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Comparative Analysis of Mining Damage Evaluation Methods for Mining Buildings

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Abstract: In the eastern mining areas of China, coal mining under buildings is more common. In order to alleviate the contradiction between coal mining under buildings and the relationship between workers and farmers, it is necessary to evaluate the degree of damage to buildings in a more objective and scientific way. Taking the buildings in the surface movement basin in Fengfeng Mining District of Handan City as the research object, 15 residential buildings with different degrees of damage were selected as sampling points, and data including four surface movement deformation parameters and five parameters of the buildings' own attributes were collected. In order to objectively calculate the influence of each indicator, two methods, namely principal component analysis and AHP entropy weighting, were used to calculate the influence of the indicators on the damage of the buildings. The results show that the index system selected in the paper is scientific and objective, with the building's own attributes accounting for 0.57. In the evaluation model using principal component analysis, the evaluation of the building damage evaluation results exactly matches the evaluation of the field survey results, which proves the feasibility of applying the method to the evaluation of mining damage in mining areas. The significance of Bartlett's test of 0.228 showed that the indicators were extremely uncorrelated, proving that the AHP entropy method of assigning weights is applicable to the evaluation of mining damage to buildings in mining areas in an indicator system where the indicators are weakly correlated.

Keywords: Mining Damage Assessment; PCA; AHP; Entropy Weight Method; Correlation.

1. Introduction

In this paper, the residential houses of two villages in a mining area in Handan City, Hebei Province, located under two coal mining working faces, 2516 and 2521, were selected for the study. The two workings completed mining from October 2015 to February 2016 and from February 2016 to October 2016, respectively. The dwellings in both villages are relatively neatly arranged, with a north-south aisle between the two rows. Most were built around the 1990s, with stone and concrete foundations and brick and concrete structures, and vary considerably. The main cracks in the damaged houses in the two villages are mainly vertical cracks at the top and bottom of the walls, vertical cracks under the windows, vertical cracks at the window and door heads, and diagonal cracks at the top and bottom of the walls or diagonal cracks at the top and bottom of the walls. There are also some horizontal cracks. The distribution of houses and working faces in the study area and the extent of mining impacts are shown in Figure 1.

The "three under" coal mining refers to the technology of coal mining under buildings, water bodies and railways. The volume of "three under" coal mining in China is more than 13 billion tons, and the volume of coal mining under buildings accounts for about 60% of the total volume of coal mining [1], especially in the eastern mining areas of China. Due to the shortage of oil and gas resources and the current situation of having abundant coal resources, it is difficult to change the energy structure in which coal resources dominate in a longer period of time [2], but the problems such as compensation for damage to buildings caused by coal mining under buildings not only bring huge economic pressure on coal mines [3], but also affect the relationship between local workers and farmers. Therefore, solving the coal mining problem has far-reaching significance for national development.

Due to the massive mining of coal mines under villages in the early years, China has accumulated some experience in mine subsidence and building damage assessment, and since the revision of the Mining Regulations for Buildings, Water Bodies, Railways and Coal Pillars of Major Shafts and Coal Presses [4] (hereinafter referred to as the Regulations) in 2017, it has been used as a standard for building damage level assessment. Subsequently, many scholars have conducted many studies in this field. There are two broad approaches: first, the innovation of the existing regulations. For example, Gu Xiaomin and Wu Zuoqi [5], based on the study of the above-mentioned Regulations and the existing criteria for evaluating mining damage to various types of features, developed a computerized system for the economic evaluation of buildings in mining areas. Cui Ximin [6] and others established an index system that integrates the building's own factors on the basis of inheriting the advantages of existing standards, proving that under the same conditions of surface deformation, the longer the building is deformed, the more serious it is, and also illustrating the scientific nature of introducing the building's own factors. Second, a new model of evaluation method is established. For example, Guo Wenbing et al. established a fuzzy clustering evaluation model and a neural network model for predicting building mining damage [7]. Since, in practice, cracks are used as criteria for housing survey and re-grading to determine compensation schemes, so that the actual grading criteria are different from the predicted results, precisely because the building's own factors also affect the damage to the building [8]. He Rong and Wang Bin [9] used gray theory correlation models to evaluate the damage to buildings; Liu Xiaopeng and Guo Guangli [10] introduced the resistance properties of buildings as indicators of the damage to buildings caused by mining, which provided some guidance for the prevention and protection of the damage to buildings in the areas affected by mining subsidence and the subsequent identification and compensation work. Some scholars have even used machine learning methods to evaluate building damage on this basis [11]. Based on the research results of these scholars [12], it is clear that the damage to buildings in mining areas is not only the result of a single factor, but also the result of a combination of factors, including the building itself, the geological conditions of the mining area, and the underground mining method.

