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Quality evaluation of surrounding rocks in a mine shaft based on the game gray target model

Li-Ping Guo[1] and Xin-Bao Gu[2]*

[1]School of Architecture, Nanyang Institute of Technology, Nanyang, Henan, China, [2]School of Civil Engineering, Nanyang Institute of Technology, Nanyang, Henan, China

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EDITED BY
Fanyu Zhang,
Lanzhou University, China

REVIEWED BY
Dan Ma,
China University of Mining and Technology, China
Zhengzheng Cao,
Henan Polytechnic University, China

*CORRESPONDENCE
Xin-Bao Gu,
15823405952@163.com

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Accurate evaluation of surrounding rock quality grade can help guarantee the safety of tunnel design and construction; hence, it has great significance in the construction of mine shafts. Accordingly, the uniaxial saturated compressive strength of the rock block R_c, rock quality index *RQD*, rock softening coefficient k_R, integrity coefficient of the rock mass k_v, depth H, unit weight of the rock mass γ, coefficient of quantification of the angle between the principal structural plane and shaft axis k_2, and weight of the groundwater k_1 are first selected as the indexes of assessment to introduce the game gray target model. Then, the gray target model of the surrounding rocks in a mine shaft project is established. The weight coefficient of each index is next calculated using the combination weighting method based on game theory, and the synthetic target center distance of each sample is determined using the gray target model. Finally, the quality level of the asphalt pavement is determined. The suggested model can be used to mine a small data sample to the maximum extent possible, thereby minimizing the information shortage caused by the small sample to a certain extent, to evaluate the final quality grade of the surrounding rocks quantitatively. Thus, the proposed approach provides a new scheme for the future quality assessments of surrounding rocks.

KEYWORDS

quality assessment, surrounding rocks, mine shaft, game gray target model, level

1 Introduction

Given the rapid development of Chinese infrastructure, the number and scale of construction projects in underground engineering have also grown. As essential components of underground engineering, the surrounding rocks in subway tunnels play vital roles in the entire subway system (Gu X. B. et al., 2021). The surrounding rocks in a tunnel constitute a complex geological body, and the quality of such surrounding rocks is affected by the rock mass structure, geological characteristics, and other factors (Gu and Wu, 2019). Accurate evaluation of the surrounding rock quality grade can provide safety guarantees for tunnel design and construction, reduce safety risks, promote efficient construction operations, and reduce cost and economic losses. Therefore, it is of great practical significance to evaluate the quality grades of the surrounding rocks in subway tunnel constructions (Gu et al., 2021b).

There is abundant literature on evaluating surrounding rock quality grade (Zhou et al., 2016). Li et al. (2014) assessed the stability of the surrounding rock mass using a fuzzy comprehensive evaluation method combined with rock mass characteristics and support parameters. Wang F. F. et al. (2019) used unascertained measure theory to evaluate the surrounding rock quality of a subway tunnel. Zhong et al. (2019) assessed the stability of tunnel surrounding rocks using a combination of game and extension theories. Based on the European distance method, Wang J. C. et al. (2019) evaluated the toughness of surrounding rocks in a subway tunnel. Xue et al. (2020) used a two-dimensional cloud model combined with an apriori algorithm to determine the stability grade of surrounding rocks. Geng et al. (2014) investigated the influence of tunnel span on rock mass quality and provided a basis for tunnel design and construction using the improved rock mass quality index method. Wu et al. (2020) applied a continuous interval mathematical model to evaluate the rock mass quality of a slope. Liu et al. (2018) applied a deep learning technique to classify the surrounding rocks. In recent years, experts and scholars have attempted to use the extension theory method (Zhengzheng et al., 2024), fuzzy comprehensive evaluation method (Yang, 2018), cloud model method (He et al., 2021), rough set theory method (Yang et al., 2018), unknown measure method (Zhou et al., 2021), and ideal point method (Jiang and Wang, 2021) to evaluate the stabilities of surrounding rocks in tunnels.

The above models and methods have improved the development of quality assessments for surrounding rocks. These research efforts have first enriched the classification and evaluation theories of surrounding rock quality; second, the randomness and fussiness of the evaluation indicators are considered to enhance the accuracies of the evaluation results; third, evaluations of the non-linearities of the surrounding rock quality have been performed to provide solutions for the evaluation indicators that are otherwise difficult to quantify, while reducing the influences of human factors (Zhao et al., 2024).

However, these approaches have some shortcomings (Shao et al., 2022) in terms of three aspects. 1) A single weighting method is used in these approaches, and the weighting process does not include the subjective importances of the influencing factors, objective relationships between the factors, and differences in the factors themselves. 2) The evaluation processes are complex; for example, the membership functions are difficult to determine. 3) Upon commencing the evaluation and grading processes, subjective influences cannot be exerted on the evaluations based on actual engineering needs, and the evaluations therefore lack flexibility. The above limitations greatly restrict the evaluations of surrounding rock quality.

