model based on hierarchical analysis and applied it to two deep tunnels typically found in karst regions. Qiu et al. [17] analyzed the key factors involved in the deformation of the rock surrounding high-speed railroad tunnels. They then predicted the degree of deformation of the rock surrounding the Zhengwan high-speed railroad tunnel using rough set theory and cloud model theory.

The theoretical methods used to evaluate and predict hazard risks mentioned above have achieved some valuable results for specific hazards and engineering circumstances. The related system engineering theories used mainly focus on disasters such as rockburst, water and mud burst, bottom slab damage, roof fall, and gas protrusion in metal mines, coal mines, road tunnels, etc. However, few studies have focused on evaluating the risks associated with the hazards encountered in phosphate mines, especially with respect to roof fall. Different types of projects and environments (e.g., mines and water conservancy and hydropower projects) employ different engineering structures and involve different ground stress levels and construction factors. Thus, the factors that cause disasters to occur are also different. At the same time, the hazard levels predicted using different methods may also be inconsistent. Therefore, the appropriateness and reliability of the technical methods mentioned above must be researched much more thoroughly if they are to be used to evaluate the risk of roof fall occurring in phosphate mines.

In this work, the phosphate mine in Shanshuya in China is used as an engineering background. We first established an index system for evaluating the risk of roof fall occurring in such mines. Four evaluation models are then used to evaluate the risk of roof fall occurring in the phosphate mine.

(i) A set-pair analysis (SPA) model based on the combination weight of hierarchical analysis and entropy weight method (COW-SPA model)

(ii) A fuzzy comprehensive evaluation (FCE) model using hierarchical analysis (AHP-FCE model)

(iii) An evaluation technique based on the entropy weight method (EWM) and similarity to the ideal solution ranking approach (EWM-TOPSIS model)

(iv) A method employing gray relational analysis (GRA) to evaluate the risk (GRA model)

The suitability of each of the four evaluation models is subsequently analyzed. A further evaluation method is then developed for phosphate mines which is a combination of the four original evaluation models. The results of the study can be used to provide technical support for those evaluating the risk of roof fall occurring in phosphate mines.

## 2. Engineering Background

The Shanshuya phosphate mine is located in Hubei province in China. It has a design capacity of 1.5 million tons per year, and the depth of the ore body can be up to 750 m. The thickness of the ore body is less than 10 m [18, 19]. The mine contains massive deposits of sedimentary phosphate rock, and some of the rock in the area is hard and brittle. The mine area is dominated by the presence of karst fissure water and water ingresses directly into the mine through the top and bottom slabs. The hydrogeological conditions are deemed to be of medium type.

The roof above the ore layer of the mine consists of a thin–medium layer of dolomite with a heavy mud content. This reduces the mechanical strength of the rockmass. Faults and fissures are extensively developed in the mine area (there are 26 faults and 623 fissures). The maximum width of the fault fracture zone is 35 m, the fracture distance is 76 m, and the fissures are up to 10 cm wide. The integrity of the rock is thus poor and the fault fractures well developed. The ultimate compressive strengths of the rock masses

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Table 1: Summary of the four evaluation models employed in this work.

| Model | Description |
|---|---|
| COW-SPA | The relationship between determinism and uncertainty of a system is examined from the same, different, and opposite aspects. It is used to deal with multifactor uncertainty problems. |
| AHP-FCE | An effective multifactor decision-making method used to make a comprehensive evaluation of things influenced by multiple factors. Based on the membership grade theory in fuzzy mathematics. |
| EWM-TOPSIS | Evaluation objects are ranked according to their distance from positive and negative ideal solutions to the multiobjective decision problem. The judging object deemed closest to the positive ideal solution is taken to be the optimal value. The judging object deemed farthest to the positive ideal solution is the worst value. |
| GRA | A multifactor analysis method based on gray system theory. The differences and correlations between the elements of the system are examined by quantitatively analyzing the dynamic development of the system. When the comparative and reference series curves are similar, they are considered to have a high degree of correlation; otherwise, they are considered to have a low degree of correlation. |

surrounding the top and bottom of the mine are in the range 84–183 MPa, their shear strengths are in the range 4.8–32.4 MPa, their moduli of elasticity are in the range 17-38 GPa, and their softening coefficients are in the range 0.52–0.78.

The commonly-used room and pillar method as well as the single-pass mixed-transport layered mining method are used in the mine. The natural tendency of the mined area to crumble is used to fill the goaf area and thus manage the roof space. The height of the quarry at the phosphate mine is above 4 m in places which makes it difficult to inspect the roof pumice. Hazards are therefore difficult to detect and safely deal with in a timely manner. The above-mentioned issues make it very likely that roof fall will occur and lead to accidents. Various disasters occurred during mining, no doubt exacerbated by excavation disturbance, among which roof fall was one of the most common hazards. It is therefore very important to evaluate the risk of roof fall occurring in the phosphate mine. If this can be achieved, it will be possible to take appropriate remedial measures in a timely manner in order to ensure the safe operation of the mine.

## 3. Evaluating the Risk of Roof Fall

*3.1. Outline of the Four Evaluation Models.* The models used for mine disaster risk evaluation are numerous. Four evaluation models are used to evaluate the risk of roof fall occurring in the phosphate mine in this paper: the COW-SPA model [20–22], AHP-FCE model [23, 24], EWM-TOPSIS model [25, 26], and GRA model [14, 27]. In the risk assessment of a certain disaster, the influence that the different indicators have on the risk of disaster occurring varies. Therefore, the weights allocated to the indicators therefore need to be reasonable. Combining weights, subjective weights, objective weights, and no weights are used in the above four evaluation models, which are typical and with a wider coverage. The essential features of these models are outlined in Table 1 and Figure 1.

The likelihood that roof fall will occur can generally be divided into 4 or 5 levels [28, 29]. In this paper, we use 5 risk levels, referred to as low, slight, moderate, intense, and extremely intense (Table 2).

*3.2. Construction of a Risk Evaluation Index System for Roof Fall.* Phosphate mines are complex environments, and there are many factors that can contribute to the occurrence of a disaster. In addition, these factors interact with each other and must be treated as a set of impact factors that can, together, lead to roof fall.