For different mining sites, different mining factors, geological conditions, age of construction, structure and other factors have different degrees of influence on the level of damage to buildings. In order to reduce the pressure on coal mines to compensate for the damage to buildings and to evaluate the extent of mining damage to buildings more scientifically and accurately, it is necessary to optimize the mining damage evaluation index system and to select more comprehensive indicators, including surface movement deformation and the building's own characteristics, for evaluation. Therefore, in this paper, we also use the factors of the building's own resistance to deformation to evaluate the degree of damage to the building; at the same time, no scholars have used principal component analysis to determine the degree of influence of the indicators in the evaluation of mining damage, so we verify the applicability of principal component analysis in the evaluation of mining damage in this paper. The AHP entropy method is also used as a comparison to investigate the applicability and limitations of the two methods.

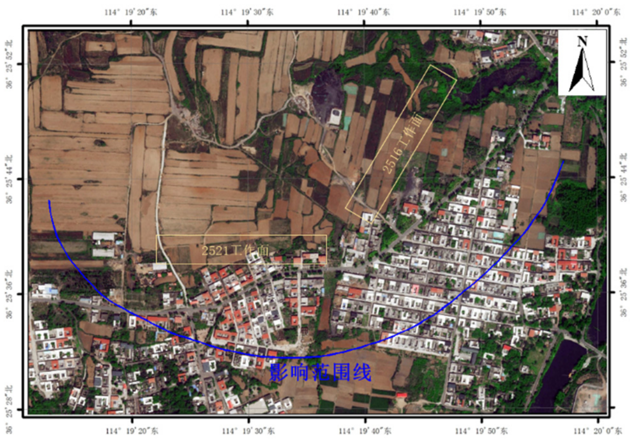

Fig 1. Summary map of research area

The yellow boxes in the figure show the distribution of the 2521 and 2516 working faces in the experimental area; the blue curves show the extent of damage to residential buildings under the influence of the mining situation of the two working faces.

2. Influencing Factors and Index System of Building Damage in Mining Areas

In the evaluation of mining damage to buildings in mining areas, the influence of the selection of the index system on the accuracy of the evaluation results still exists. For example, when the crack width is used as the reference indicator, the indicator quantity is selected at a certain time, which may be after the end of deformation, but the whole deformation process may not be in a trend, and the development of the crack may first become larger and then smaller or even close. But the final state data is not reflected; although the introduction of machine learning method can improve the accuracy of damage grade prediction, it needs to select a certain number of data sets of training samples, and if the sample indicators are not comprehensive enough or the grade distribution is not uniform, the final prediction accuracy may not be particularly satisfactory. Therefore, in this paper, the index system is constructed with full consideration of both the effects of mining and the building's own characteristics in the selection of indexes. Not only the surface movement deformation caused by mining, but also the age, structure and size of the building are taken into account. Two methods, Principal Component Analysis and AHP Entropy Weighting, were used to determine the weights, and then the damage level of the buildings in the mine area was evaluated using the weights [13] and TOPSIS (Distance between superior and inferior solutions) method, in order to compare and analyze which method is more suitable for evaluating the damage level of the buildings and the inapplicability of the two methods.

