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Mining Method Optimization of Gently Inclined and Soft Broken Complex Ore Body Based on AHP and TOPSIS: Taking Miao-Ling Gold Mine of China as an Example

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Abstract: The gently inclined thin to medium thickness ore body under a weak rock stratum is one of the typical difficult bodies to mine. In order to solve the fuzziness, randomness, and uncertainty in the process of mining method optimization for such ore bodies, a multi-level, multi-factor, multi-objective, and multi-index comprehensive evaluation system involving technology, economy, construction, and safety was constructed by combining the analytic hierarchy process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS). Taking the Miao-ling gold mine in China as an example, the AHP-TOPSIS comprehensive decision model of mining method optimization is established, the comprehensive superiority degrees of the four mining schemes are 67.57%, 45.07%, 56.07%, and 31.63%, and the upward horizontal drift backfill mining method is determined as the optimal scheme. The method is verified in the actual production of the mine, which not only ensures the safe production of the mine, but also achieves better technical and economic effects. The research results provide a reference for the optimization of mining methods for gently inclined and soft broken complex ore bodies at home and abroad.

Keywords: mining method; soft broken complex ore body; improved AHP; comprehensive evaluation index

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1. Introduction and Background

1.1. Retrospective: The Progress of Mining Method Optimization and Evaluation in China

Beginning in the 2000s, Chinese mining engineers and researchers began to try to apply mathematical methods or systems engineering methods to the optimization of mining operation and production.

Around 2007, a growing number of Chinese researchers began publishing their research in international journals: In 2008, Z. Li et al. [1] adopted the analytic hierarchy process (AHP) in order to develop a framework of sustainability assessment indicators and methods for mining communities. Their research was published in the journal *International Journal of Sustainable Development and World Ecology* and provided a useful tool for monitoring key policy outcomes, measuring progress toward targets, comparing the development characteristics of different mining communities, and informing decision making. In 2010, H. Si et al. [2] established an environmental evaluation system for environmental conditions, resource protection, and economic benefits based on the analysis of environmental pollution from coal mining and the increasing demand for raw coal in order to promote the sustainable development of coal mining. Combined with the analytic hierarchy process (AHP), they put forward a method to calculate the weight of each index and environmental sustainability, used the index system to evaluate the environmental sustainability of coal mining in the Qi-jiang area in Western China, and verified the effectiveness of the index system. The significance of this study is that the environmental assessment system established by the researchers can be used as a tool to assess the environmental impact of mining areas and measures to promote the sustainable development of coal mining: also in 2010, S. Su, J. Yu, and J. Zhang [3] paid attention to the development of urban mining. They established a scientific and applicable method to accurately measure the degree of sustainable development of mineral resources (DSDMR). Their research will accelerate the adaptive genetic algorithm (AGA), analytic hierarchy process (AHP), and fuzzy comprehensive judgment to measure the sustainability of mineral resources, which is of great inspiration to the future development of China's mining industry.

Since 2010, mining technology in China has developed rapidly, and more and more researchers have applied mathematical models, physical models, and even machine learning to the optimization of mining methods. For example, in 2012, Y. H. Teng and W. Zhu [4] developed a method to predict the height of the fracture zone in coal mining through on-site measurement and numerical and physical simulation. In 2013, H. Jang and E. Topal [5] focused on the transcendental control of the drilling and blasting method in mining. They used multiple regression analysis and an artificial neural network to develop an over-mining prediction model as an over-mining warning and prevention system, which can effectively predict potential over-mining.

Around 2020, as China advocated for the construction of green mines, more and more researchers began focusing on the sustainable development of mining. For example, in 2018, Yu et al. [6] focused on the impact of mining on the safety of surface structures and the environmental health status of surrounding mining areas, and developed an evaluation method for the surface settlement mechanism and surrounding rock stability by using mathematical and physical models, and in 2020, Bao et al. [7] evaluated the impact of mining activities on the city.

To put it simply, in recent years in China, more and more mining researchers have applied mathematical models, physical models, systems engineering methods, and artificial intelligence, such as deep neural networks, to the optimization of mining methods and the assessment of the impact caused by mining. However, the systems engineering method has had good application effects on mining optimization in China in the past 20 years. Even in 2021, Li et al. [8] used the fractal-AHP-vulnerability index method to optimize the mining methods.

1.2. Background: Status Quo of Miao-Ling Gold Mine in Henan Province, China

The western part of Henan Province is the second largest gold-producing base in China, and the altered rock type gold deposit in the fractured zone is the main gold mineralization type in this area [9]. Due to the multi-stage tectonic superposition in the fracture zone, ductile and brittle rocks such as mylonite, cataclastic rock, fault breccia, and fault greccia are mostly developed in the fracture zone, while ore bodies occur in and around the fracture zone [10]. Under the influence of fault tectonic activity, the joints of the roof and floor of the surrounding rock of the ore body are relatively developed, forming weak rock layers of several meters to tens of meters. The phenomenon of splints and floor heave often occurs in the mining engineering, threatening the safety of the operation [11]. At the same time, most ore bodies are gently inclined thin to medium thick vein ore bodies, the caved ore is difficult to release, and the stope operation conditions are poor [12]. Therefore, it is of great practical significance to carry out optimization research on mining methods [13] in combination with the engineering and technical conditions of such ore bodies to promote the progress of mining technology for complex and difficult mining bodies.

As mining method selection is a multi-level, multi-factor, multi-objective, and multi-index decision-making process involving technology, economy, construction, and safety, traditional mining method determination based on experience and analogy is often characterized by great fuzziness, randomness, and uncertainty [14]. According to Liang [15], based on fuzzy theory and the Tomada de Deciso Interativa Multicriterio method, the index system of seabed mining method selection is established from the aspects of technical feasibility, safety status, economic benefit, and management complexity. G. Tian, Z. Guo, and S. Li [16] optimized the treatment of landslides and side slopes, especially Tarva landslides, by using the AHP-fuzzy comprehensive evaluation model. M. Javanshirgiv and M. Safari [17] carried out a mining method optimization study based on the fuzzy TOPSIS method. On the basis of the above research, considering the inconsistency of decision measures in the construction of a judgment matrix in the traditional analytic hierarchy process (AHP), this paper proposes constructing a consistency judgment matrix through a transfer matrix, and using the improved AHP-TOPSIS evaluation model to obtain the weight vector value at one time, so as to obtain the weight value without a consistency test. It was applied to the mining method optimization process of Miao-ling gold mine in China in order to provide a reference for the safe and efficient mining of gently inclined and soft broken complex ore bodies at home and abroad.