Some roof fall disasters in phosphate mines are caused by factors relating to the personnel involved. System safety theory holds that information about the machinery and environment is constantly fed back to the brain via our senses. Accidents may therefore occur if people fail to perceive and recognize the dangers involved and fail to make the correct response in time. Therefore, the effect of personnel cannot be ignored. Human error is mainly manifested in the form of lack of skilled operating technique, weak safety awareness, lack of necessary safety knowledge and skills, failure to inspect and pry the pumice, or not thoroughly inspect and pry the pumice, etc. The behavior of the personnel may also be unsafe (undertaking risky or illegal operations, not investigating and dealing with hidden dangers, etc.). Other personnel-related factors that may be important are mainly related to their degree of personal education, the quality of their safety education, the training they received, etc.

From the point of view of the mechanical equipment and technical factors, it has been shown that the choice of mining method directly determines the safety of the project. That is, roof fall and wall caving disasters are more likely to occur if unreasonable mining methods are used during the exploitation of the phosphate mines. Employing safety measures is an effective way of preventing roof fall disasters. Roof fall and wall caving accidents are more likely to occur if there is an absence of support, an unreasonable choice of support, support is applied in an untimely manner, the quality of the support fails to meet proper requirements, or there are reduced levels of support in the mining site or roadway. As the roof of the phosphate mines has a complex geological structure, the general method involving knocking on the roof is not a useful way of recognizing the potential for disaster. We also note that if advanced detection technology is not used, the personal safety of the inspector will be threatened during the detection process. Therefore, the adaptability of the equipment is of great significance to safe production from phosphate mines. For example, it is difficult for small-

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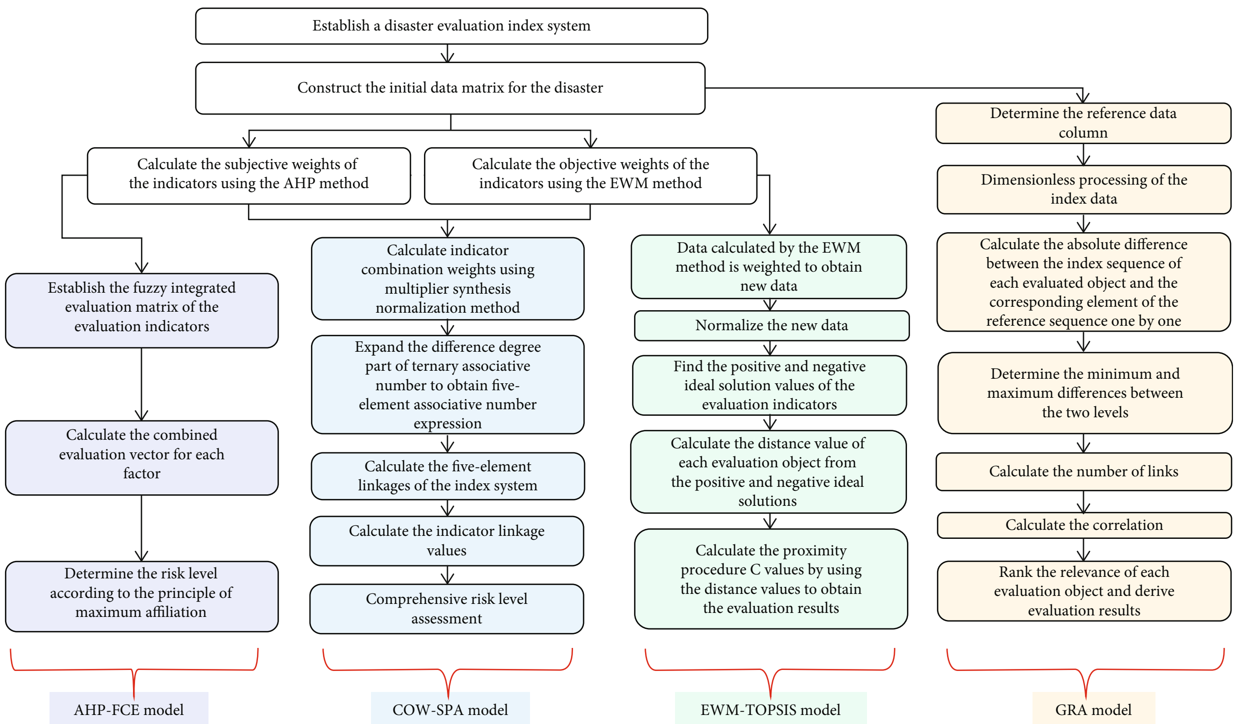


Figure 1: Diagram highlighting the basic principles of the four evaluation models.

Table 2: Classification criteria used to quantify the risk of roof fall occurring.

| Risk level | Definition |
|---|---|
| Low (I) | Extremely low probability that roof fall will occur; if it does, the damage caused will be minimal and have almost no impact. |
| Slight (II) | Low probability of roof fall occurring; the impact on construction and safety of the personnel is small. |
| Moderate (III) | High probability of roof fall occurring; the impact on construction and safety of the personnel cannot be ignored. |
| Intense (IV) | Even higher probability of roof fall occurring; the impact on construction and safety of the personnel is greater. |
| Extremely intense (V) | Extremely high probability of a roof fall disaster occurring. The situation is of great concern as damage is likely to be caused to machinery and equipment and there are likely to be casualties. |

scale equipment to control the roof plate when rock drilling. On the other hand, it is difficult for large-scale equipment to enter the working area due to space limitations.

The deposit formed in the Shanshuya phosphate mines passes through a geological fracture zone which features faults and folds, leading to the development of joint fissures within the rock body. The integrity of the rock body is very low which destabilizes the quarry and leads to the occurrence of roof fall and wall caving. The stress balance will also be affected by the presence of nearby quarries. Overdigging and overmining (or mechanical disturbance and blasting vibration during mining) will further reduce the stability of the quarry. Furthermore, if roof fall does occur in one quarry, then, the surrounding quarries will also be affected, and this will clearly increase the probability of roof fall occurring in them as well. The pressure distribution in the mining site is affected by the mining depth and the fault distribution. In phosphate mines, the ground pressure is mainly determined by geological and engineering factors and mining depth. As the mining depth increases, the ground pressure increases. This makes roof fall more likely to occur and increases the severity of the event when it does.