According to the results of the current study, there are many factors that affect the mining damage of a building, such as the structure of the building, the foundation, the time of construction, the location of the building in relation to the working face, the distance, the construction materials and other factors; the geological conditions in the mining area, the characteristics of the rock layer, the degree of mining and other aspects of influence, so the mining damage assessment of buildings in mining areas should fully consider the above factors. This is the only way to achieve an objective and scientific damage assessment for different mining areas. In this paper, nine factors have been selected to influence the damage assessment in the following two areas.

The surface movement deformation includes four indicators: subsidence, curvature deformation, inclination and horizontal deformation; the building characteristics include the position of the long axis of the building in relation to the strike of the mining face (hereinafter referred to as "move towards"), structure, foundation, construction time and building size. As the selected indicator system contains three definite categories of indicators for building structure, foundation and orientation, which need to be quantified in the subsequent calculation, the following is the subdivision of these three categories of indicators:

3. Comparative Analysis of the Principal Component Analysis and the AHP Entropy Method

3.1. Principal Component Analysis for the Determination of the Weights

Principal component analysis (PCA) is widely used to reduce the redundancy and redundant dimensionality of data. Most signals can be characterized by the first few principal components (eigenvectors), and the rest of the eigenvectors are mainly redundant data. The purpose of PCA algorithm is to reduce the dimensionality, and the main idea is to map n-dimensional data to k-dimensions, and the k-dimensional vectors are called principal components.

Table 1. Membership degree of certain index

structure	Subgrade	Move towards	Membership degree
Brick-concrete structure I	Concrete foundation	perpendicularity	1
Brick-concrete structure II	Stone foundation	intersect	2
Brick wood (stone) structure	Soil foundation	parallel	3
Brick-soil structure	Natural foundation	-	4

The Indicator System constructed and the sampled data are shown in the following figure:

Table 2. Sampling point data

Number	subsidence /mm	Tilt amount (mm/m)	Curvature (10^{-3}/m)	Horizontal deformation (mm/m)	Move towards	Structure	Subgrade	Year of construction/yr	size/m^2
H1	96	0.25	0.003	0.12	2	1	1	5	300.616
H2	78	0.31	0.002	0.06	1	1	2	7	323.699
H3	92	0.66	0.004	0.24	2	1	1	8	305.547
H4	301	2.41	0.014	1.42	3	2	2	11	215.919
H5	420	2.66	0.019	0.77	3	2	2	12	233.352
H6	722	1.92	0.013	1.09	2	4	4	40	240.905
H7	152	0.37	0.004	0.2	2	2	1	9	194.359
H8	30	0.11	0.001	0.07	2	1	1	16	283.092
H9	50	0.08	0.003	0.06	2	2	2	7	165.542
H10	60	0.09	0.003	0.19	2	1	2	13	278.797
H11	365	1.14	0.002	0.24	2	2	3	15	277.034
H12	160	0.10	0.004	0.10	2	2	3	25	177.299
H13	46	0.12	0.004	0.08	2	3	3	23	297.573
H14	48	0.11	0.007	0.17	2	3	3	25	368.795
H15	530	0.36	0.031	0.36	2	3	2	27	773.528

The work of PCA is to find a set of mutually orthogonal axes sequentially from the original space, and the choice of new axes is closely related to the data itself. The first new axis is chosen in the direction of the largest variance in the original data, the second new axis is chosen in the plane orthogonal to the first axis that makes the largest variance, and the third axis is chosen in the plane orthogonal to the 1st,2nd axis that makes the largest variance. Similarly, n such axes can be obtained. The new axes obtained in this way show that most of the variance is contained in the first k axes, and the last axes contain almost zero variance, so we can ignore the remaining axes and keep only the first k axes that contain most of the variance. This is equivalent to keeping only the dimensional features that contain most of the variance and ignoring the feature dimensions that contain almost zero variance to realize the dimensionality reduction of the data features [14]. It can be applied to mining damage assessment of buildings in mining areas, where different features have different magnitude and range of variance and need to be standardized. The standard deviation method is used to normalize the attribute data set. The building index data obtained from the mine site are first standardized. The standard deviation method can be used to normalize the attribute data set and obtain the standardization matrix.