2. Materials and Methods

2.1. The Weight Vector Determined Based on the Improved AHP

The AHP is a multi-criteria, multi-objective, and multi-scheme decision analysis method that combines qualitative and quantitative methods [18]. In the decision making of the actual mining scheme, it is difficult to construct a judgment matrix meeting the requirement of consistency at one time because of the subjectivity of experts in the decision-making measure, especially when there are many factor indexes. If the inconsistent judgment matrix examined is the result of comprehensive and serious thinking by experts, even if the judgment matrix is reconstructed through an additional expert survey, it will not have much practical significance, because the shift in expert judgment quasi-measurement focus is non-conscious [19]. Therefore, this paper adopts an improved AHP that can reconstruct the judgment matrix and calculate the weight vector without adjusting the initial data of experts. It can not only avoid the expenditure waste caused by multiple expert investigations, but also reduce the repeated calculations caused by adjusting the judgment matrix [20,21].

2.1.1. Constructing the Comparison Matrix

The comparison matrix A is constructed as Equation (1), and the value of element a_{ij} in A is the relative importance of element x_i in the index layer to element x_j.

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} = \begin{pmatrix} \frac{x_1}{x_1} & \frac{x_1}{x_2} & \cdots & \frac{x_1}{x_n} \\ \frac{x_2}{x_1} & \frac{x_2}{x_2} & \cdots & \frac{x_2}{x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{x_n}{x_1} & \frac{x_n}{x_2} & \cdots & \frac{x_n}{x_n} \end{pmatrix} \quad (1)$$

2.1.2. Constructing the Consistency Judgment Matrix

In order to avoid the measurement inconsistency of the initial comparison matrix, this paper introduces an improved AHP [22] and used the concept of the optimal transfer matrix to obtain the index weight value at one time. The theorems and methods introduced are as follows:

Theorem 1. Matrix $A =)_{n\times n}$, U = 1, 2, ... , n. If $a_{ij} = \frac{1}{a_{ji}}$, while $a_{ij} = a_{ik} \cdot a_{kj}$, $i, j, k \in U$. Then, matrix A is the consistency matrix.

Theorem 2. Matrix $A =)_{n\times n}$, $B =)_{n\times n}$, $b_{ij} = lg^{a_{ij}}$, $i, j, k \in U$, U = 1, 2, ... , n. If matrix A is the consistency matrix, then $b_{ij} = -b_{ji}$, while $b_{ij} = b_{ik} + b_{kj}$, B is called the transfer matrix of A; conversely, if B is the transfer matrix of A, then A is the consistency matrix.

Theorem 3. Matrix $B =)_{n \times n}$, $C =)_{n \times n}$. If $b_{ij} = -b_{ji}$, the optimal transfer matrix C of B satisfies $c_{ij} = \frac{1}{n}\sum_{k=1}^{n}\left(b_{ik} - b_{jk}\right), i, j, k \in U, U$ = 1, 2, ... , n.

The process of solving the weight vector by the improved AHP is shown in Figure 1.

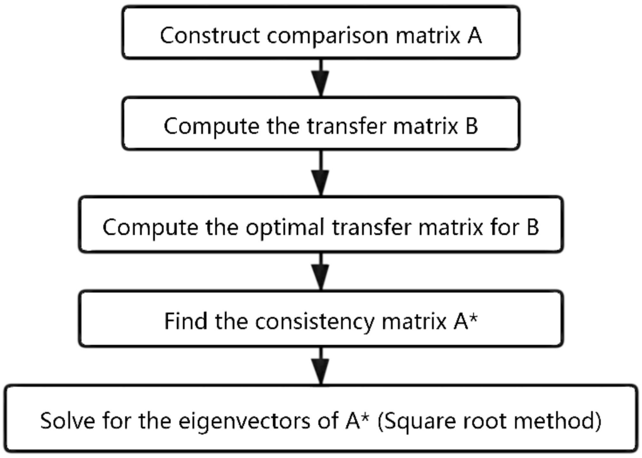

Figure 1. Flow chart of the improved AHP method to solve the weight vector.

2.2. Construction of the AHP-TOPSIS Comprehensive Evaluation Model

The technique for order preference by similarity to ideal solution (TOPSIS) is used to define positive and negative ideal solutions, and evaluate the superiority of the proposed scheme according to its proximity to the ideal solution. The general goal is to approach the positive ideal solution, but move away from the negative ideal solution [23].

2.2.1. The Initial Evaluation Matrix Is Established

There are $P_1, P_2, \ldots, P_m$, m alternatives.

All schemes are combined to form $P = \{P_1, P_2, \ldots, P_m\}$; the evaluation index of each scheme is set as the standard set $X = \{X_1, X_2, \ldots, X_n\}$ jointly composed of $X_1, X_2, \ldots, X_n$; and the corresponding evaluation index can be expressed as $X_{ij}(i = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$, that is, X_{ij} is the J evaluation index of the ith scheme [24].

Then, the initial evaluation matrix P can be described as Equation (2).

$$P = (X_{ij})_{m \times n} = \begin{pmatrix} X_{11} & X_{12} & \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots & X_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ X_{m1} & X_{m2} & \cdots & X_{mn} \end{pmatrix} \tag{2}$$

2.2.2. Establishment of the Standardized Decision Matrix

Considering the complexity of all evaluation objects and the incompatibility of all evaluation indicators, dimensionless processing of all evaluation indicators is required [25]. The elements of the standardized decision matrix $Q = (q_{ij})_{m \times n}$ are calculated as follows:

The indicator where bigger is better can be described as Equation (3):

$$q_{ij} = \frac{x_{ij} - \min\limits_{j}(x_{ij})}{\max\limits_{j}(x_{ij}) - \min\limits_{j}(x_{ij})} \tag{3}$$

The smaller the better indicator can be described as Equation (4):

$$q_{ij}{}' = \frac{\max\limits_{j}(x_{ij}) - x_{ij}}{\max\limits_{j}(x_{ij}) - \min\limits_{j}(x_{ij})} \tag{4}$$

where $\max\limits_{j}(x_{ij})$ represents the maximum data in the J column of matrix P; $\underset{j}{min}(x_{ij})$ represents the minimum data in the J column of matrix P.

2.2.3. Construction of the Weighted Standardized Decision Matrix

By multiplying the above standardized decision matrix Q and the corresponding weight w_i of each indicator [26], the weighted standardized matrix R can be obtained as Equation (5).

$$R = (r_{ij})_{m\times n} = \begin{pmatrix} w_1q_{11} & w_2q_{12} & \cdots & w_nq_{1n} \\ w_1q_{21} & w_2q_{22} & \cdots & w_nq_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_1q_{m1} & w_2q_{m2} & \cdots & w_nq_{mn} \end{pmatrix} \tag{5}$$

2.2.4. Calculation of Closeness of the Evaluation Object

The ideal solution of the weighted standardized decision matrix can be described as Equation (6),

$$\begin{cases} R^+ = \left\{ (\max\limits_{j}(q_{ij}) | X_j \in J_1), (\min\limits_{j}(q_{ij}) | X_j \in J_2) \right\} \\ R^- = \left\{ (\min\limits_{j}(q_{ij}) | X_j \in J_1), (\max\limits_{j}(q_{ij}) | X_j \in J_2) \right\} \end{cases} \tag{6}$$

where R^+ and R^- are the positive and negative ideal solutions, respectively; J_1 and J_2 are the benefit and cost indicator sets, respectively.