Safety post responsibility systems are an important way of improving production safety and help ensure that workers remain safe. A mine safety management system is another important measure aimed at regulating the behavior of the workers involved in the production process. As such systems reduce the use of dangerous practices, they can clearly help achieve safe production from the phosphate mine. Mine operators should therefore implement a strict phosphate mine safety management system to prevent and control the occurrence of roof fall. In addition, if the site is not properly supervised and inspected, or the roof clearance operation is not analyzed and interpreted accurately, any hidden dangers will not be found and addressed in time. This could result in the occurrence of disasters such as roof fall. Thus, it is essential that timely and regular supervision and inspection of the mining work be carried out by the phosphate mining

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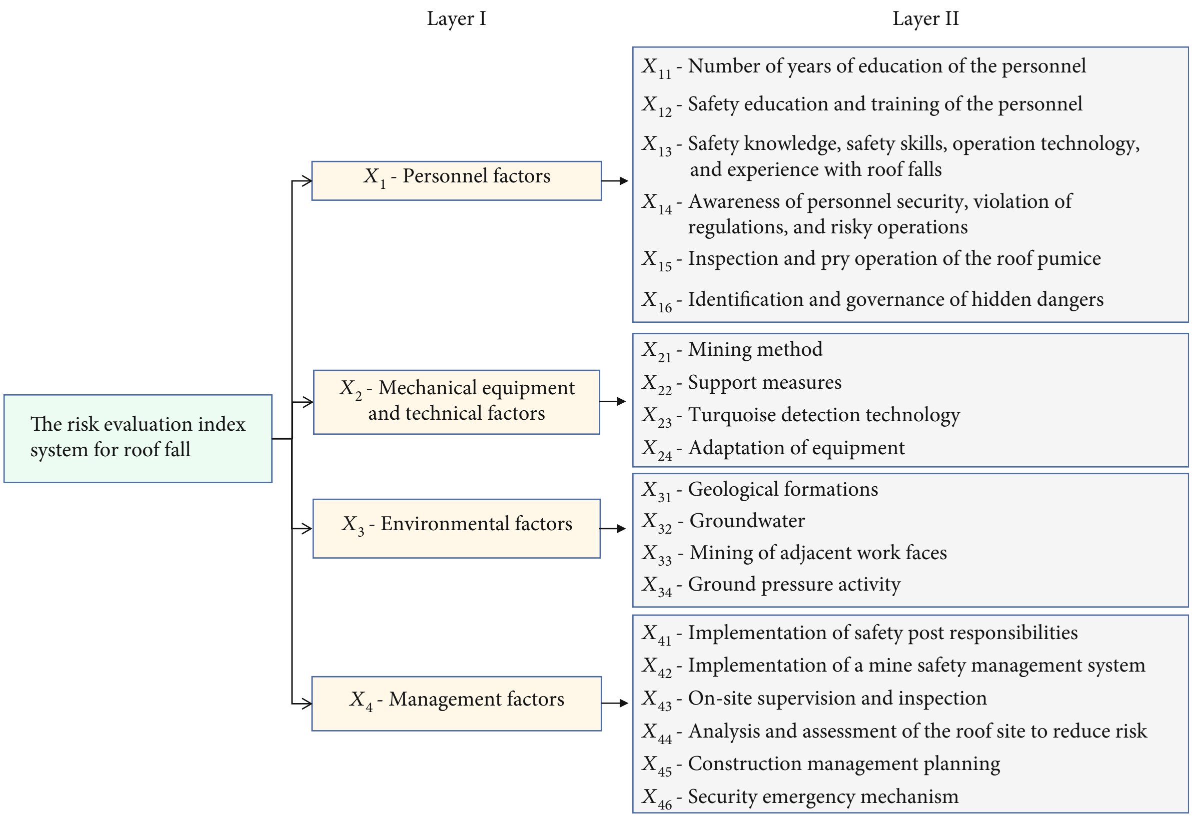


Figure 2: Indicators used to create a risk evaluation index for roof fall in phosphate mines.

enterprise. Such activity is highly conducive to safe construction and improves the emergency handling system of the mine. Besides, the time the quarry is exposed is another important factor controlling the occurrence of roof fall. If the construction process is not properly organized, the roof may be exposed for an excessive amount of time and so the factors inducing roof fall will have a greater opportunity to have an effect. The safety emergency mechanism is an important reference factor for safe conditions in phosphate mines and can effectively prevent and control possible accidents.

In order to comprehensively reflect the influence of the various factors mentioned above (and ensure the evaluation results are scientific and reliable), a risk evaluation index is established for roof fall in phosphate mines in this work. The index is to be based on the above analysis and field investigations carried out in the Shanshuya phosphate mine. As shown in Figure 2, the index system is divided into two layers: the first layer divides the factors into four categories relating to personnel, mechanical equipment and technical aspects, the environment, and management practices. The second layer shows how the 20 factors are distributed (6 are personnel factors, 4 are mechanical equipment and technical factors, 4 are environmental factors, and 6 are management factors). These index factors can, of course, be dynamically optimized as new information comes to light in the phosphate mine.

*3.3. Indicator Weights.* The influence that the different indicators have on the risk of roof fall occurring varies. The weights allocated to them therefore need to be reasonable and scientifically determined if the prediction results are to be accurate. To this end, subjective weights, objective weights, and combined weights of the indicators are calculated using the AHP, EWM, and multiplicative synthetic normalization methods, respectively.

