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Level evaluation of concrete dam fractures based on game theory combination weighting-normal cloud model

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Hazard evaluation of concrete dam fractures is vital for safe operations. The width (S_1), length (S_2), and depth (S_3) of fractures are adopted as the assessment index, and the game theory combination weighting-normal cloud model is introduced. The normal cloud model of certain dam fractures is subsequently established. The weight coefficients of each index are calculated using game theory combination weighting, and the certainty degree of each index is determined using the cloud model. Finally, the hazard levels of the concrete dam fractures are judged. The proposed model solves the fuzziness and randomness of different indexes; the conclusions demonstrate that the model is feasible for the hazard assessment of concrete dam fractures, and its accuracy is very high; therefore, a new approach can be provided for future hazard-level assessments of concrete dam fractures.

KEYWORDS

level evaluation, concrete dam fracture, game theory, combination weighting method, normal cloud model

1 Introduction

Cracks are common in the operation of concrete dams, and their appearance has become a hidden danger to the safety of dam operations (Gu and Wu, 2019; Gu et al., 2021a). For timely action, the damage assessment of cracks investigates their influence on dam safety operations and engineering benefits. For example, the gravity arch dam in Longyangxia, China, has 35 cracks. Nine of the cracks are within the range of 10–30 m in length and 0.3–1.6 mm in surface width. These pose a safety hazard to the dam, so accurately assessing concrete dam fractures has great practical significance. As some uncertainties exist between the quantitative monitoring values and qualitative indicators, fracture evaluation is fuzzy and random (Gu et al., 2021b; Gu et al., 2021c). Therefore, accurately assessing concrete dam fractures has become a hot topic.

Many researchers have adopted methods to accurately assess the hazard grade of concrete dam fractures (Zhou et al., 2016; GuWu and Ma, 2022). For example, Zhang et al. considered the influence of cracks on the structure and durability of dams (ZHANG et al., 2022). The comprehensive evaluation of the entire serviceability of concrete dams was performed using evidence theory in conjunction with the displacement and stress conditions. Lu et al. (Lu et al., 2012) used variable fuzzy sets and extenics to verify damage from structural cracks in concrete dams. Zhang et al. (Zhang and Yang, 2018) developed a cloud matter-element model for the fuzzy attribution of rank evaluation. The damage level of cracks is determined based on the maximum membership degree criterion. Feng et al. (Xue-hui, 2015) established the cloud-entropy weight model due to many factors, such as dam deformation and seepage. Zhou et al. (Zhou et al., 2008) analyzed the nature of the cloud model and discussed the comprehensive evaluation method for dam operational behaviors in conjunction with methods to determine the subjective, objective, and comprehensive weights of the evaluation indexes. Zhao et al. (Zhao and Liu, 2005) applied evidence theory to dam safety monitoring and proved the method's effectiveness. A dam surface crack detection algorithm based on adaptive region growth and local K-means clustering is proposed by Zou et al. (Zou et al., 2023); at present, CNN convolutional neural network method (Zhang et al., 2023) has also been applied in the field of concrete structure crack detection.

Although these methods promote the development of concrete dam fractures, they still require improvements (Gu et al., 2019; Gu et al., 2022a) due to complex calculation processes, low efficiency, etc. The game theory combination weighting method overcomes these insufficiencies by assessing the hazard grade of concrete dam fractures. The technique applies a game theory combination to determine the weights of each evaluation index. The normal cloud method then calculates the certainty and uncertainty degrees of each index. Finally, a fundamental synthetic matrix of a certain degree is constructed to determine the hazard level of concrete dam fractures.

The paper is organized as follows. Section 2 introduces the theory and methodology based on game theory combination weighting. Section 3 provides an engineering example of concrete dam fractures and analyzes the results. Section 4 draws conclusions.

2 Methodology

2.1 Combination weighting method

The standard weight calculation methods are divided into subjective, objective, and combination weights. Combination weighting is most common where two or three kinds of subjective and objective weights are combined to get the comprehensive weight. This process reduces errors caused by a single method (Klauer et al., 2012; Gu et al., 2022b). This study applies the entropy weight method and criteria importance through the inter-criteria correlation (CRITIC) method to calculate the index weights. The combination weights are obtained using game theory.

2.1.1 Entropy method

The entropy weight method is an objective approach to determining the weight coefficients based on the different degrees of information utility values for each evaluation index (Zhou et al., 2015; Chen and Zhou, 2019). This approach reflects the discreteness degree among index data. Its calculative process is given as follows:

① Construct the original matrix of the assessment index X

Assuming there are m evaluation indexes and n evaluation objects. Then, x_{ij} is the corresponding value of the ith assessment index at the jth assessment object. Its origin assessment matrix can be expressed as:

$$X = \left(x_{ij}\right)_{m\times n}(i = 1, 2, ..., m; j = 1, 2, ..., n) \tag{1}$$

② Normalization and forward processing

Various types of indicators and dimensional differences make it necessary to rule out the associated impacts, and dimensionless processing of each index is required. These are expressed as:

$$Y = \left(y_{ij}\right)(i =)1, 2, ..., m, j = 1, 2, ..., n) \tag{2}$$

The positive indicators are:

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

The negative indicators are:

$$y_n = \frac{\max\left(x_{ij}\right) - x_{ij}}{\max\left(x_{ij}\right) - \min\left(x_{ij}\right)} \tag{4}$$

where y_{ij} is the standard value of the ith assessment index at the jth assessment object.