Then the distance between the evaluation object and the ideal solution can be described as Equation (7):

$$\begin{cases} f_i^+ = \sqrt{\sum\limits_{j=1}^{n} (r_{ij} - r_j^+)^2} \\ f_i^- = \sqrt{\sum\limits_{j=1}^{n} (r_{ij} - r_j^-)^2} \end{cases} \tag{7}$$

where f_i^+ and f_i^- are, respectively, the distance between the evaluation object and the positive and negative ideal solution; r_i^+ and r_i^- are elements of R^+ and R^-, respectively.

The closeness vector E^+ between each evaluation object and the positive ideal solution can be described as Equation (8).

$$E_i{}^+ = \frac{f_i^-}{f_i^+ + f_i^-}, \quad e^+ \in [0, 1] \tag{8}$$

The matrix E composed of E^+ is called the comprehensive evaluation matrix. Under the same first-level index, the advantages and disadvantages of the evaluation object can be preliminarily judged by the descending arrangement of progress values (close to one is superior, and close to zero is inferior).

3. Results: Examples of Application

3.1. Engineering Background and Comprehensive Evaluation Index System of Mining Method Optimization

The Miao-ling gold deposit is a structural altered rock type gold deposit (see Figure 2); the ore body occurrence is strictly controlled by the faults striking nearly north to south, mainly distributed along the fault structural belt and its hanging wall altered surrounding rock, which is mostly vein-like, lenticular, etc., with the characteristics of expansion and narrowing, branching compounds. At present, the ore body is mainly mined, with the grade of 2.86 g/t. Ore body dip is 250°~290°, the dip angle is 16°~57°, and the thickness of the ore body is 0.60~23.46 m. The ore is of cataclastic type and alteration type. The surrounding rock is rhyolite, and the joints and fissures are well-developed. There is local kaolin mineral development, which is argillaceous, as well as water softening and poor stability. The contact relationship between the surrounding rock and the ore body floor is obvious, but the gradual metasomatic alteration relationship with the roof is not obvious. With the increase in mining intensity, the ore resources continue to move down, and the occurrence of ore also changes, mainly manifested as the dip angle becoming slow (20°~30°) and ore transport becoming difficult (see Figure 3). The complex phenomenon of ore-body branching occurs frequently, and the occurrence changes are complicated. The stability of the surrounding rock becomes worse, the phenomenon of roof collapse occurs frequently, the ore dilution becomes serious, and the safety problem becomes prominent. The geological grade of ore becomes low, and the cost per ton of ore increases.

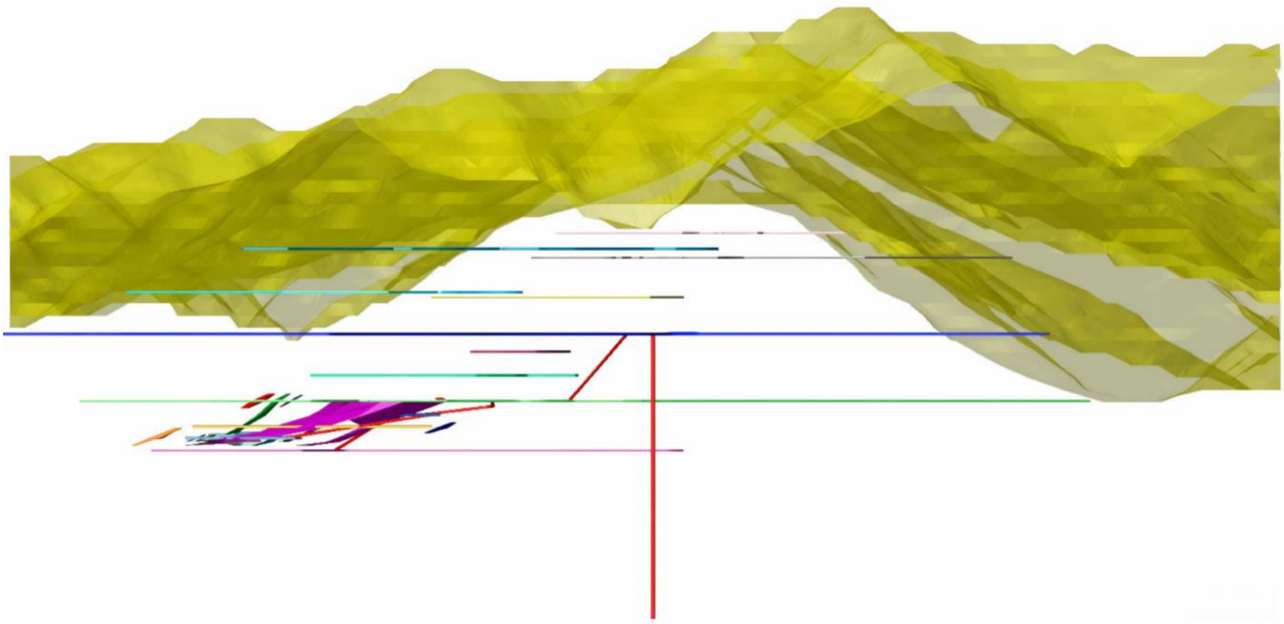

Figure 2. Three-dimensional model of Miao-ling gold mine.

According to the occurrence status of the ore body and mining technical conditions, especially the stability of the ore rock and the thickness, grade, and dip angle of the ore body, the following four filling mining comparison schemes are proposed: upward horizontal drift filling mining method (Plan I), upward horizontal slicing and filling mining method (Plan II) (see Figure 4), pre-control roof sublevel stopping filling mining method (Plan III), and medium-deep hole room pillar subsequent filling mining method (Plan IV) (see Figure 5), as shown in Table 1.

Figure 3. Picture of occurrence of ore body in Miao-ling gold mine.