Table 3: Criterion level judgment matrix.

| | $X_1$ | $X_2$ | $X_3$ | $X_4$ | Weight |
|---|---|---|---|---|---|
| $X_1$ | 1 | 2 | 3/2 | 1/2 | 0.2600 |
| $X_2$ | 1/2 | 1 | 2 | 2/3 | 0.2133 |
| $X_3$ | 2/3 | 1/2 | 1 | 1/3 | 0.1317 |
| $X_4$ | 2 | 3/2 | 3 | 1 | 0.0395 |
| $\lambda_{max} = 4.1229$ | | CR = 0.0460 | | | |

The evaluation index system established in Tables 3–7 is assessed using the AHP method based on judgment criteria specified on scales of 1–9. A judgment matrix is thus constructed by pairwise comparison of the influencing factors at each level of the index layer (Tables 3–7). To do this, careful consideration is given to the information in the literature related to the classification of risk factors associated with roof fall hazards in phosphate mines, as well as the actual situation on the ground in the Shanshuya phosphate mine. Based on the existing experience, we discussed with the

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Table 4: Judgment matrix for $X_1$ (personnel factors).

| | $X_{11}$ | $X_{12}$ | $X_{13}$ | $X_{14}$ | $X_{15}$ | $X_{16}$ | Weight |
|---|---|---|---|---|---|---|---|
| $X_{11}$ | 1 | 1/2 | 1/3 | 1/3 | 1/3 | 1/3 | 0.0169 |
| $X_{12}$ | 2 | 1 | 1/2 | 1/2 | 1/3 | 1/2 | 0.0256 |
| $X_{13}$ | 3 | 2 | 1 | 1 | 1/2 | 1 | 0.0460 |
| $X_{14}$ | 3 | 2 | 1 | 1 | 1/2 | 1 | 0.0460 |
| $X_{15}$ | 3 | 3 | 2 | 2 | 1 | 2 | 0.0793 |
| $X_{16}$ | 3 | 2 | 1 | 1 | 1/2 | 1 | 0.0460 |
| $\lambda_{max} = 6.0686$ | | CR = 0.0109 | | | | | |

Table 5: Judgment matrix for $X_2$ (mechanical equipment and technical factors).

| | $X_{21}$ | $X_{22}$ | $X_{23}$ | $X_{24}$ | Weight |
|---|---|---|---|---|---|
| $X_{21}$ | 1 | 1/2 | 2 | 3 | 0.0625 |
| $X_{22}$ | 2 | 1 | 2 | 3 | 0.0879 |
| $X_{23}$ | 1/2 | 1/2 | 1 | 2 | 0.0399 |
| $X_{24}$ | 1/3 | 1/3 | 1/2 | 1 | 0.0230 |
| $\lambda_{max} = 4.0709$ | | CR = 0.0266 | | | |

Table 6: Judgment matrix for $X_3$ (environmental factors).

| | $X_{31}$ | $X_{32}$ | $X_{33}$ | $X_{34}$ | Weight |
|---|---|---|---|---|---|
| $X_{31}$ | 1 | 3 | 2/3 | 1/3 | 0.0241 |
| $X_{32}$ | 1/3 | 1 | 1/3 | 1/5 | 0.0103 |
| $X_{33}$ | 3/2 | 3 | 1 | 1/3 | 0. 0292 |
| $X_{34}$ | 3 | 5 | 3 | 1 | 0. 0680 |
| $\lambda_{max} = 4.0644$ | | $CR$ =0.0241 | | | |

Table 7: Judgment matrix for $X_4$ (management factors).

| | $X_{41}$ | $X_{42}$ | $X_{43}$ | $X_{44}$ | $X_{45}$ | $X_{46}$ | Weight |
|---|---|---|---|---|---|---|---|
| $X_{41}$ | 1 | 1 | 3/2 | 1/5 | 1/5 | 1/2 | 0.0268 |
| $X_{42}$ | 1 | 1 | 3/2 | 1/5 | 1/5 | 1/2 | 0.0268 |
| $X_{43}$ | 2/3 | 2/3 | 1 | 1/7 | 1/7 | 1/3 | 0.0183 |
| $X_{44}$ | 5 | 5 | 7 | 1 | 1 | 3 | 0.1363 |
| $X_{45}$ | 5 | 5 | 7 | 1 | 1 | 3 | 0.1363 |
| $X_{46}$ | 2 | 1/2 | 3 | 1/3 | 1/3 | 1 | 0.0505 |
| $\lambda_{max} = 6.0077$ | | CR = 0.0012 | | | | | |

experts related to the roof fall disaster of the Shanshuya phosphate mine and combine the characteristics of roof fall disaster of the phosphate mine to determine which index has a greater impact on the upper level factors. Finally, as illustrated by a relatively important numerical value, the judgment matrices for the criterion layer and corresponding risk indicators are shown in Tables 3–7.

The data in Tables 3–7 is used to calculate the maximum eigenvalues and weights of each evaluation index. The tables, therefore, also present the calculated values of the maximum characteristic root ($\lambda_{max}$) and consistency ratio (CR), as well as the weights of the factors. The consistency indicators are calculated to check the consistency of the judgment matrix evaluation results. The consistency checks show that CR < 0.1 for each matrix, indicating that the judgment matrices and weights are acceptable and consistent.

The resulting set of weights for the 20 indicators in layer II in the risk index system is therefore:

$$\begin{aligned}\omega_{ai} = (&0.0169,0.0257,0.0463,0.0463,0.0801,0.0463,0.0617,\\&0.0876,0.039,0.0226,0.0102,0.0238,0.0292,0.0686,\\&0.0268,0.0268,0.0183,0.1366,0.1366,0.0505).\end{aligned} \tag{1}$$

Similarly, the set of weights for the indicators in layer I is

$$\omega_{ai}{}' = (0.2617, 0.2108, 0.1319, 0.3956). \tag{2}$$

The objective weighting calculations are performed using the EWM method. Clearly, the number of experienced scholars involved in this process should be appropriate. Generally, 5 to 10 experienced scholars are thought to be appropriate (in terms of the convenience with which information is collected and ease with which the modeling calculations are performed). Three scholars and two mine staff are invited to take part in this study. The three scholars had each been engaged in roof fall research in phosphate mines for many years, and the two mine staff had a rich variety of practical experience in such mines. Each indicator in the evaluation index system in Table 3 is objectively evaluated and judged according to the fuzzy risk factor classification information in Table 4 and actual situation in the Shanshuya phosphate mine in Hubei Province. Five risk levels: low (I), slight (II), moderate (III), intense (IV), and extremely intense (V) are set for each evaluation index. The results for each indicator, as determined by the evaluation committee, are shown in Table 8.