③ Calculating information entropy of the ith assessment index (Gu and Wu, 2016)

$$h_i = \frac{1}{\ln n}\sum_{j=1}^{n} e_{ij} \ln e_{ij} \tag{5}$$

$$e_{ij} = \frac{y_{ij}}{\sum_{j=1}^{n} y_{ij}} \tag{6}$$

④ Calculation of weights ω_{1i}

$$\omega_{1i} = \frac{1 - h_i}{m - \sum_{i=1}^{m} h_i} \tag{7}$$

where $0 < \omega_{i1i} \leq 1, \sum_{i=1}^{m} \omega_{1i} = 1, i = 1, 2, ..., m.$

2.1.2 The CRITIC method

CRITIC is an objective weighting method proposed by Diakoulaki (ZHOU et al., 2017) that synthetically measures the index weight by calculating variability and conflicts of the index. Its calculative procedure is given as follows:

① There are m estimated objects and n assessment indexes assumed. These construct the matrix $A = \left(a_{ij}\right)_{m\times n}$, where $i = 1, 2, ..., m; j = 1, 2, ..., n.$

② The matrix A is standardized based on the Z-score method and is expressed as:

$$a^*_{ij} = \frac{a_{ij} - \overline{a_j}}{s_j}(i = 1, 2, ..., m; j = 1, 2, ..., b) \tag{8}$$

where $\overline{a_j} = \frac{1}{a}\sum_{i=1}^{m} a_{ij}$, $s_j = \sqrt{\frac{\sum_{i=1}^{m}\left(a_{ij} - \overline{a_j}\right)}{a-1}}$, and $\overline{a_j}$ and s_j are the mean value and standard deviation of the jth assessment index, respectively.

FIGURE 1
Location of the survey area.

FIGURE 2
Layout of the concrete dam.

③ Calculate the coefficient of variation for different indexes as:

$$BY_j = \frac{s_j}{\overline{a_j}} (j = 1, 2, \ldots n) \tag{9}$$

where BY_j is the variation coefficient of the *jth* index.

④ The coefficients of the correlation are calculated based on the standardization matrix A^*. Their expressions are given as $X = (r_{kl})_{n \times n} (k = 1, 2, \ldots, n, l = 1, 2, \ldots, b)$, where r_{kl} are the coefficients of correlation between the *kth* and *lth* indexes, and:

$$r_{kl} = \frac{\sum_{i=1}^{m} (a_{ik} - \overline{a_k})(a_{il} - \overline{a_l})}{\sqrt{\sum_{i=1}^{m} (a_{ik} - \overline{a_k})^2} \sqrt{\sum_{l=1}^{m} (a_l - \overline{a_l})^2}} (r_{kl} = r_{lk}; k = 1, 2, \cdots, m, l = 1, 2, \cdots, m) \tag{10}$$

where a_{ik} and a_{il} are the standard value of measured values at the *kth* and *lth* indexes for the *ith* assessment object in the standardization matrix A^*, respectively. The $\overline{a_k}$ and $\overline{a_l}$ are the mean of the standard value of the measured values at the *kth* and *lth* indexes in the standardization matrix A^*, respectively.

⑤ Calculate the quantitative coefficient about the degree of independence for different assessment indexes. Its expression is (Zhao et al., 2021):

$$\eta_j = \sum_{k=1}^{n} \left(1 - \left|r_{kj}\right|\right) (j = 1, 2, \ldots, n) \tag{11}$$

⑥ Quantitative coefficients of the comprehensive information and the degree of independence of each index are solved as:

$$C_j = BY_j \sum_{k=1}^{n} \left(1 - r_{kj}\right) (j = 1, 2, \ldots, n) \tag{12}$$

⑦ Determination of the weight of each evaluation index can be expressed as:

$$\omega_j = \frac{C_j}{\sum_{j=1}^{n} C_j} (j = 1, 2, \ldots, n) \tag{13}$$

TABLE 1 Information on the fractures.

Number	Dam block	State		
		S_1/mm	S_2/m	S_3/m
1	1#	0.175	8.7	1.2
2	2#	0.25	8	2.1
3	3#	0.15	4.4	0.5
4	4#	0.1	6	2.4
5	5#	0.15	11.5	0.6
6	6#	0.1	2	2.55
7	7#	0.2	3.2	1.52
8	8#	0.16	6.5	0.9
9	9#	0.25	7.1	1.2
10	10#	0.11	5.6	1.5

TABLE 2 Classification for fracture hazards.