To overcome the abovementioned drawbacks, the game gray target model was applied in this work to assess the surrounding rock quality. Gray target decision-making is a type of uncertainty system used to obtain information when there are very few samples or if the data are poor (Tan et al., 2019). This method can be used to mine and develop data to the maximum extent possible based on known information from a small number of samples. This technique has been applied in finance, military, and other fields to achieve good results (Li and Wu, 2017). Hence, this approach is applied in this study to evaluate and analyze the quality levels of surrounding rocks in a mine shaft.

The remainder of this paper is organized as follows: Section 2 introduces the theory and methodology of the game gray target model. Section 3 provides an engineering example of the surrounding rocks considered in this work. Section 4 presents the assessment model and results analyses. Section 5 presents the conclusions of this study.

2 Methodology

2.1 Principles of the game gray target model

Gray target decision-making is an important method for solving multiattribute decision-making problems from an objective perspective, and it can effectively reduce the loss of original information in the decision-making process (Zhou et al., 2014). Its basic idea is that an optimal data sequence is found from an existing set of sequences to construct a standard model. Then, the standard model is applied as the target, and the gray target model is built by comparing other models with the standard; the degree of likeness between the models is then evaluated to assess the target before calculating the target distance to determine the evaluation grade. Considering the errors in accuracy based on single-weight gray target models, the combination weighting method based on game theory was adopted in this work; then, the combined weights of the critic and entropy methods were optimized to obtain the optimal weight.

2.2 Establishment of the decisive matrix

Assuming that there are m samples to be evaluated $A_i(i = 1, 2, ..., m)$ and n evaluation indexes $A_j(j = 1, 2, ..., m)$, the sample matrix is given by $A = \{a_{ij}\}(i = 1, 2, ..., n)$.

Suppose that c_j is the mean value of evaluation index, then

$$c_j = \frac{1}{m}\sum_{i=1}^{n} a_{ij} \tag{1}$$

where $i = 1, 2, 3..., m; j = 1, 2, 3..., n$.

Let x_{ij} be the standardized processing result for the economic indicators, which is expressed as (Zhengzheng et al., 2024)

$$x_{ij} = \frac{a_{ij} - c_j}{\max\left(\max\left\{a_{ij}\right\} - c_j, c_j - \min\left\{a_{ij}\right\}\right)} \tag{2}$$

For the cost-type indicator, this formula becomes

$$x_{ij} = \frac{c_j - a_{ij}}{\max\left(\max\left\{a_{ij}\right\} - c_j, c_j - \min\left\{a_{ij}\right\}\right)} \tag{3}$$

From Eqs 1–3, the decisive matrix is expressed as

$$X = \begin{Bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{Bmatrix}$$

2.3 Calculation of the target center distance

For the decisive matrix X, if $x_j^{0+} = \max\left\{x_{ij} | 1 < i < m\right\}$, then $x^{0+} = \left\{x_1^{0+}, x_2^{0+}, ..., x_m^{0+}\right\}$ is the positive center of the gray target, and $x^{0-} = \left\{x_1^{0-}, x_2^{0-}, ..., x_m^{0-}\right\}$ is the negative target center. The distance

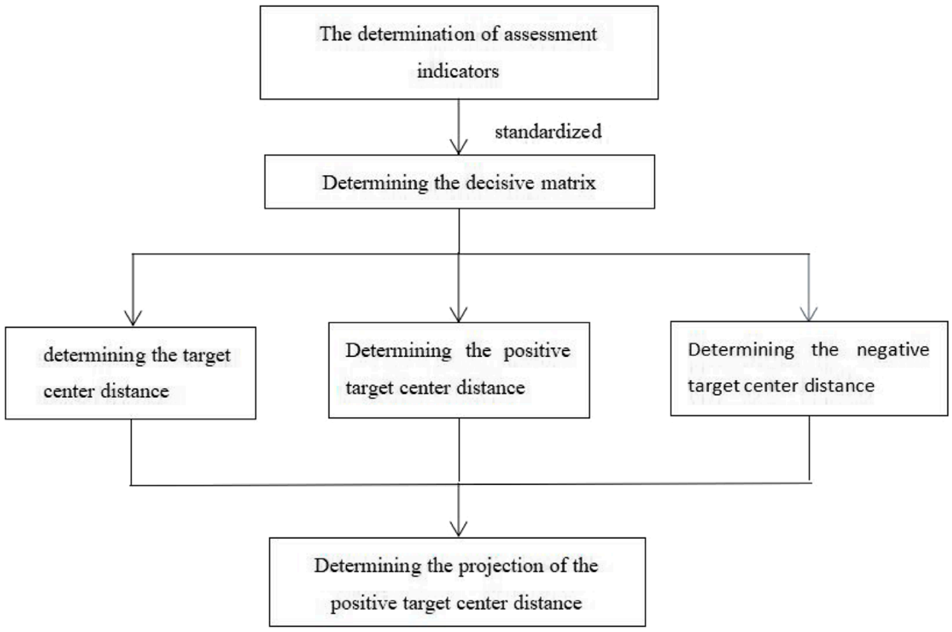

FIGURE 1
Calculation of the target center distances.