Using the EWM method and data in Table 8, the set of weights for the indicators in layer II is found to be:

$$\begin{aligned}\omega_{bi} = (&0.0279, 0.0140, 0.0477, 0.0477, 0.0839, 0.0477, 0.0839,\\&0.0477, 0.0477, 0.0574, 0.0279, 0.0839, 0.0140, 0.0338,\\&0.0839, 0.0839, 0.0574, 0.0477, 0.0477, 0.0140).\end{aligned} \tag{3}$$

Similarly, the set of weights for the indicators in layer I is found to be:

$$\omega_{bi}{}' = (0.2689, 0.2367, 0.1596, 0.3346). \tag{4}$$

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Table 8: Results of the normalization procedure for each evaluation index.

| Indicator | Evaluation level | | | | |
|---|---|---|---|---|---|
| | Low | Slight | Moderate | Intense | Extremely intense |
| $X_{11}$ | 0.2 | 0.4 | 0.4 | 0 | 0 |
| $X_{12}$ | 0 | 0.2 | 0.2 | 0.4 | 0.2 |
| $X_{13}$ | 0 | 0 | 0.4 | 0.6 | 0 |
| $X_{14}$ | 0 | 0 | 0.4 | 0.6 | 0 |
| $X_{15}$ | 0 | 0 | 0 | 1 | 0 |
| $X_{16}$ | 0 | 0 | 0.4 | 0.6 | 0 |
| $X_{21}$ | 0 | 0 | 1 | 0 | 0 |
| $X_{22}$ | 0 | 0 | 0.4 | 0.6 | 0 |
| $X_{23}$ | 0 | 0.4 | 0.6 | 0 | 0 |
| $X_{24}$ | 0 | 0.8 | 0.2 | 0 | 0 |
| $X_{31}$ | 0 | 0.4 | 0.4 | 0.2 | 0 |
| $X_{32}$ | 0 | 1 | 0 | 0 | 0 |
| $X_{33}$ | 0.2 | 0 | 0.2 | 0.4 | 0.2 |
| $X_{34}$ | 0 | 0 | 0.6 | 0.2 | 0.2 |
| $X_{41}$ | 0 | 1 | 0 | 0 | 0 |
| $X_{42}$ | 0 | 1 | 0 | 0 | 0 |
| $X_{43}$ | 0.2 | 0.8 | 0 | 0 | 0 |
| $X_{44}$ | 0 | 0 | 0.6 | 0.4 | 0 |
| $X_{45}$ | 0 | 0 | 0.6 | 0.4 | 0 |
| $X_{46}$ | 0.2 | 0.4 | 0.2 | 0.2 | 0 |

The multiplier synthesis normalization method is subsequently applied to the calculated weights to find the combined weights for the evaluation indices. The combined weights for the indicators in layer II are found to be

$$\omega_i = (0.0093,0.0071,0.0433,0.0433,0.1318,0.0433,\\ 0.1015,0.0820,0.0365,0.0254,0.0056,0.0392,0.0080,\\ 0.0455,0.0441,0.0441,0.0206,0.1278,0.1278,0.0139). \tag{5}$$

The combined weights of the indicators in layer I are similarly found to be:

$$\omega_i{}' = (0.2571, 0.1823, 0.0769, 0.4837). \tag{6}$$

Based on these results of the calculated combination of weights, the indicators in layer I can be ranked in order of importance according to their weights: management factors, personnel factors, mechanical equipment and technology factors, and environmental factors. In layer II, six secondary indices have significant weights: $X_{15}$ (inspection and pry operation of the top), $X_{21}$ (mining method), $X_{22}$ (support measures), $X_{34}$ (ground pressure activity), $X_{44}$ (analysis and assessment of the roof site to reduce risk), and $X_{45}$ (construction management planning). The influence of these indices on the likelihood of roof fall occurring in Shanshuya phosphate mines is correspondingly larger than the others.

*3.4. Results Obtained Using the Four Models.* The results of the risk evaluations made using the four models are shown in Figure 3 and summarized in Table 9. The different evaluation models evaluate the situation from their own perspectives, and each evaluation model will have its limitations. Therefore, the results obtained using the different evaluation models are different. The ranking of the scores is based on the ranking of the maximum membership grade principle.

The moderate risk level (level III) has the largest score according to the COW-SPA, AHP-FCE, and GRA models (therefore, they predict that the risk of roof fall occurring is moderate). The COW-SPA and AHP-FCE models suggest that the intense risk level (level IV) is ranked second, so these evaluation models are tending toward intense risk (level IV). On the other hand, the GRA method ranks level II second, so this evaluation model is tending toward slight risk (level II). Finally, in the EWM-TOPSIS model, the score obtained for the moderate risk level (level III) ranks second and that obtained for the slight risk level (level II) is the largest. Hence, this model predicts that the risk level is slight tending toward moderate.

As can be seen from Figure 1, each evaluation model actually invokes different analytic processes from different perspectives. As a result, even though the same objects are being evaluated, the results produced by the different evaluation models are inconsistent (Table 9). Therefore, in order to take full advantage of the strengths of the various models and hopefully achieve more accurate evaluation results, it is necessary to combine the evaluation results produced by the different evaluation models. The final results should thereby be more reliable and credible.

## 4. Combined Evaluation Based on the Four Methods

*4.1. Combined Evaluation Method.* In order to make the evaluation results consistent, a combined evaluation method is proposed based on the original set of methods. Due to the different properties of the various methods (as different mechanisms are employed), the individual evaluation methods may lead to different evaluation results. However, for any one given object, the evaluation results obtained using these different evaluation methods should not be too much different. When we use an evaluation method to evaluate the value of each evaluation level, we are actually establishing a superiority order for the evaluation levels. If we only form a combination evaluation based on the ordering relationships (or, alternatively, just the evaluation values), the final combined evaluation result may be not good. Thus, it is difficult to obtain a reasonable and scientific evaluation result.