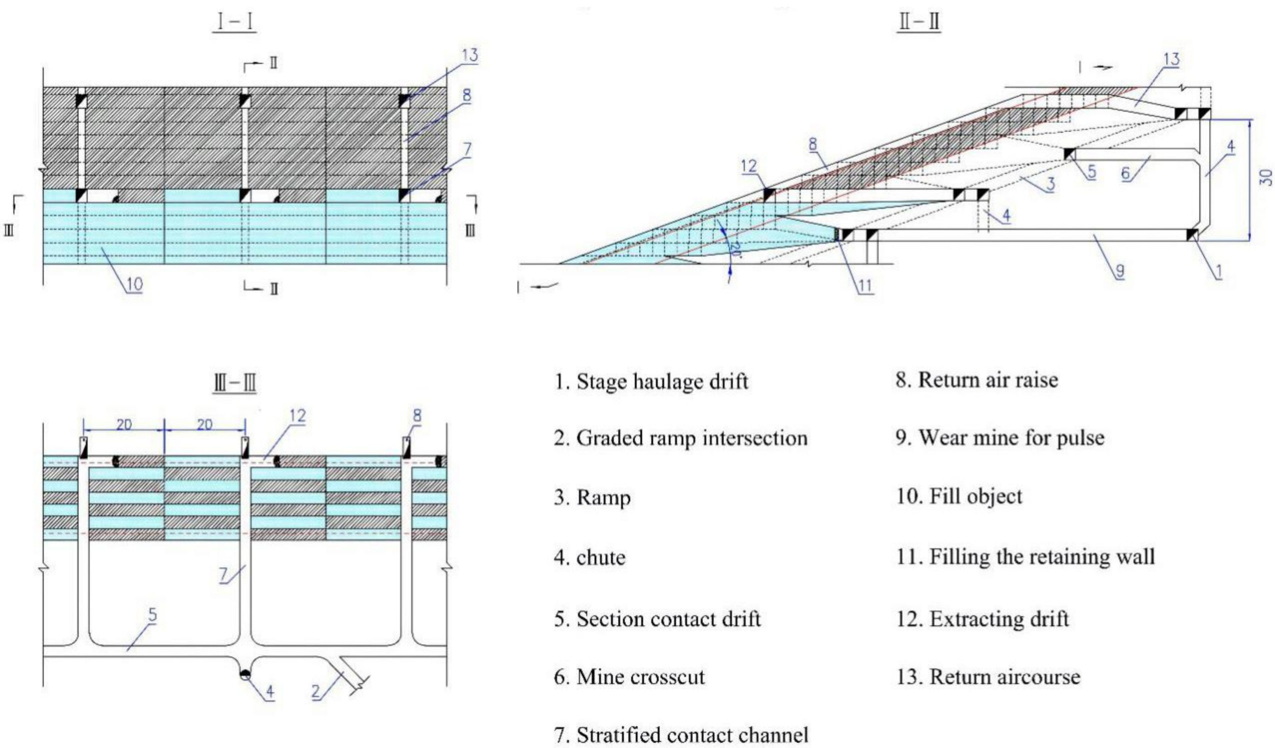

Figure 4. Plan II: upward horizontal slicing and filling mining method in Miao-ling gold mine. I-I: front view; II-II: side view; III-III: top view.

Since only Plans II and IV have practical applications in Miao-ling gold Mine, mining method maps for only Plan II and Plan IV are attached below in Figures 4 and 5, respectively.

According to the basic principle of the AHP, the comprehensive evaluation (O) index system of mining method optimization for a moderately inclined, medium-thick ore body (i.e., target layer) was established [22], as shown in Figure 6.

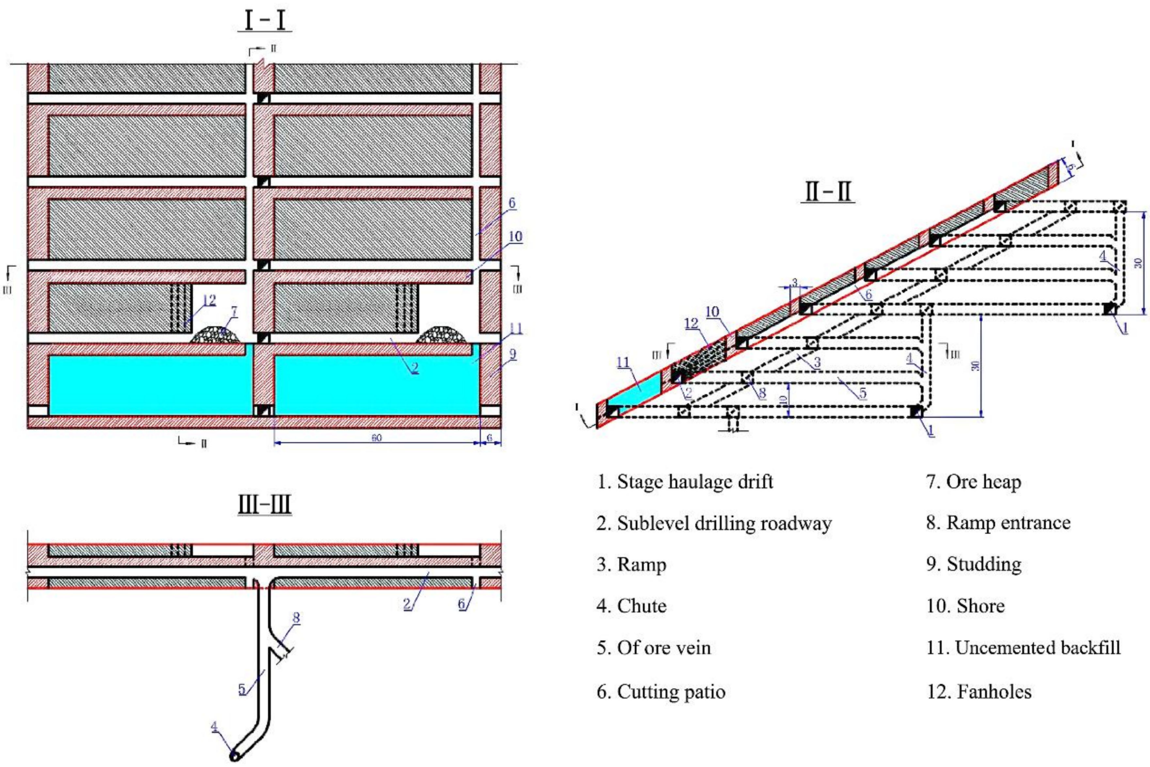

Figure 5. Plan IV: medium-deep hole room pillar subsequent filling mining method in Miao-ling gold mine. I-I: front view; II-II: side view; III-III: top view.

Table 1. Comparison of evaluation indexes of each backfill mining method.