FIGURE 2
Mine shaft considered in this study.

between x^{0+} and x^{0-} is regarded as the interval d^0 between the positive and negative target centers and is given by

$$d^0 = |x^{0+} - x^{0-}| = \left(\sum_{j=1}^{n} \omega_j \left(x_j^{0+} - x_j^{0-}\right)^2\right)^{1/2} \tag{4}$$

where ω_j is the optimal weight of the *jth* index obtained using game theory.

The positive target center distance d_i^+ is the distance between x_i and x^{0+} given by

$$d_i^+ = |x_i - x^{0+}| = \left(\sum_{j=1}^{n} \omega_j \left(x_{ij} - x_j^{0+}\right)^2\right)^{1/2} \tag{5}$$

The negative target center distance d_i^- is the distance between x_i and x^{0-} given by

$$d_i^- = |x_i - x^{0-}| = \left(\sum_{j=1}^{n} \omega_j \left(x_{ij} - x_j^{0-}\right)^2\right)^{1/2} \tag{6}$$

The distance from any sample point x_i to the positive target center is $d_i^+ < d^0$, such that x_i is located on a sphere with x^{0+} as the center and d^0 as the radius; the distance from any sample point x_i to the negative target center is $d_i^- < d_0$, such that x_i is located on a sphere with x^{0-} as the center and d^0 as the radius. Thus, the sample point x_i, positive target center d_i^+, and negative target center d_i^- are three points in space that are collinear or triangular. Therefore, the degree of danger of a sample can be measured from the projection of the positive target center distance on the line between the positive and negative target centers. By assuming that the angle between the positive target center distance and line between the positive and negative target centers is θ, the target center distances can be obtained according to the law of cosines (Figure 1):

$$d_i^* = d_i^+ \cos\theta = \frac{(d_i^+)^2 + (d^0)^2 + (d_i^-)^2}{2d^0} \tag{7}$$

2.4 Classification of the quality grade

From the definitions of the target center distances, it is found that the comprehensive target distance quantitatively reflects the quality grade of a sample. Assuming that the samples to be evaluated have t quality grades, let $D = (d_1, d_2, ..., d_m)$ be the set of comprehensive target center distances S of the samples to be evaluated, and $B =$

TABLE 1 Learning samples for the surrounding rock quality evaluation indexes.

Serial number	R_c	H	k_v	γ	RQD	k_1	k_2	k_R	Quality level
1	219.12	760	0.924	25.86	100	10	0.45	0.78	I
2	169.84	768	0.973	25.84	100	15	0.45	0.74	I
3	19.42	777	0.857	24.15	50	4	0.4	0.49	V
4	20.11	783	0.832	24.3	80	7	0.4	0.91	V
5	41.61	791	0.849	24.89	75	7	0.4	0.62	IV
6	56.86	800	0.724	25.61	73	10	0.4	0.72	IV
7	86.79	830	0.602	25.35	90	15	0.3	0.65	III
8	104.01	840	0.653	25.27	94	7	0.3	0.79	III
9	104.01	843	0.633	25.7	85	7	0.3	0.79	III
10	104.01	862	0.887	25.7	82	7	0.3	0.79	II
11	104.1	869.4	0.887	25.72	85	7	0.3	0.75	II
12	92.74	880	0.887	25.4	83	10	0.4	0.58	II

$(B_1 \quad B_2 \quad \ldots \quad B_t)$ be the ordered set of the t quality grades; let f be a positive integer such that $1 \le f < t$, and the thresholds of the fth set are $g_f = \max\{B\}$ and $c_f = \min(B_f)$, then $h_f = \alpha c_{f+1} + (1-\alpha) g_f$ for $\alpha \in (0,1)$, $h_0 = 0, h_q = +\infty, d = (d_1 \quad d_2 \quad \ldots \quad d_i)$ are the critical comprehensive target center distances of the different quality grades. The interval distribution set of comprehensive target distances for the t quality grades can then be obtained as follows:

$$D_{ij} = \{d | h_0 > d_1 > h_1, \ldots, h_{t-1} > d_t > h_t\} \tag{8}$$

2.5 Determination of the index weights

(1) Critic method

The critic method is a kind of weight-assignment method (Zhou et al., 2008) that uses the variability and conflict between different evaluation indexes for weighting to comprehensively measure the evaluation index. Its procedure is as follows:

① Standardization processing of the data

Each evaluation index is quantified to be dimensionless to eliminate the influences of different variables. If the evaluation index is of the benefit type, then the calculation formula is

$$y = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \tag{9}$$

If the evaluation index is of the cost type, then the calculation formula is

$$y = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \tag{10}$$

Here, y is the normalized processing value; $\max(x_{ij})$ and $\min(x_{ij})$ are the maximum and minimum values from a set of evaluation indexes.