Second, the eigenvectors are reordered by calculating the eigenvalue matrix and the eigenvector matrix and sorting the eigenvalues from highest to lowest, where the eigenvector with the highest eigenvalue is the first principal component of the data set, indicating the vector with the highest variance in the data and also indicating most of the common information in the attributes used. Then, the selected principal components are merged and the features are reconstructed in the attribute domain to facilitate the analysis.

The ith principal component is calculated as:

$$F_i = w_{i1}X_1 + w_{i2}X_2 + \cdots + w_{in}X_n \tag{1}$$

In the formula: Fi is the ith principal component; n is the number of influencing factors, i is the number of principal components; θ_j is the coefficient corresponding to each variable in the component matrix; wij=θj/√λi denotes the corresponding weight of each variable in the ith principal component, and λi denotes the corresponding eigenvalue of the ith principal component.

The composite score is calculated according to the formula.

$$F = \alpha_1 F_1 + \alpha_2 F_2 + \cdots + \alpha_i F_i \tag{2}$$

In the formula: αi is the percentage of variance of the ith principal component.

The composite score index is a function of the three principal components, and the principal component formula is also a function of the original index system when it is introduced, where the coefficients of each index are normalized to the weights of the corresponding index.

Table 3. Weight of PCA

Indicators	curvature	Size	Year of construction	Structure	subsidence	Subgrade	Horizontal deformation	Tilt amount	Move towards
Weights	0.1749	0.1639	0.1551	0.1533	0.1510	0.0950	0.0637	0.0348	0.0083

3.2. The Weights are Determined Using the AHP Entropy Weighting Method

As the hierarchical analysis method is too subjective in relation to the actual data, the entropy weighting method is introduced to overcome the shortcomings of excessive subjectivity, and the joint weighting of AHP-entropy weighting method aims to take into account the subjective and objective factors, optimize the weighting values of evaluation indexes, and build a combined weighting evaluation model of mining damage to achieve the accuracy and reliability of evaluation results.

3.2.1. Hierarchical Analysis Method of Weight Determination

Analytic Hierarchy Process (AHP) is a method for transforming qualitative analysis problems into quantitative analysis problems proposed by American operations researcher Satie [15]. The hierarchical analysis method makes decisions by comparing the importance between evaluation indicators and follows the way of thinking of decomposition, comparative judgment, and synthesis. The specific steps for establishing hierarchical analysis are as follows:

(1) Establishing the hierarchical structure

Combined with the actual measurement data in the study area, the ground motion deformation and the building's own characteristics were finally determined as the primary indicators, and the subsidence, curvature, inclination, horizontal deformation, building orientation, structure, foundation, construction time and building size were taken as the secondary indicators. The hierarchical structure model established in this way is shown in Table 4.

(2) Constructing the Judgment Matrix

Since the constructed hierarchical model is divided into two levels, when constructing the judgment matrix, the judgment matrix should also be constructed separately according to different levels. The first is the judgment matrix from the target level to the first level of indicators.

Table 4. Damage evaluation index system of mining area building

Evaluation Indicators	Tier 1 Indicators	Tier 2 Indicators
Extent of building damage	Surface movement deformation	Subsidence
		Curvature
		Tilt amount
		Horizontal deformation
	Properties of the building itself	Move towards
		Structure
		Subgrade
		Year of construction
		Size of building

$$A = P(B_{ij}) = \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} = \begin{bmatrix} 1 & 9/4 \\ 4/9 & 1 \end{bmatrix} \quad (3)$$

B_{ij} indicates the relative importance of B_i to B_j, and the same can be constructed for the indicator scoring matrix from the first layer to the second layer, where the elements are obtained from the expert scoring as in the first layer.