Project		**Plan I**	**Plan II**	**Plan III**	**Plan IV**
Criterion Layer	**Index Layer**				
Economic indicators S_1	X_1/(Chinese yuan/t)	94.2	84.7	88.6	78.5
	X_2/(%)	95	90	92	85
	X_3/(%)	6	8	8	25
Technical indicators S_2	X_4/(t/d)	100	150	140	180
	X_5/(m^3/kt)	79.6	79.6	71.5	62.8
	X_6	8	4	6	4
	X_7	6	4	8	4
	X_8/(%)	5	6	8	10
Safety indicators S_3	X_9	140	180	200	320
	X_{10}	8	8	8	6

The evaluation system chart contains criterion layers: namely, economic index (S1), including the total cost of mining and filling (X1), ore recovery rate (X2), and ore dilution rate (X3); second, technical index (S2), including stope production capacity (X4), 1000 t cutting ratio (X5), flexibility and adaptability of the scheme (X6), construction difficulty (X7), ore bulk rate (X8); third, safety index (S3), mining roof exposed area (X9), and ventilation conditions (X10). X1, X2, X3, X4, X5, X8, and X9 in the evaluation system are quantitative indicators, which can be comprehensively estimated by analogy with similar mines at home and abroad and based on obtained expert opinions. X6, X7, and X10 in the evaluation system are qualitative indicators. Given five grades, they are very good, good, general, poor, and very poor, respectively, corresponding to 10, 8, 6, 4, and 2 in sequence.

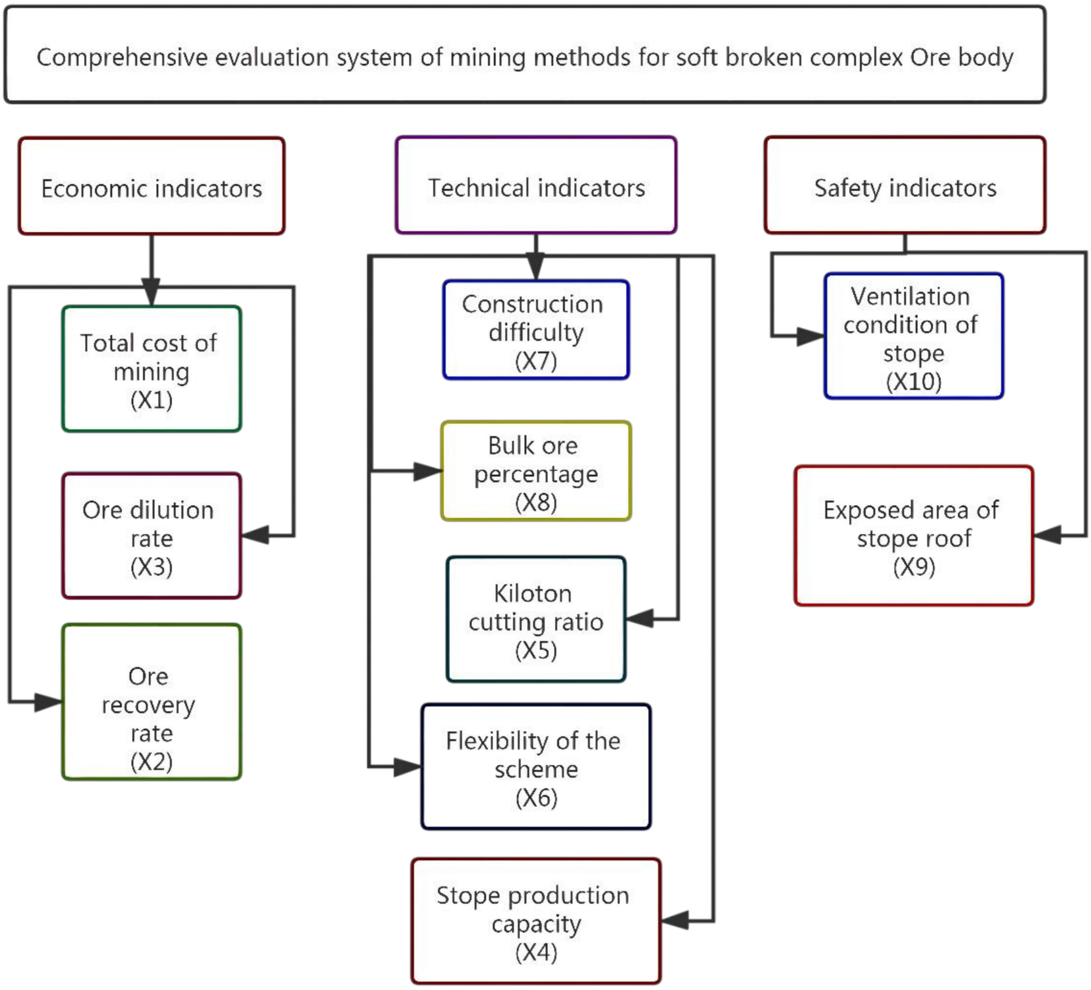

Figure 6. Evaluation system chart of mining methods for soft fracture complex ore body.

3.2. Index Weight Determination

The total cost depends on the mining technical condition, mineral filling mining method, mechanization level, management level, and the cost of a local quantity machine for a mine. After determining the mining method, the index shows little change in a short time, and the ore recovery rate and impoverishment rate index are important to the mine's economic benefit. This paper assumes that if the surrounding rock is excluding gold (gold grade is zero), then every one ton of ore lost in the process of mining, the enterprise economic losses on the numerical equivalent of selecting one profitable ton of ore, mixed with the processing fee for one ton of ore, is equal to one of the selecting ore comprehensive cost; obviously, the two rates index is based on the total cost index, which is filled in the mining work on mining efficiency indicators. For most precious metal mines with low ore grade, the index of dilution rate is more important than the index of recovery rate [27].

According to the basic principle of the AHP and comparison scale table, combined with the situation of Miao-ling gold mine in China and discussed with relevant experts and scholars, the initial comparison matrix of the criterion layer index (S_0), economic index (S_1), technical index (S_2), and safety index (S_3) is determined as Equation (9).

$$S_0 = \begin{pmatrix} 1 & 1 & 4 \\ 1 & 1 & 2 \\ \frac{1}{4} & \frac{1}{2} & 1 \end{pmatrix} S_1 = \begin{pmatrix} 1 & 3 & 2 \\ \frac{1}{3} & 1 & \frac{2}{3} \\ \frac{1}{2} & \frac{3}{2} & 1 \end{pmatrix} S_2 = \begin{pmatrix} 1 & \frac{3}{8} & \frac{1}{2} & \frac{3}{4} & \frac{3}{2} \\ \frac{8}{3} & 1 & \frac{4}{3} & 2 & 4 \\ 2 & \frac{3}{4} & 1 & \frac{3}{2} & 2 \\ \frac{4}{3} & \frac{1}{2} & \frac{2}{3} & 1 & 2 \\ \frac{2}{3} & \frac{1}{4} & \frac{1}{3} & \frac{1}{2} & 1 \end{pmatrix} S_3 = \begin{pmatrix} 1 & \frac{5}{7} \\ \frac{7}{5} & 1 \end{pmatrix} \quad (9)$$

According to the improved AHP algorithm, the consistency judgment matrix and the total ranking weight of hierarchy can be obtained without tests, as shown in Table 2.