In this study, a new method is proposed for making a combined evaluation based on a set of methods. In our method, the different level scores obtained for the factors and the ranking factors obtained using the multiple evaluation methods are combined to reflect the properties of the

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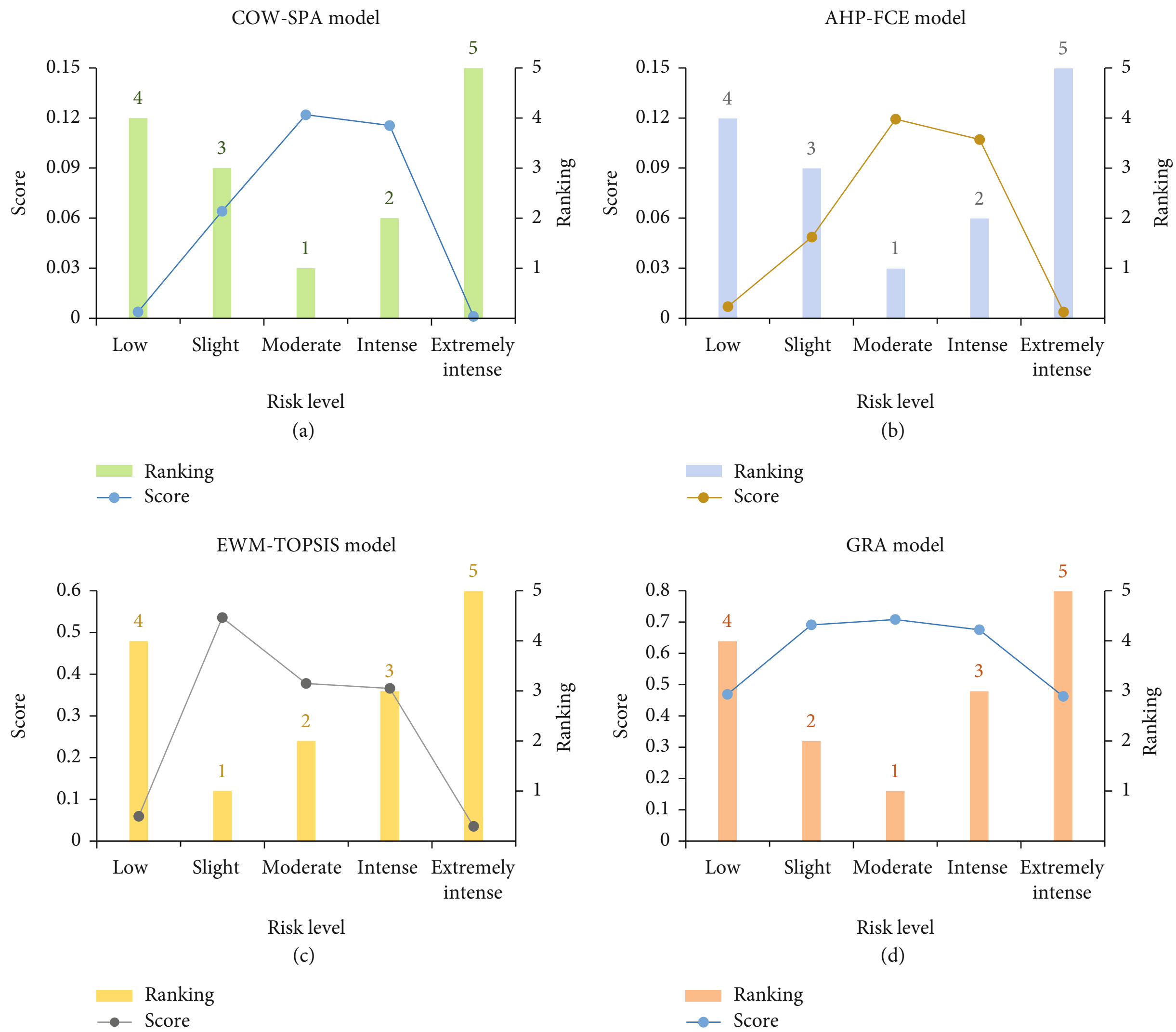


Figure 3: Evaluation results obtained using the four models.

Table 9: Comparison of the evaluation results.

| Evaluation model | Evaluation result |
|---|---|
| COW-SPA | Moderate risk (III) with a bias toward intense risk (IV) |
| AHP-FCE | Moderate risk (III) with a bias toward intense risk (IV) |
| EWM-TOPSIS | Slight risk (II) with a bias toward moderate risk (III) |
| GRA | Moderate risk (III) with a bias toward slight risk (II) |

objects more comprehensively. By combining the different methods, we can complement each of their strengths. At the same time, information about the different methods can be used to eliminate the problem of inconsistent evaluation results. In this way, an evaluation result that is reasonable and scientific can be obtained.

More specific details of the steps involved are given below. A flowchart outlining the calculations involved in the combined evaluation method is given in Figure 4. The set of methods used in this work is {COW-SPA, AHP-FCE, EWM-TOPSIS, and GRA}, and the calculations proceed as follows:

(1) *Calculate the membership grade, $\mu_{ij}$.* The original data can be normalized to a same dimension to eliminate the occurrence of weighting imbalance:

$$\mu_{ij} = \frac{X_{ij} - \min\left(X_{ij}\right)}{\max\left(X_{ij}\right) - \min\left(X_{ij}\right)} \times 0.9 + 0.1, i = 1, 2, \cdots, m; j = 1, 2, \cdots, n, \quad (7)$$

where $X_{ij}$ represents the evaluation value obtained for the $i$ -th risk level using the $j$ -th evaluation method. In effect, $\mu_{ij}$ gives the grade of membership which quantifies the "excellence" of the $i$ -th risk level assessment according to the $j$ -th evaluation method.