② The variability among the evaluation indexes is generally expressed using the standard deviation σ_j, whose formula is

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{n} (x_{ij} - x_j)^2}{n}} \tag{11}$$

where x_j is the mean of the jth evaluation index, and n is the total number of jth evaluation indexes.

③ The correlation coefficient of the evaluation index is calculated as

$$r_{xy} = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2 \sum (y - \bar{y})^2}} \tag{12}$$

④ The conflict coefficient of the evaluation index is calculated as

$$C_j = \sum_{m=1}^{n} (1 - r_{mj}) \tag{13}$$

⑤ The weight coefficient ω_j of the evaluation index is calculated as

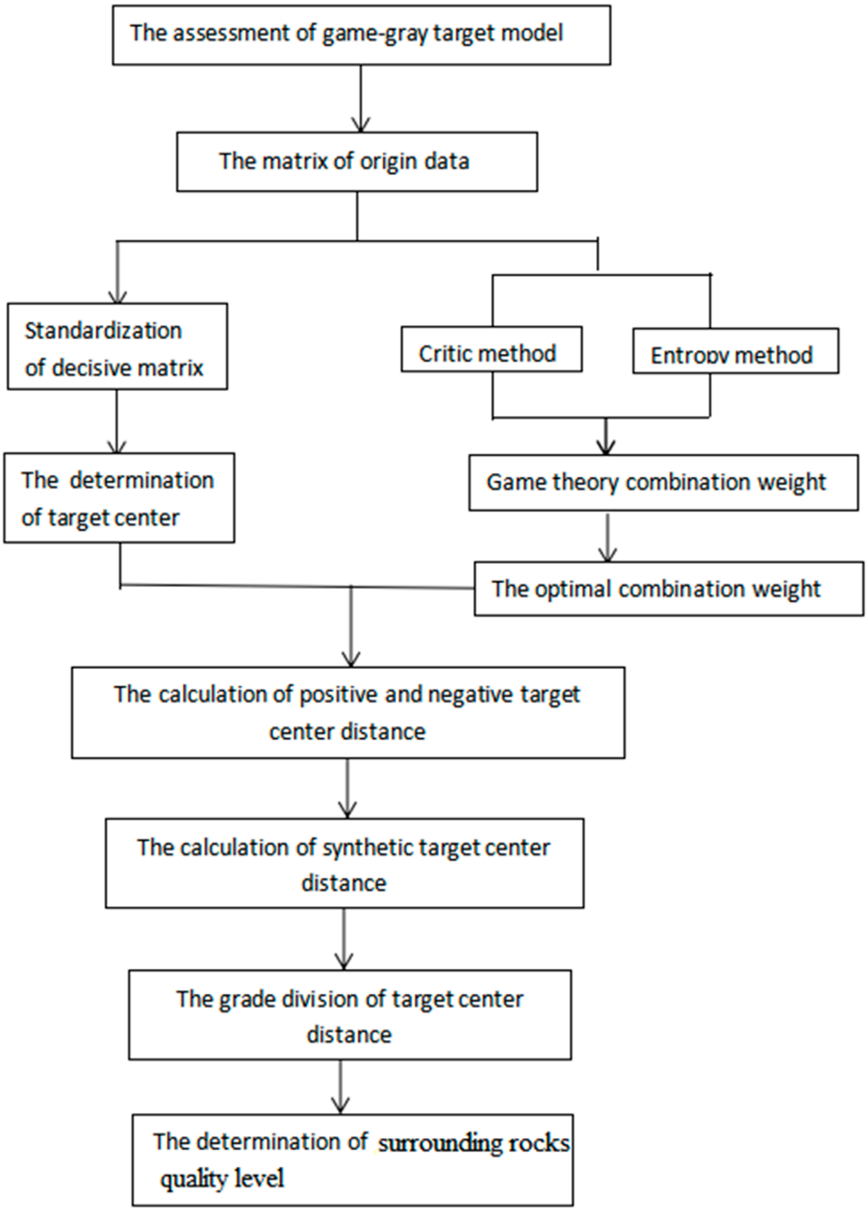

FIGURE 3
Flowchart of the assessment framework.

$$\omega_j = \frac{\sigma_j \times C_j}{\sum_{j=1}^{n} \sigma_j \times C_j} \tag{14}$$

(2) Entropy method

The entropy weighting method is used to determine the entropy value of an index according to the variance of the evaluation index, and its specific calculation method is based on a previously reported approach (Gu et al., 2019).

(3) Game theory combination weighting method

To avoid information loss caused by using a single weighting method and improve the accuracies of the weights, the combination weighting method based on game theory (Gu et al., 2021c) is applied to optimize the weights obtained from several other weighting methods to obtain the optimal weight as follows.