Table 2. Final administrative levels compositor.

X	S			Weight (W)
	S_1 (0.472)	S_2 (0.377)	S_3 (0.151)	
x_1	0.545			0.258
x_2	0.182			0.086
x_3	0.273			0.129
x_4		0.13		0.049
x_5		0.348		0.131
x_6		0.261		0.098
x_7		0.174		0.066
x_8		0.087		0.033
x_9			0.417	0.063
x_{10}			0.583	0.087

3.3. Comprehensive Evaluation of Factors and Indicators

Construct the initial judgment matrix P according to Equation (10).

$$P = \begin{pmatrix} 94.2 & 95 & 6 & 100 & 79.6 & 8 & 6 & 5 & 140 & 8 \\ 84.7 & 90 & 8 & 150 & 79.6 & 4 & 4 & 6 & 180 & 8 \\ 88.6 & 92 & 8 & 140 & 71.5 & 6 & 8 & 8 & 200 & 8 \\ 78.5 & 85 & 25 & 180 & 62.8 & 4 & 4 & 10 & 320 & 6 \end{pmatrix} \tag{10}$$

According to Equations (3)–(5), the standardized decision matrix R can be described as Equation (11).

$$R = \begin{pmatrix} 0 & 0.086 & 0.129 & 0 & 0 & 0.098 & 0.033 & 0.033 & 0 & 0.087 \\ 0.156 & 0.043 & 0.115 & 0.031 & 0 & 0 & 0.066 & 0.026 & 0.014 & 0.087 \\ 0.092 & 0.06 & 0.115 & 0.025 & 0.063 & 0.049 & 0 & 0.02 & 0.021 & 0.087 \\ 0.258 & 0 & 0 & 0.049 & 0.131 & 0 & 0.066 & 0 & 0.063 & 0 \end{pmatrix} \tag{11}$$

According to Equation (6), the ideal solution of the weighted normalized matrix is calculated. In the comprehensive evaluation index system of each scheme, X1, X3, X5, X7, and X8 belong to the cost indicator, and X2, X4, X6, X9, and X10 belong to the benefit indicator, so the positive ideal solution and negative ideal solution of the weighted standardized matrix can be described as Equation (12).

$$\begin{cases} R^+ = \begin{pmatrix} 0, & 0.086, & 0, & 0.049, & 0, & 0.098, & 0, & 0, & 0.063, & 0.087 \end{pmatrix} \\ R^- = \begin{pmatrix} 0.258, & 0, & 0.129, & 0, & 0.131, & 0, & 0.066, & 0.033, & 0, & 0 \end{pmatrix} \end{cases} \tag{12}$$

According to Equation (7), calculate the distance between each scheme and the positive ideal solution and the negative ideal solution as Equation (13).

$$\begin{cases} f_1^+ = 0.159 \\ f_1^- = 0.331 \end{cases}, \begin{cases} f_2^+ = 0.239 \\ f_2^- = 0.196 \end{cases}, \begin{cases} f_3^+ = 0.178 \\ f_3^- = 0.227 \end{cases}, \begin{cases} f_4^+ = 0.336 \\ f_4^- = 0.155 \end{cases} \tag{13}$$

3.4. Final Evaluation of Mining Methods

According to Equation (8), the closeness degree E^+ of each scheme to the positive ideal solution is calculated as Equation (14):

$$E^+ = \begin{pmatrix} 0.6757, & 0.4507, & 0.5607, & 0.3163 \end{pmatrix} \quad (14)$$

This method was tested in the mine. The ore block is arranged along the direction of the ore body; the length of the ore block is 40 m, the width is the thickness of the ore body, and the middle section is 30 m high. The middle section is divided into three sections with a height of 10 m, and each section is further divided into three layers with a height of 3.3 m and a path width of 3.5 m.

According to the statistical data of the mining path, the main technical and economic indicators were as follows: the production capacity of the mining path was 105 t/d, the recovery rate was 95.7%, the dilution rate was 5.34%, the cutting ratio was 69.8 m^3/kt, and the total cost of mining and filling was 89 yuan/t, which achieved the expected effect.

4. Discussion

We developed this mining method optimization based on the AHP and TOPSIS by referring to and borrowing from the literature [18–26,28–30], which was helpful. Through this study, we can judge that the upward horizontal drift filling mining method is the most suitable mining method for Miao-ling gold mine in Henan Province in China by using the AHP and TOPSIS. However, it led to the following questions:

(1) Are the AHP and TOPSIS the most suitable evaluation methods for mining method optimization?

Although many research experts use the AHP or TOPSIS in the optimization process of mining methods or mining production [31,32], there are other methods that are also applicable.

Different methods should be selected according to specific situations. For example, in 2021, J. Sheng et al. [33] proposed four deep mining schemes for large deep ore bodies, which were optimized by the vague set model.

There are even some researchers who are trying to use artificial intelligence techniques, such as machine learning, for mining method optimization, and that is what we are working on. In conclusion, the optimization of mining methods depends on different circumstances to decide what assessment method to use.

(2) Is the upward horizontal drift filling mining method the most suitable mining method in China or in the world?

For this matter, obviously not. Each mine has its suitable mining method; however, intelligent mining is undoubtedly the development trend of all mines, both in China and around the world.

With the continuous progress and development of science and technology, artificial intelligence has begun to show a global development trend, and intelligent mining is no exception. In China, the concept of intelligent mining was put forward around 2017 [34], and many Chinese universities have gradually taken intelligent mining as the basic discipline construction. C. Qi, once an outstanding research expert in Australia, now one of the top intelligent mining research experts in China, has long been engaged in intelligent mining research: As early as 2018, he began to apply artificial intelligence methods to slope stability analysis, backfill mining methods, and the optimization of backfill materials [35,36]; he is also pursuing research into intelligent mining [37,38].

In the world, there are also many outstanding researchers studying intelligent mining. Choi [39,40], a mining research expert from South Korea, has been devoted to the research of transportation robots in mining; Yu H. [41–44] is also committed to the study of intelligent rail transportation in underground mines; Danial J.A. [44,45], a mining and rock mechanics expert from Iran, used artificial bee colony techniques to evaluate the brittleness coefficient of rock during mining; and A. Jha [46,47], a mining researcher from the United States, has also been conducting research on the application of artificial intelligence technology in mining blasting and mine ventilation.

Due to the progress of science and technology, mining technology is in continuous development; therefore, we think that, one day, intelligent mining can be realized, improving the efficiency of mining while ensuring the safety of workers, which is good news for people all over the world.