Table 5. Index judgment matrix

index	Tilt amount	Horizontal deformation	Subsidence	Curvature	Move towards	Subgrade	Structure	Year of construction	size
Tilt amount	1	1/3	1/7	1/9	-	-	-	-	-
Horizontal deformation	3	1	1/5	1/6	-	-	-	-	-
subsidence	7	5	1	1/4	-	-	-	-	-
Curvature	9	6	4	1	-	-	-	-	-
Move towards	-	-	-	-	1	1/3	1/3	1/7	1/9
Subgrade	-	-	-	-	3	1	1/5	1/4	1/6
Structure	-	-	-	-	3	5	1	1/2	1/4
Year of construction	-	-	-	-	7	4	2	1	1/3
Size	-	-	-	-	9	6	4	3	1

(3) Consistency check

$$CR = \frac{\lambda_{max} - n}{RI(n-1)} \quad (4)$$

In the formula: CR is the random consistency ratio; λ_{max} is the maximum eigenvalue; RI is the average random consistency index and is only related to the value of the number of indicators n. The correlations are shown in Table 6.

Table 6. RI value table

n	1	2	3	4	5
RI	0.00	0.00	0.58	0.90	1.12

Only when the random consistency ratio CR < 0.1, the consistency test of the judgment matrix is qualified, and the judgment matrix and the calculated weights can be used in this case. In particular, it should be noted that when the number of indicators is less than or equal to 2, the RI value of the matrix is 0. That is, the consistency test is not required for the second-order judgment matrix.

Among the judgment matrices in the paper, the CR value of the judgment matrix of the surface movement deformation is 0.092<0.1; the CR value of the judgment matrix of the building's own characteristics is 0.067<0.1, and the consistency tests of both judgment matrices pass, and the judgment matrix and the weights calculated based on it are valid.

The weights calculated based on the judgment matrices of the two major categories of indicators are shown in Table 7:

Table 7. Weight of AHP

	Surface movement deformation	Properties of the building itself	Comprehensive weight
	0.44	0.56	
subsidence	0.26934	-	0.11851
Tilt amount	0.04224	-	0.01859
Curvature	0.60036	-	0.26416
Horizontal deformation	0.08806	-	0.03875
Move towards	-	0.03834	0.02147
Structure	-	0.15451	0.08653
Subgrade	-	0.06515	0.03648
Year of construction	-	0.24466	0.13701
Size	-	0.49735	0.27852

3.2.2. Entropy Weighting Method for Determining the Weights

Since the hierarchical analysis method determines the weights based on the experts' scores, the subjectivity of this method [16] is too strong, and in order to make the determined weights more objective, the entropy weighting method is used here to determine the weights separately and finally calculated together with the weights determined by the hierarchical analysis method. The entropy weighting method is a relatively objective method of assigning weights, and this method uses the magnitude of the entropy value of the data corresponding to each index to determine the weights of the corresponding index.

Generating the original data matrix:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix} \tag{5}$$

where n is the number of sampling points and m is the number of indicators.

Normalization operation

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \tag{6}$$

Calculating information entropy

$$e_j = \frac{\left(-\sum_{i=1}^{n} P_{ij} \ln P_{ij}\right)}{\ln n} \tag{7}$$

In the formula: ej is the entropy of the jth sampling point; n is the number of sampling points.

Calculating entropy weights

$$S_{bj} = \frac{(1-e_j)}{m-\sum_{j=1}^{m} e_j} \tag{8}$$

3.2.3. Combined Determination of Weights

After determining the weights by each of the two methods, the weights obtained by the two methods need to be integrated, and the integrated weights are as follows:

$$C_j = \frac{W_j S_j}{\sum_{j=1}^{n} W_j S_j} \tag{9}$$

In the formula: C_j is the combined weight of the jth indicator; W_j is the weight of the jth indicator determined by the hierarchical analysis method; Sj is the weight determined by the jth indicator determined by the entropy weight method.