① The weight sets ω_1 and ω_2 are obtained from the entropy weighting and critic methods, and a_1 and a_2 are assumed to be their respective linear combination coefficients. Then, the weight sets ω_1 and ω_2 are linearized as

TABLE 2 Decisive matrix values for the evaluation indexes.

Serial number	R_C	H	k_v	γ	RQD	k_1	k_2	k_R
1	1.00	−0.90	0.54	0.46	0.51	0.19	1.00	0.26
2	0.61	−0.78	0.78	0.44	0.51	1.00	1.00	0.09
3	−0.59	−0.63	0.22	−1.00	−1.00	−0.78	0.38	−1.00
4	−0.58	−0.54	0.10	−0.87	−0.09	−0.30	0.38	0.83
5	−0.41	−0.41	0.19	−0.37	−0.24	−0.30	0.38	−0.43
6	−0.29	−0.27	−0.41	0.25	−0.30	0.19	0.38	0.00
7	−0.05	0.21	−0.99	0.03	0.21	1.00	−0.88	−0.30
8	0.08	0.37	−0.75	−0.04	0.33	−0.30	−0.88	0.30
9	0.08	0.41	−0.84	0.32	0.06	−0.30	−0.88	0.30
10	0.08	0.71	0.37	0.32	−0.03	−0.30	−0.88	0.30
11	0.08	0.83	0.37	0.34	0.06	−0.30	−0.88	0.13
12	−0.01	1.00	0.37	0.07	0.00	0.19	0.38	−0.61

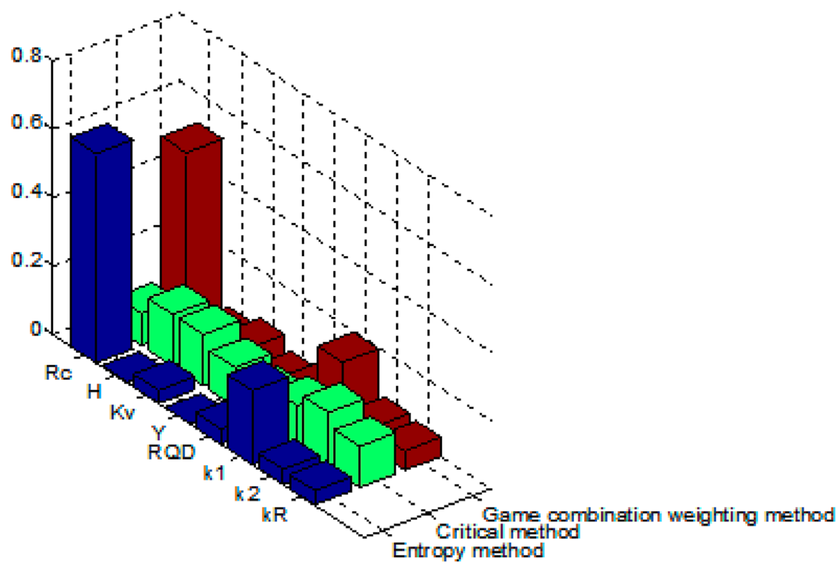

FIGURE 4
Graphical depiction of the individual and combined weight coefficients.

$$\omega = a_1\omega_1^T + a_2\omega_2^T \tag{15}$$

② Based on game theory, the linear combination coefficients a_1 and a_2 in Eq. 15 are optimized and expressed as

$$\min \left\| a_k\omega_k^T - \omega_k \right\|^2 (k = 1, 2) \tag{16}$$

③ Based on the differential properties of a matrix, the linear differential equations for optimizing the first derivative condition of Eq. 15 is

$$\begin{bmatrix} \omega_1\omega_1^T & \omega_1\omega_2^T \\ \omega_2\omega_1^T & \omega_2\omega_2^T \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} \omega_1\omega_1^T \\ \omega_2\omega_2^T \end{bmatrix} \tag{17}$$

TABLE 3 Positive and negative target center distances for the different rock samples.

Sample number	Positive target center distance d^+	Negative target center distance d^-
1	0.5168	1.4543
2	0.4591	1.421
3	1.5518	0.4414
4	1.3423	0.6769
5	1.264	0.5621
6	1.1043	0.6978
7	1.0428	0.9709
8	1.0848	0.7355
9	1.0937	0.7253
10	1.0228	0.8083
11	1.0253	0.8087
12	0.9065	0.8816

Based on Eq. (7), the magnitudes of the synthesized target center distances are shown in Table 4.