5. Conclusions

(1) Taking Miao-ling gold mine in China as an example, the AHP-TOPSIS comprehensive decision model of mining method optimization was established. According to Section 3.4., the comprehensive superiority degrees of mining Plans I–IV are 67.57%, 45.07%, 56.07%, and 31.63%, respectively, so Plan I (the upward horizontal drift backfill mining method) is the best. The upward horizontal drift filling mining method was determined as the optimal scheme, and the mining effect was verified through a field industrial test, which provides a reference for the optimization of mining methods for gently inclined and soft broken complex ore bodies at home and abroad.

(2) Based on the selection of technical and economic mining methods, we constructed a multi-level, multi-factor, multi-objective, and multi-index mining method for a slowly inclined soft broken ore body to improve the comprehensive evaluation system determined by experience and that is limited by fuzziness, randomness, and unpredictability.

(3) To introduce an improved AHP, using the concept of the optimal transfer matrix, which eliminates the need to test the index weight of vector-valued for a one-time gain, overcomes the barycenter offset caused by the decision-making measure and the inconsistency of the judgment matrix, and simplifies the weight vector of the calculation process, reduced by adjusting the weight vector of repeated calculations.

Finally, we claim that this paper serves just as a guide to starting the conversation. In our future research, we will continue to study mining method optimization, especially the application of machine learning, and we hope many more experts and researchers will be interested and engage in the research in this field.

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References

1. Li, Z.; Zhao, Y.; Zhao, H. Assessment indicators and methods for developing the sustainability of mining communities. *Int. J. Sustain. Develop. World Ecol.* **2008**, *15*, 35S–43S. [CrossRef]
2. Si, H.; Bi, H.; Li, X.; Yang, C. Environmental evaluation for sustainable development of coal mining in Qijiang, Western China. *Int. J. Coal Geol.* **2010**, *81*, 163–168. [CrossRef]
3. Su, S.; Yu, J.; Zhang, J. Measurements study on sustainability of China's mining cities. *Expert Syst. Appl.* **2010**, *37*, 6028–6035. [CrossRef]

4. Zhu, W.; Teng, Y.H. Characteristic of Development of the Fractured Zone in Mining under Medium Hard Overburden Using Fully-Mechanized Top-Coal Caving Method. *Appl. Mech. Mater.* **2012**, *226–228*, 1312–1317. [CrossRef]
5. Jang, H.; Topal, E. Optimizing overbreak prediction based on geological parameters comparing multiple regression analysis and artificial neural network. *Tunn. Undergr. Space Technol.* **2013**, *38*, 161–169. [CrossRef]
6. Yu, Y.; Chen, S.-E.; Deng, K.-Z.; Wang, P.; Fan, H.-D. Subsidence Mechanism and Stability Assessment Methods for Partial Extraction Mines for Sustainable Development of Mining Cities—A Review. *Sustainability* **2018**, *10*, 113. [CrossRef]
7. Bao, K.; He, G.; Jin, L.; Yang, J.; Zhou, Q. Study on Sustainable Development of Mining Cities by the Method of Relative Resources Carrying Capacity and GM (1, 1) Model. *Pol. J. Environ. Stud.* **2020**, *29*, 3983–3995. [CrossRef]
8. Li, J.-L.; Wang, S.-W.; Wang, Y.; Wang, X.-Y.; Wang, X.-X. Water Inrush Risk Assessment of Coal Floor After CBM Development Based on the Fractal-AHP-Vulnerlability Index Method. *Geotech. Geol. Eng.* **2021**, *39*, 3487–3497. [CrossRef]
9. Lin, C.; He, Y.; Chen, X.; Shi, L.; Zhang, X.; Qi, X.; Hao, R.; Gong, R.; Zhang, J. Relationship between ductile shear zone and gold mineralization—Taking Jinchangyu gold mine, eastern Hebei Province, China. *Int. J. Rock Mech. Min. Sci. Geomech. Abstr.* **1996**, *33*, A104. [CrossRef]
10. Wu, J. Research on sublevel open stoping recovery processes of inclined medium-thick orebody on the basis of physical simulation experiments. *PLoS ONE* **2020**, *15*, e0232640. [CrossRef]
11. Chen, D.; Wu, X.; Xie, S.; Sun, Y.; Zhang, Q.; Wang, E.; Sun, Y.; Wang, L.; Li, H.; Jiang, Z.; et al. Study on the Thin Plate Model with Elastic Foundation Boundary of Overlying Strata for Backfill Mining. *Math. Probl. Eng.* **2020**, *2020*, 8906091. [CrossRef]
12. Lin, Y. Research on Mining Technology of Steeply Inclined Thin Ore Body in High-grade Content Mine. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *632*, 022038. [CrossRef]
13. Ligen, Y.; Xiumin, X. Research on the Comprehensive Evaluation Model of Knowledge Capital of Mining Enterprise Based on AHP and Fuzzy Mathematics. In Proceedings of the 2009 Second International Conference on Intelligent Computation Technology and Automation, Changsha, China, 10–11 October 2009; Volume 2, pp. 784–787.
14. Yavuz, M. The application of the analytic hierarchy process (AHP) and Yager's method in underground mining method selection problem. *Int. J. Min. Reclam. Environ.* **2013**, *29*, 1–23. [CrossRef]
15. Liang, W.-Z.; Zhao, G.Y.; Hao, W.U.; Chen, Y. Optimization of mining method in subsea deep gold mines: A case study. *J. Transac. Nonferrous Metals Soc. China* **2019**, *29*, 2160–2169. [CrossRef]
16. Tian, G.; Guo, Z.; Li, S. Optimization of Tawa Landslide Treatment Scheme Based on the AHP-Fuzzy Comprehensive Evaluation Method. *IOP Conf. Ser. Earth Environ. Sci.* **2020**, *598*, 012032. [CrossRef]
17. Javanshirgiv, M.; Safari, M. The selection of an underground mining method using the fuzzy topsis method: A case study in the kamar mahdi ii fluorine mine. *Min. Sci.* **2017**, *24*, 161.
18. Sensuse, D.I.; Sari, F.R. penerapan metode analytic hierarchy process dalam sistem penunjang keputusan untuk pemilihan asuransi. *J. Sist. Inf.* **2008**, *4*, 100. [CrossRef]
19. Yu, H.; Wang, N.; Pan, J. Application of Fuzzy Extension Analytic Hierarchy Process in Location Selection of Logistics Center. *J. Phys. Conf. Ser.* **2021**, *1995*, 012035. [CrossRef]
20. Dogan, O. Process mining technology selection with spherical fuzzy AHP and sensitivity analysis. *Expert Syst. Appl.* **2021**, *178*, 114999. [CrossRef]
21. Ke, X.; Feng, M.; Xiang, M. The application of analytic hierarchy process and fuzzy comprehensive evaluation in the evaluation of ecological security in coal mine areas. *Int. J. Netw. Virtual Organ.* **2018**, *18*, 80. [CrossRef]
22. Asghari, M.; Nassiri, P.; Monazzam, M.R.; Golbabaei, F.; Arabalibeik, H.; Shamsipour, A.; Allahverdy, A. Weighting Criteria and Prioritizing of Heat stress indices in surface mining using a Delphi Technique and Fuzzy AHP-TOPSIS Method. *J. Environ. Heal. Sci. Eng.* **2017**, *15*, 1. [CrossRef]
23. Hwang, C.-L.; Lai, Y.-J.; Liu, T.-Y. A new approach for multiple objective decision making. *J. Comput. Oper. Res.* **1993**, *20*, 889–899. [CrossRef]
24. Rezaiee-Pajand, M.; Ghalishooyan, M.; Salehi-Ahmadabad, M. Comprehensive evaluation of structural geometrical nonlinear solution techniques Part I: Formulation and characteristics of the methods. *Struct. Eng. Mech.* **2013**, *48*, 849–878. [CrossRef]
25. Masum, A.K.M.; Karim, A.R.; Bin Al Abid, F.; Islam, S.; Anas, M. A New Hybrid AHP-TOPSIS Method for Ranking Human Capital Indicators by Normalized Decision Matrix. *J. Comput. Sci.* **2019**, *15*, 1746–1751. [CrossRef]
26. Ibrahim, M.R.; Suseno, J.E.; Surarso, B. Emergency Service Search using Ant Colony Optimization Algorithm and AHP-TOPSIS Method. *J. Phys. Conf. Ser.* **2021**, *1943*, 012104. [CrossRef]
27. Zhao, L.; Li, H.; Wang, Z.; Peng, D.; Xue, Y.; Ai, X. Comprehensive Evaluation of Power Grid Security and Benefit Based on BWM Entropy Weight TOPSIS Method. *IOP Conf. Ser. Earth Environ. Sci.* **2020**, *619*, 12053. [CrossRef]
28. Zhou, J.; Chen, C.; Armaghani, D.J.; Ma, S. Developing a hybrid model of information entropy and unascertained measurement theory for evaluation of the excavatability in rock mass. *Eng. Comput.* **2020**, *1*, 24. [CrossRef]
29. Zhou, J.; Chen, C.; Wang, M.; 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]
30. Zhou, J.; Chen, C.; Khandelwal, M.; Tao, M.; Li, C. Novel approach to evaluate rock mass fragmentation in block caving using unascertained measurement model and information entropy with flexible credible identification criterion. *Eng. Comput.* **2021**. [CrossRef]