Table 8. Weight of EWM and comprehensive weight

Index	Subsidence	Tilt amoun	Curvature	Horizontal deformation	Move towards	Structure	Subgrade	Year of construction	Size
Weight of Entropy weight method	0.12732	0.17676	0.12254	0.17785	0.03607	0.10671	0.0848	0.07731	0.09063
Weight of AHP	0.11851	0.01859	0.26416	0.03875	0.02147	0.08653	0.03648	0.13701	0.27852
Comprehensive weight	0.14158	0.03083	0.30374	0.06466	0.00727	0.08664	0.02903	0.09939	0.23686

In the weight assigned by the entropy weighting method, we can see that the weight of the building's own attributes is about 0.4, which is different from the weight distribution of the principal component analysis and hierarchical analysis methods, and this will definitely affect the subsequent rating results.

4. Damage Evaluation based on TOPSIS Evaluation Model

Combined with the measured data in the study area, the degree of mining damage in the study area was classified into four classes according to the current specifications, as shown in Table 9.

Table 9. Classification of building damage grade

index	I	II	III	IV
subsidence (mm)	<100	100~300	300~500	≥500
Tilt amount (mm/m)	<1.5	1.5~4	4~10	≥10
Curvature (mm/m^2)	<0.1	0.1~0.3	0.3~0.6	≥0.6
Horizontal deformation(mm/m)	<1	1~4	4~8	≥8
Year of construction (year)	10	10~25	25~40	≥40

Based on the data from the selected sampling points within the impact area and the requirements of the current "Regulations" specification, the selected residential buildings were also evaluated for damage and classified into four grades in accordance with the specification. The proximity interval of the damage classification of the buildings at the sampling points for the results of the TOPSIS calculation is divided as follows:

Grade 1 damage

Grade 1 damage: $0 \le C \le 0.25$

Grade 2 damage: $0.25 \le C < 0.5$

Grade 3 damage: $0.5 \le C < 0.75$

Grade 4 damage: $0.75 \le C \le 1$

4.1. TOPSIS Evaluation Model

TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution), also called the distance method of optimal and inferior solutions. The principle is to rank the evaluation object by determining the distance between the object and the optimal solution and the worst solution.

Decision Matrix Construction

$$V = \begin{bmatrix} V_{11} & \cdots & V_{1m} \\ \vdots & \ddots & \vdots \\ V_{n1} & \cdots & V_{nm} \end{bmatrix} \tag{10}$$

In the formula: n is the number of sampling points; m is the number of participating indicators; Vij is the value of the evaluation indicator m in the evaluation unit n; i=1, 2, ..., m.

The TOPSIS normalization matrix is obtained. The original evaluation index matrix V is processed according to very large and very small indicators to obtain the normalization matrix. Very large indicators are defined as indicators with larger values that have a greater impact on deformation, and vice versa for very small indicators. The qualitative indicators must be converted to quantitative indicators before they can be defined as very large or very small indicators. Depending on the indicator system, building orientation is a very small indicator, and the inverse of the indicator data is taken to obtain the normalization matrix X.

$$X = \begin{bmatrix} X_{11} & \cdots & X_{1m} \\ \vdots & \ddots & \vdots \\ X_{n1} & \cdots & X_{nm} \end{bmatrix} \tag{11}$$

By normalizing the normalization matrix and eliminating the effect of magnitude, the normalized matrix Z is obtained.

$$Z = \begin{bmatrix} Z_{11} & \cdots & Z_{1m} \\ \vdots & \ddots & \vdots \\ Z_{n1} & \cdots & Z_{nm} \end{bmatrix} \tag{12}$$

In the formula: Zij=Xij/ $\sqrt{\sum_{i=1}^{n} X_{ij}^{2}}$, i=1,2……, n; j=1,2……, m.