④ The optimal combination coefficients a_1 and a_2 are obtained through Eq. 16. Then, these values are normalized as $a_1^* = \frac{a_1}{(a_1+a_2)}$ and $a_2^* = \frac{a_2}{(a_1+a_2)}$. Finally, the comprehensive weight ω is obtained as

$$\omega = a_1^* \omega_1^T + a_2^* \omega_2^T \tag{18}$$

3 Engineering overview

The new main shaft of the mine shaft project considered in this work was located in a denudation low mountain and hill area (Figure 2), with a designed depth of 1,135 m and diameter of 6.0 m. The new main shaft passed through nine types of rocks, namely, altered trachyte, albite granite, altered diabase, albite quartz syenite porphyry, fault breccia, albite granite porphyry, cataclastic granite, k-feldspar granite, and k-feldspar quartz diorite. There were five types of joints with different occurrences in the surrounding rocks as well as many alteration weak zones and fracture zones. There was uniform fractured water in the surrounding rocks of the shaft, whose upper part was a weak absorbent layer and the lower high-stress area was a relatively water-resistant layer. The field tests demonstrated that in most cases, the vertical stresses were similar for the quality of the overlying strata (γ_h); because of the complex geological conditions in the mining area, the horizontal stresses in different areas of the rock mass were not the same. These stresses usually varied between 1.258 γ_h and 1. 874 γ_h, but the horizontal stress gradually approached the gravity stress of the original rock with increasing depths.

4 Construction of the assessment model

4.1 Determination of the evaluation indexes

The selection of indicators should consider the ease of access of the site, convenience, and practices. Accordingly, eight influential factors were selected as the assessment indexes: uniaxial saturated compressive strength of the rock block R_c, rock quality index RQD, rock softening coefficient k_R, integrity coefficient of the rock mass k_v, depth H, unit weight of the rock mass γ, coefficient of quantification of the angle between the principal structural plane and shaft axis k_2, and weight of the groundwater k_1. The assessment results were divided into five grades as excellent (I), good (II), common (III), inferior (IV), and bad (V). Twelve groups of monitoring data and assessment results from the mine were adopted as the learning samples, and these specific data are shown in Table 1.

4.2 Construction of the assessment frame

The flowchart depicting the determination of the quality levels of the surrounding rocks in the mine shaft is shown in Figure 3, and the specific procedures are as follows.

(1) The sample matrix of the origin matrix is constructed;
(2) the decisive matrix of original data is established based on Eqs 2, 3;
(3) the optimal combination weights of the different samples are obtained according to Eqs 9–17;
(4) the target centers of the different samples are found using the decisive matrix and Eq. 4;
(5) the positive and negative target center distances of the different samples are determined according to Eqs 5, 6;
(6) the target center distances of the different samples are determined using Eq. 7;
(7) the quality levels are partitioned according to the target center distance ranges in combination with Eq. 8;
(8) the final quality grade of the surrounding rocks is determined.

4.3 Determination of the standard decisive matrix values

Four of the indicators listed in Table 1 are of the benefit type. Using Eqs 1–3 and the information in Table 1, the decisive matrix values are obtained as shown in Table 2.

TABLE 4 Synthesized target center distances for the rock samples.

Sample	Synthetic target center distance d_i^*	Sample	Synthetic target center distance d_i^*	Sample	Synthetic target center distance d_i^*
1	0.2884	5	1.2209	9	1.0386
2	0.3002	6	1.0573	10	0.9561
3	1.4985	7	0.8822	11	0.9574
4	1.2394	8	1.0285	12	0.8523

TABLE 5 Critical values of the synthesized target center distances.

Grade ranking	Critical values		
	g_f	c_f	h_f
B_1	0.3002	0.2884	0.5763
B_2	0.9574	0.8523	0.9198
B_3	1.0386	0.8822	1.0479
B_4	1.2209	1.0523	1.2302
B_5	1.4983	1.2394	

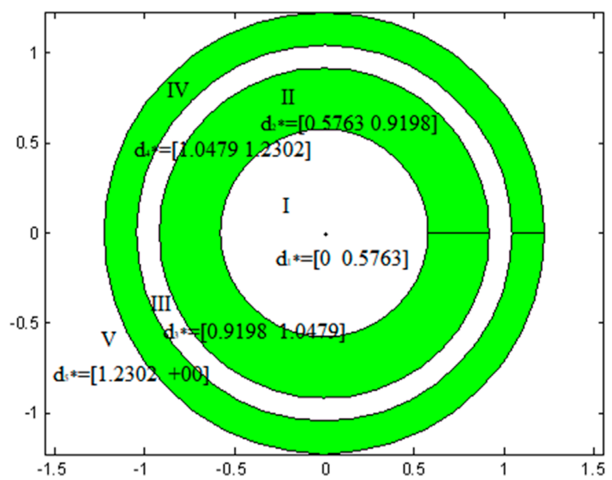

FIGURE 5
Grade target distances for surrounding rock quality.