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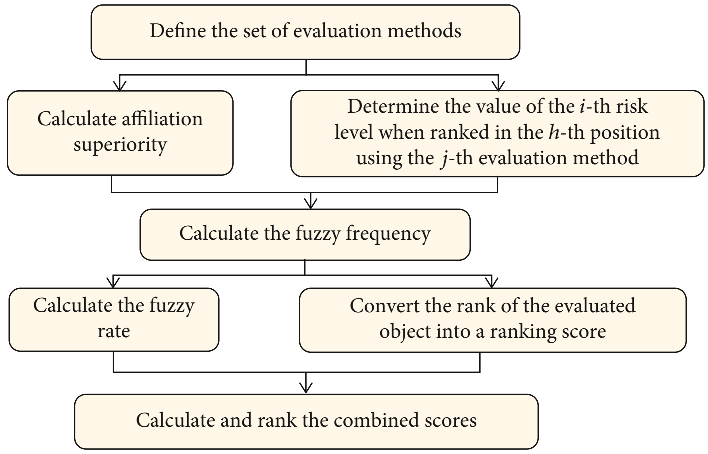


Figure 4: Flow chart outlining the combined evaluation method.

Table 10: The calculated membership grade.

| Model | Level | | | | |
|---|---|---|---|---|---|
| | Low | Slight | Moderate | Intense | Extremely intense |
| COW-SPA | 0.12047 | 0.5693 | 1 | 0.9513 | 0.1 |
| AHP-FCE | 0.1247 | 0.4500 | 1 | 0.9056 | 0.1 |
| EWM-TOPSIS | 0.1431 | 1 | 0.7162 | 0.6946 | 0.1 |
| GRA | 0.1256 | 0.9378 | 1 | 0.8793 | 0.1 |

Table 11: The calculated fuzzy rates.

| Value of $h$ | Level | | | | |
|---|---|---|---|---|---|
| | Low | Slight | Moderate | Intense | Extremely intense |
| 1 | 0 | 0.25 | 0.75 | 0 | 0 |
| 2 | 0 | 0.2671 | 0.2040 | 0.5289 | 0 |
| 3 | 0 | 0.3931 | 0 | 0.6069 | 0 |
| 4 | 1 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 1 |

(2) *Calculate the Fuzzy Rate*. Fuzzy logic is used to reflect the variability of the evaluation values of the various evaluation methods with respect to the different risk levels. To determine the evaluation value of each risk level, we let $P_{ih}$ denote the fuzzy frequency with which the $i$ -th risk level is ranked in the $h$ -th position $(1 \le h \le 5)$

$$P_{ih} = \delta_i \mu_i^{(j)} E = \left(f_{i1}\ f_{i2} \cdots f_{\mathrm{in}}\right)^T_{1\times m}. \tag{8}$$

In Eq. (8), $\delta_i = [\delta_{ih}^{(j)}]_{m\times n}$, $\mu_i^{(j)} = \mathrm{diag}\left(\mu_i^{(1)} \mu_i^{(2)} \cdots \mu_i^{(n)}\right)$, and $E = (1\ 1 \cdots 1)^T_{1\times \mathrm{m}}$. If the $i$-th risk level is ranked $h$ under the $j$-th evaluation method, the value of $\delta_{ih}^{(j)}$ will be 1; otherwise, it is 0. The expression for the fuzzy rate is

$$W_{ih} = \frac{P_{ih}}{\sum_{h=1}^{m} P_{ih}}. \tag{9}$$

(3) The rank of the evaluated object $X_i$ is converted into a ranking score using the expression

$$Q_h = \frac{(m - h + 0.01) \times (\mathrm{m} - h + 1)}{2}, \tag{10}$$

where $Q_h$ denotes the score of $X_i$ in the $h$ -th position in order of superiority. In fact, $Q_h$ is a deterministic sequence.

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Table 12: Combined evaluation results calculated using the chosen method set.

| | Level | | | | |
|---|---|---|---|---|---|
| | Low | Slight | Moderate | Intense | Extremely intense |
| Original score | 1.01 | 5.2994 | 8.7468 | 5.0138 | 0.005 |
| Normalized score | 0.1156 | 0.6059 | 1 | 0.5732 | 0.0006 |
| Ranking | 4 | 2 | 1 | 3 | 5 |

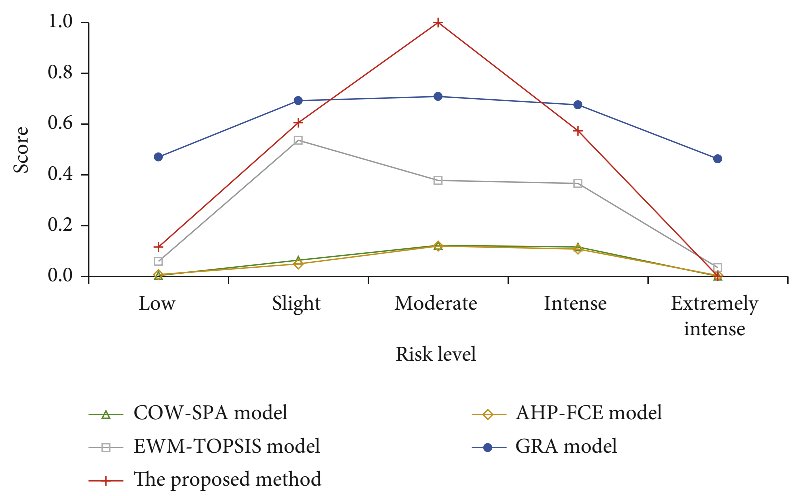
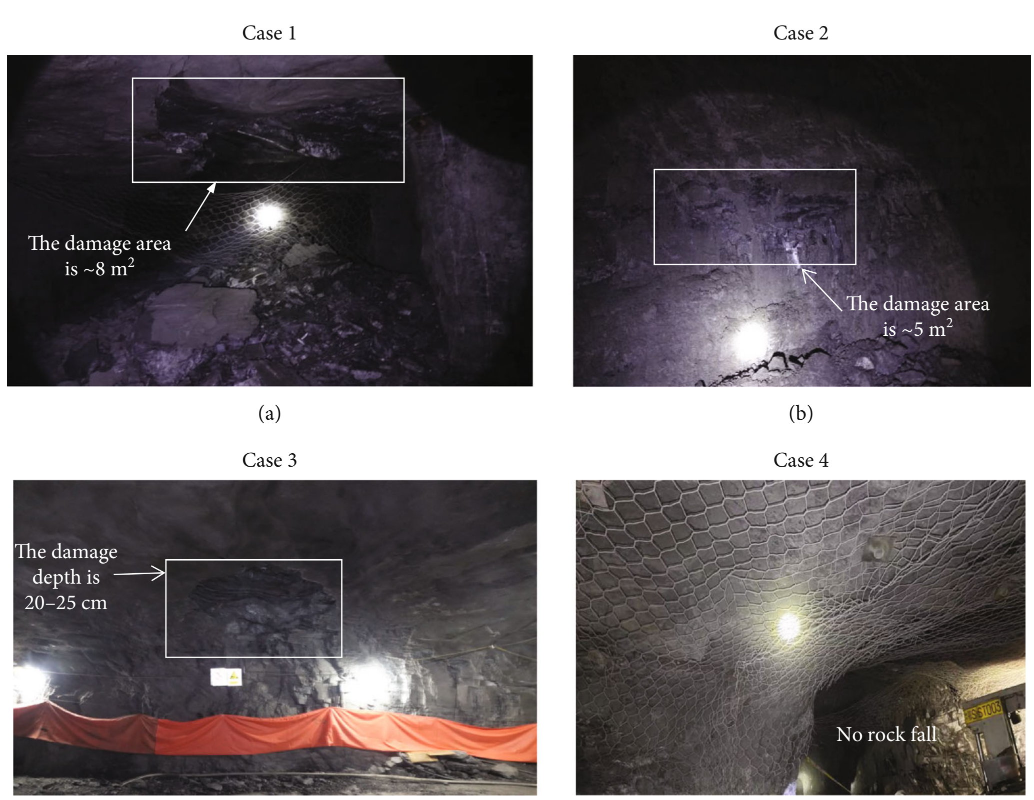