Distance calculation: Euclid's algorithm is chosen to calculate the distance in this study. Define the maximum (minimum) value:

Z^+=(max{Z_{11},Z_{21}…Z_{n1}},max{Z_{21},Z_{22}…Z_{n2}} max{Z_{1m},Z_{2m}…Z_{nm}});

Z=(min{Z_{11},Z_{21}…Z_{n1}},min{Z_{21},Z_{22}…Z_{n2}} min {Z_{1m},Z_{2m}…Z_{nm}});

Define the distance between i (i=1, 2, ..., n) evaluation objects and the maximum value as D_i^+ and the distance between i (i=1, 2, ..., n) evaluation objects and the minimum value as D_i^-, calculated as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^{m}\left(Y_i^+ - y_{ij}\right)^2} \tag{13}$$

$$D_i^- = \sqrt{\sum_{j=1}^{m}\left(Y_i^- - y_{ij}\right)^2} \tag{14}$$

Calculation of the Relative Closeness (C)

The closeness is defined as the degree of damage to the building at the sampling point and is expressed by C. The value of the closeness C is taken between 0 and 1. The smaller the value of C, the better the evaluation result, i.e., the lower the degree of damage to the building. If C=0, it means that it is at the optimal level, i.e., no damage, and C=1, it means that it is at the worst level. In this study, the proximity represents the damage level of the building, and the damage level of the building is judged according to the different proximity values of different sampling points. The formula for calculating the proximity is as follows:

$$C = \frac{D_i^-}{(D_i^+ + D_i^-)} \tag{15}$$

The TOPSIS method considers all evaluation indices to be of equal importance, but in practical problems, the influence of evaluation indices is often of different degrees, so this paper introduces two methods to determine the weights before establishing separate evaluation models for building damage.

Table 10. TOPSIS calculation results and grading

Sampling sites	Composite Score Index (PCA)	Composite Score Index (AHP-Entropy method)	Field survey results	Result of PCA	Result of AHP-Entropy method
H1	0.10942985	0.12610952	I	I	I
H2	0.16523115	0.15698726	I	I	I
H3	0.12877853	0.14454212	I	I	I
H4	0.38170933	0.38435902	II	II	II
H5	0.40765616	0.42674994	II	II	II
H6	0.64353898	0.55486792	III	III	III
H7	0.16188463	0.14114432	I	I	I
H8	0.14262744	0.13417697	I	I	I
H9	0.164142	0.12095112	I	I	I
H10	0.15996936	0.13904486	II	II	I
H11	0.32414297	0.26315612	II	II	II
H12	0.30816011	0.23132825	II	II	I
H13	0.35329797	0.27468776	II	II	II
H14	0.38736054	0.32277752	II	II	II
H15	0.65136138	0.71316711	III	III	III

In the calculation results of the above table, it can be seen that there are obvious differences between the building mining damage grades classified according to the comprehensive score of TOPSIS using the two methods respectively, among which the evaluation results assigned with the principal component analysis method are in full agreement with the evaluation results of the current code; while the evaluation results assigned with the joint hierarchical analysis method and the entropy power method have two sampling points out of 15 with different grades.

4.2. Validation of the Index System

Table 11. Verify data index system

Number	Condition of the building itself				Geological mining conditions					
	Building condition/S	Relationship with mining area /U	Length L/m	Breadth W/m	Comprehensive impact index of mining /Q	Coal mining height/m	Coal mining depth/m	Coal seam inclination α/(°)	Platts index/Z	Top plate control mode/ T
1	0.8	3.0	36.0	10.0	0.923	2.2	180	20.0	4.8	0
2	1.0	2.0	25.0	8.0	0.924	2.2	188	23.0	4.9	0
3	1.0	4.0	12.6	8.6	0.925	2.8	275	25.0	4.8	0
4	0.6	5.0	22.0	14.0	0.345	4.5	476	14.6	5.0	1
5	0.2	4.0	26.0	12.0	0.404	4.5	512	18.9	4.6	1
6	1.0	1.0	19.0	5.9	0.312	3.6	454	28.0	2.0	1
7	0.8	3.0	16.0	6.2	0.324	3.0	543	19.0	3.4	1
8	0.6	2.0	27.0	4.6	0.341	2.5	157	13.0	4.2	0
9	1.0	4.0	21.0	6.0	0.803	3.2	219	15.0	3.7	0
10	0.6	2.0	36.0	12.0	0.327	10.0	543	8.0	2.0	0
11	1.0	3.0	15.8	13.0	0452	4.8	185	27.0	4.6	1
12	1.0	2.0	14.0	5.0	0.442	4.8	214	24.0	4.1	1
13	0.4	3.0	12.4	6.0	0.713	3.0	186	15.0	5.0	0
14	0.6	2.0	14.0	5.5	0.721	3.0	210	14.0	4.5	0
15	1.0	3.0	12.0	6.0	0.712	3.0	193	15.0	5.0	0
16	0.8	4.0	10.0	6.0	0.401	4.2	559	17.0	5.0	1
17	0.6	2.0	14.0	5.5	0.586	4.8	458	25.0	4.6	0
18	0.8	2.0	20.0	12.0	0.413	4.8	132	19.0	5.2	1
19	0.4	4.0	36.0	12.0	0.412	3.0	514	25.0	4.6	0
20	0.6	1.0	15.0	14.0	1.000	4.5	445	14.0	4.8	0