4.4 Determination of the index weights

1) Determining the weight coefficients $\omega_1$based on the entropy method

From Table 2, the corresponding set of weight coefficients is obtained as

$$\omega_1 = [0.6122 \quad 0.0042 \quad 0.0379 \quad 0.0008 \quad 0.0447 \quad 0.2149 \quad 0.0445 \quad 0.0409]$$

2) Calculating the weight coefficients $\omega_2$based on the critic method

From Eqs 9–11 and the information in Table 1, the correlation coefficients are calculated as

$$r = \left[0.0797 \begin{matrix} 1 & 0.0768 & 0.282 & 0.7898 & 0.8075 & 0.4875 & 0.1675 & 0.2811 \\ 0.0768 & 1 & 0.2661 & 0.3117 & 0.0724 & 0.1288 & 0.7461 & 0.0121 \\ 0.282 & 0.2661 & 1 & 0.0351 & 0.0098 & 0.036 & 0.6242 & 0.0797 \\ 0.7898 & 0.3117 & 0.0351 & 1 & 0.7068 & 0.5018 & 0.1596 & 0.2879 \\ 0.8075 & 0.0724 & 0.0098 & 0.7068 & 1 & 0.6207 & 0.04 & 0.5645 \\ 0.4875 & 0.1288 & 0.036 & 0.5018 & 0.6207 & 1 & 0.2129 & 0.025 \\ 0.1675 & 0.7461 & 0.6242 & 0.1596 & 0.04 & 0.2129 & 1 & 0.1814 \\ 0.2811 & 0.0121 & 0.0797 & 0.2879 & 0.5645 & 0.025 & 0.1814 & 1 \end{matrix} \right]$$

Using Eq. 12, the standard deviations of the individual columns are obtained as

$$C = [4.1079 \quad 5.386 \quad 5.6672 \quad 4.2073 \quad 4.1783 \quad 4.9874 \quad 4.8683 \quad 5.5684]$$

Similarly, using Eq. 13 the set of weights of the evaluation indexes is obtained as

$$\omega_2 = (0.095 \quad 0.1504 \quad 0.1504 \quad 0.1136 \quad 0.0901 \quad 0.121 \quad 0.159 \quad 0.1204)$$

3) Determining the combined weights

From Eqs. 14–18, the combined set of weights ω is obtained as

$$\omega = [0.5131 \quad 0.0322 \quad 0.0595 \quad 0.0224 \quad 0.0534 \quad 0.1969 \quad 0.0664 \quad 0.0561]$$

The individual and combined weights are graphically depicted in Figure 4.

4.5 Determination of the target center distances

The positive and negative target centers are respectively obtained as $x^{0+} = [1 \quad 1 \quad 0.78 \quad 0.46 \quad 0.51 \quad 1 \quad 1 \quad 0.83]$ and $x^{0-} = [-0.59 \quad -0.9 \quad -0.99 \quad -1 \quad -1 \quad -0.78 \quad -0.88 \quad -1]$. According to Eq. 4, the interval between the positive and negative target centers is $d_0 = 1.678$. Then, from Eqs 5, 6, the positive target

TABLE 6 Monitoring data for the evaluation indexes.

Serial number	R_c	H	k_v	γ	RQD	k_1	k_2	k_R
13	72.74	889.12	0.887	25.56	81	7	0.4	0.55
14	62.41	900	0.818	25.57	100	10	0.45	0.63
15	60.67	914	0.953	25.45	85	10	0.45	0.63
16	62.41	932	0.818	25.45	78	7	0.4	0.6
17	90.14	942	0.738	25.5	88	7	0.4	0.61

TABLE 7 Synthesized target distances of the predicted grades.

Sample number	13	14	15	16	17
d_i^*	1.1447	0.7833	0.8241	1.3694	0.7019
grade	IV	II	II	V	II

center distances d^+ and negative target center distances d^- of the different samples are calculated, as shown in Table 3.

4.6 Determination of the quality grade of the surrounding rocks

The comprehensive target distance of each sample was arranged according to the quality grade, and the critical value of the target distance for each quality grade was obtained, as shown in Table 5. Using Eq. 8, the target distance for each quality grade can be derived, as plotted in Figure 5.

4.7 Quality grade prediction of the surrounding rocks

To test the rationality and accuracy of the gray target evaluation model established in this study, a mine shaft project was selected as the example; the monitoring data for 13-17# samples are shown in Table 6. Different parameters are obtained and substituted into the game gray target evaluation model, and the corresponding comprehensive target distances d_i^* are obtained. For the different d_i^* ranges shown in Figure 5, the quality grades of the surrounding rocks are evaluated, whose results are shown in Table 7. The results obtained from the suggested model were compared with those from two other methods, as shown in Figure 6.

The game gray target model was used to evaluate the quality levels of the surrounding rocks, and the assessment results are depicted in Table 7; it is seen from this table that the quality grades of the surrounding rocks for the 13–17# samples differ greatly. The quality levels for the 13# sample is IV, 16# sample is V, and the remaining samples are II; this means that the 13# sample is of inferior quality, 16# sample is of bad quality, and the rest are of good quality, for a combined quality rate of 60%. For the 13# and 16# samples, corresponding consolidation measures should be implemented; for example, shotcrete and anchor supports should be adopted to enhance the stabilities of the surrounding rocks, and no measures need to be adopted for the other samples.