Figure 5: Comparison of the results obtained using the separate models and combined evaluation method.




(a) (b) (c) (d)

Figure 6: Rock fall damage observed in the Shanshuya phosphate mine.

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(4) The combined score $FB_i$ for the $i$ -th risk level can now be calculated using the expression:

$$FB_i = \sum_{h=1}^{m} W_{ih} Q_h, \quad (11)$$

yielding values that lie in the range $[0, +\infty)$.

(5) Finally, the $FB_i$ values are ranked according to the principle of maximum membership grade. The higher the score, the higher the corresponding risk level

*4.2. Evaluation Result Obtained Using the Proposed Method.* The proposed method combines the evaluation results obtained using multiple evaluation models. The membership grade is first calculated for each evaluation model according to Eq. (7) giving the results shown in Table 10. The fuzzy frequencies of the $i$ -th ranks in position $h$ are then calculated according to Eqs. (8) and (9), giving the results shown in Table 11. The combination scores are then calculated for the different ranks according to Eqs. (10) and (11) and the final ranking result derived. The combination scores and ranks of each risk level are presented in Table 12. The results of the combined evaluation method are also shown in Figure 5 along with those obtained using the individual evaluation models.

The proposed method indicates that moderate risk (level III) has the highest ranking followed by slight risk (level II). In other words, it predicts that the risk of roof fall occurring is moderate tending toward slight. Evidence of the occurrence of roof fall in the Shanshuya phosphate mine in Hubei Province is collected, and the damage typically encountered in the mine is highlighted in Figure 6.

According to the damage information collected, roof fall is likely to occur in the Shanshuya phosphate mine. When roof fall does occur, it mainly involves an area of 1 to $10\,m^2$, and the depth and thickness of the damage lies mainly in the range 5 to 25 cm. For one roof fall, the damage area and depth of the rock mass are small. It is worth noting that the accumulation of multiple small-scale roof fall can make a large-scale roof fall phenomenon. The local damage caused by roof fall had a certain impact on personnel safety and construction, and this impact can be control if we take measures timely. The comprehensive assessment of the risk of roof fall occurring in this phosphate mine suggests that the risk is moderate risk (level III) with a bias toward slight risk and requires some risk mitigation measures to be taken to improve the safety level. The combined evaluation result is thus consistent with the actual situation in the mine.

## 5. Conclusions

This paper establishes a system of indicators that are suitable for predicting the likelihood that roof fall will occur in phosphate mines. The phosphate mine in Shanshuya, Hubei, is used as our engineering background to determine 20 evaluation indicators for roof fall belonging to four categories: personnel factors, mechanical equipment and technical factors, environmental factors, and management factors. In terms of importance, these categories are found to be ranked in the order: management factors, personnel factors, mechanical equipment and technology factors, and environmental factors.

Four typical evaluation models (COW-SPA, AHP-FCE, EWM-TOPSIS, and GRA models) are used to evaluate the risk of roof fall occurring in the phosphate mine. It was found that the results obtained using the different models are inconsistent. Two models (COW-SPA and AHP-FCE) predicted that the risk is moderate and biased toward intense. The EWM-TOPSIS model suggested the risk is slight but biased toward moderate. The GRA model predicted that the risk is moderate and biased toward slight risk.

A combined evaluation method is subsequently proposed based on the results of the four evaluation models. The new model combines the factors of differences in level scores and ranking of the evaluation results of multiple evaluation methods to give a combined evaluation. Using this approach allows the properties of the objects to be comprehensively reflected and helps eliminate the problem of inconsistency in the evaluation results. The proposed method suggests that the roof fall risk is moderate in the Shanshuya mine with some bias toward slight risk. This is consistent with the actual situation in this phosphate mine. The research results presented in this work can be used to provide technical support for engineers evaluating the risk of roof fall occurring in similar phosphate mines.

## Data Availability

The data used to support the findings of this study are included within the article.

## Conflicts of Interest

The authors declare no conflicts of interest.

## Authors' Contributions

Data collection and curation were done by Lanai Cen, Gang Yang, and Jingang Ma. Methodology was done by Lanai Cen, Guangliang Feng, and Liu Guofeng. Supervision was done by Guangliang Feng and Manqing Lin. Original draft composition was done by Lanai Cen and Gang Yang. Review and editing were done by Guangliang Feng, Manqing Lin, and Xianfu Li. All authors have read and agreed to the final version of the manuscript.

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