31. Shen, L.; Muduli, K.; Barve, A. Developing a sustainable development framework in the context of mining industries: AHP approach. *Resour. Policy* **2015**, *46*, 15–26. [CrossRef]
32. Karan, S.K.; Samadder, S.R.; Singh, V. Groundwater vulnerability assessment in degraded coal mining areas using the AHP-Modified DRASTIC model. *Land Degrad. Dev.* **2018**, *29*, 2351–2365. [CrossRef]
33. Sheng, J.; Wan, W.; Liu, D.; Jiang, F.; Li, X.; Zhang, H. Investigation of the Optimization of Unloading Mining Scheme in Large Deep Deposit Based on Vague Set Theory and Its Application. *Adv. Civ. Eng.* **2021**, *2021*, 1–13. [CrossRef]
34. Wang, J.; Huang, Z. The recent technological development of intelligent mining in China. *J. Eng.* **2017**, *3*, 439–444. [CrossRef]
35. Qi, C.; Fourie, A.; Chen, Q. Neural network and particle swarm optimization for predicting the unconfined compressive strength of cemented paste backfill. *Constr. Build. Mater.* **2018**, *159*, 473–478. [CrossRef]
36. Qi, C.; Fourie, A.; Chen, Q.; Zhang, Q. A strength prediction model using artificial intelligence for recycling waste tailings as cemented paste backfill. *J. Clean. Prod.* **2018**, *183*, 566–578. [CrossRef]
37. Qi, C.; Fourie, A.; Chen, Q.; Zhang, Q. Improved strength prediction of cemented paste backfill using a novel model based on adaptive neuro fuzzy inference system and artificial bee colony. *Constr. Build. Mater.* **2021**, *284*, 122857. [CrossRef]
38. Li, G.; Sun, Y.; Qi, C. Machine learning-based constitutive models for cement-grouted coal specimens under shearing. *Int. J. Min. Sci. Technol.* **2021**, *31*, 813–823. [CrossRef]
39. Kim, S.-M.; Choi, Y.; Suh, J. Applications of the Open-Source Hardware Arduino Platform in the Mining Industry: A Review. *Appl. Sci.* **2020**, *10*, 5018. [CrossRef]
40. Kim, Y.; Baek, J.; Choi, Y. Smart Helmet-Based Personnel Proximity Warning System for Improving Underground Mine Safety. *Appl. Sci.* **2021**, *11*, 4342. [CrossRef]
41. Li, S.; Wang, G.; Yu, H.; Wang, X. Engineering Project: The Method to Solve Practical Problems for the Monitoring and Control of Driver-Less Electric Transport Vehicles in the Underground Mines. *World Electr. Veh. J.* **2021**, *12*, 64. [CrossRef]
42. Yu, H.; Li, S. The Function Design for the Communication-Based Train Control (CBTC) System: How to Solve the Problems in the Underground Mine Rail Transportation? *Appl. Syst. Innov.* **2021**, *4*, 31. [CrossRef]
43. Nardo, M.; Yu, H. Intelligent Ventilation Systems in Mining Engineering: Is ZigBee WSN Technology the Best Choice? *Appl. Syst. Innov.* **2021**, *4*, 42. [CrossRef]
44. Di Nardo, M.; Yu, H. Special Issue “Industry 5.0: The Prelude to the Sixth Industrial Revolution”. *Appl. Syst. Innov.* **2021**, *4*, 45. [CrossRef]
45. Parsajoo, M.; Armaghani, D.J.; Asteris, P.G. A precise neuro-fuzzy model enhanced by artificial bee colony techniques for assessment of rock brittleness index. *Neural Comput. Appl.* **2021**. [CrossRef]
46. Dumakor-Dupey, N.; Arya, S.; Jha, A. Advances in Blast-Induced Impact Prediction—A Review of Machine Learning Applications. *Minerals* **2021**, *11*, 601. [CrossRef]
47. Jha, A.; Tukkaraja, P. Monitoring and assessment of underground climatic conditions using sensors and GIS tools. *Int. J. Min. Sci. Technol.* **2020**, *30*, 495–499. [CrossRef]