In the above, according to KMO and Bartlett test, it has been proved that the correlation between the indicators in the selected index system is strong, that is, the indicators influence each other. The index system is more suitable for performing factor analysis, while the index system with low correlation is not applicable. To explore the relationship between the correlation between the indicators and the assignment method, the data from the paper by Xinglin Wen [17] and others were cited as validation: the highly correlated indicator system is applicable to the principal component analysis method, and on the contrary, the indicator system with no obvious correlation between the indicators is applicable to the evaluation model of the AHP entropy weight method. The indicator system in the combination of optimized AHP + entropy weighting method using Xinglin Wen as a validation. The data in the paper are shown in Table 11.

The KMO validation of their data as well as the Bartlett spherical validation results can be obtained as shown in the following table:

Table 12. The KMO validation of their data as well as the Bartlett spherical validation results

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.420
Bartlett's Test of Sphericity	Approx. Chi-Square	51.729
	df	45
	Sig.	.228

The results of KMO and Bartlett's spherical test show that the KMO value of 0.403<0.6 shows that it is not applicable to the principal component analysis method; the significance index of Bartlett's spherical test is 0.228, which is much larger than 0.05, which shows that it does not obey the spherical test, that is, the variables are independent of each other and cannot be applied to the principal component analysis method. Since the subjectivity of the hierarchical analysis method is too strong, it can affect the final weight distribution as well as the evaluation results, so it is proved that the AHP entropy weighting method is no longer applicable in the index system with strong mutual influence among indicators.

5. Conclusion

In this paper, the index system of building damage evaluation is improved more scientifically and objectively by selecting two types of indexes, namely, surface movement deformation and building own attributes; the evaluation models based on two empowerment methods, namely, analytical principal component analysis and AHP entropy weight method, are used to evaluate the mining damage of 15 sampled buildings in the mining area, respectively. The applicability and limitations of the two methods were explored through the comparative analysis of the evaluation results.

(1) The damage to buildings in the mining area is caused by the joint effect of surface movement and deformation and the buildings' own characteristics, and the weight of their own characteristics is more than 0.5, so the index system constructed in this paper is relatively objective and applicable.

(2) Using the sampling points at different locations in the surface movement basin in the test area, the data were evaluated by principal component analysis, and the evaluation results of 15 sampling points were found to be fully consistent with the evaluation results of the existing standards, which verified the feasibility of applying the principal component analysis method to the evaluation of mining damage to buildings in mining areas.

(3) By analyzing the data of the sampling points, it was found that the Bartlett's test index was much less than 0.05, indicating that there was a strong correlation among the indicators. By comparing the evaluation results of principal component analysis and AHP entropy method, we found that the results of building damage evaluation by principal component analysis were in good agreement; through the experiments in the paper and the examination of data in the literature, we found that the AHP entropy method was more suitable for the index system with strong independence among the indicators, and the method was seriously affected by the subjective weighting of the hierarchical analysis method. It is not as objective as the principal component analysis method.

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