The comparative results of the assessment models in Figure 6 indicate that the proposed method is consistent with the actual investigations for the five different samples and that its accuracy is 100%, which is greater than the accuracy of the RBF (Radial Basis Function) method (80%) (Zhou et al., 2012). Therefore, estimating the quality levels of surrounding rocks is feasible using the proposed game gray target model. The proposed approach also provides additional details for assessing the quality levels of the surrounding rocks. For example, the quality of the 15# sample is more likely to be level II as its synthetic target distance (0.8241) is greater than that for the 17# sample (0.7019) that could likely be closer to level III. Thus, the results of the proposed model can accurately demonstrate the quality grades of the surrounding rocks and further determine the risk grade rankings for different samples at the same levels.

5 Results and discussion

Considering the uniaxial saturated compressive strength of the rock block R_c, rock quality index RQD, rock softening coefficient k_R, integrity coefficient of the rock mass k_v, depth H, unit weight of the rock mass γ, coefficient of quantification of the angle between the principal structural plane and shaft axis k_2, and weight of the groundwater k_1 as the evaluation indexed, the game gray target model is introduced in this work to evaluate the quality grades of surrounding rocks in a tunnel. Then, the quality levels of the surrounding rocks was assessed for five samples in accordance with the suggested model, and their final quality grades were determined.

(1) The proposed method was used to assess the quality levels of surrounding rocks in a new mine shaft, and the results obtained were consistent with those of actual investigations for five different samples. The accuracy with the proposed method reached 100%, which is more significant than the results of the backpropagation neural network method (80%). Therefore, it is highly feasible to estimate the quality levels of surrounding rocks using the game gray target model.

(2) The quality grades of the surrounding rocks for the 13–17# samples differ greatly; the quality levels for the 13# sample

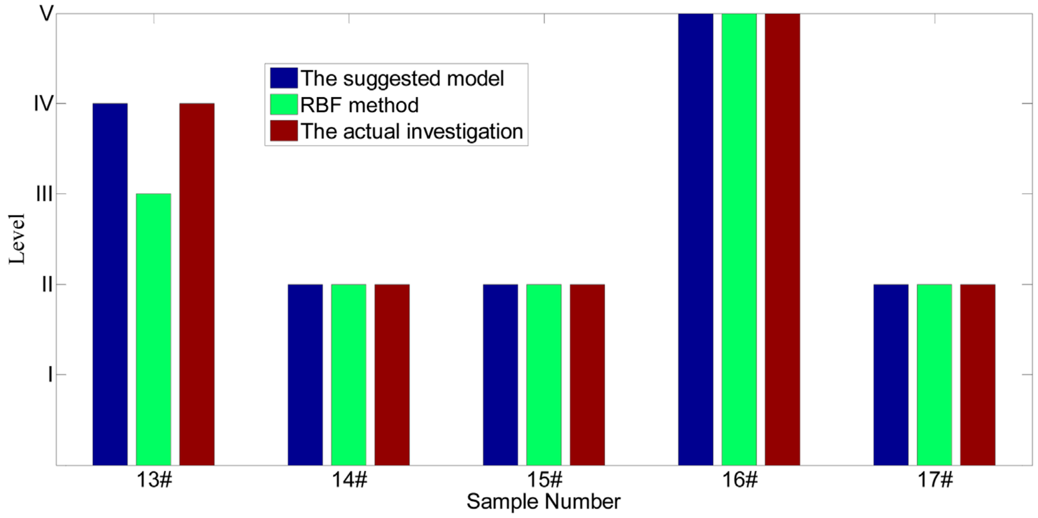

FIGURE 6
Comparison of results from three methods.

is IV, 16# sample is V, and the remaining samples are II, for a combined quality rate of 60%. For the 13# and 16# samples, corresponding consolidation measures are suggested to be implemented; for example, shotcrete and anchor supports should be adopted to enhance the stability of the surrounding rocks.

(3) The game gray target grade evaluation model can be used to mine small data sample to the maximum extent possible, thereby minimizing the information shortage caused by the small sample to a certain extent. The final quality grades of surrounding rocks can also be evaluated quantitatively using this model.
(4) The proposed method can accurately assess the water quality grade with higher reliability and efficiency. However, the calculation process is complex, so the randomness of the evaluation indexes are not considered. Hence, the proposed method can be further improved in the future. In the future work, a three-dimensional gray target model will be developed and applied to assess the water quality levels.

The results from the proposed model have been shown to accurately predict the quality levels of surrounding rocks and further help determine the quality level rankings for different samples at the same level. Thus, the suggested method is expected to provide a new avenue for quality level assessments of surrounding rocks in the future.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, and any further inquiries may be directed to the corresponding author.

Author contributions

L-PG: Conceptualization, Formal analysis, Resources, Supervision, Writing–review and editing. X-BG: Funding acquisition, Investigation, Methodology, Writing–original draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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