Risk rank	I	II	III	IV
S_1/mm	[0 0.2]	[0.2 0.3]	[0.3 0.5]	[0.5 3]
S_2/m	[0 3]	[3 5]	[5 10]	[10 15]
S_3/m	[0 0.3]	[0.3 1]	Gu et al. (2022a)	[5 10]

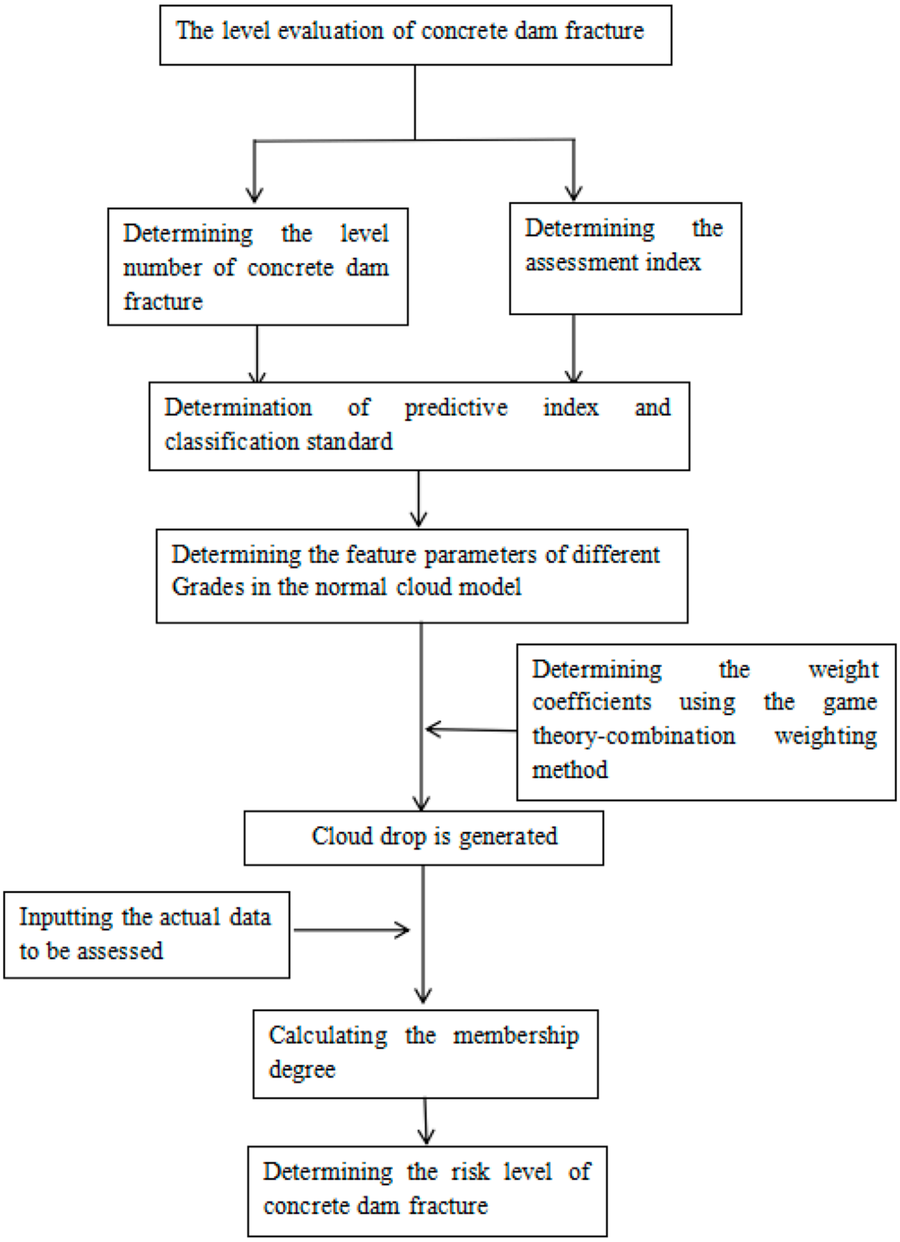

FIGURE 3
Flowchart of the assessment frame.

2.1.3 Combination weighting method of game theory

Based on game theory, the combination weight ω is obtained by combining the entropy weight and CRITIC methods. Its procedure is correlated as follows (B Zhang et al., 2018):

① The weight sets ω_1 and ω_2 are obtained by the entropy weight and CRITIC methods. It is assumed that a_1 and a_2 are the linear combination coefficients. Then, the weight sets ω_1 and ω_2 can be linearized as:

$$\omega = a_1\omega_1^T + a_2\omega_2^T \tag{14}$$

② According to game theory, the linear combination coefficients a_1 and a_2 in Formula (10) are optimized and expressed as:

$$\min \left\| a_k\omega_k^T - \omega_k \right\|^2 (k = 1, 2) \tag{15}$$

③ According to the differential properties of the matrix, the linear differential equation group for optimizing the first derivative condition of formula (15) is:

$$\begin{bmatrix} \omega_1\omega_1^T & \omega_1\omega_2^T \\ \omega_2\omega_1^T & \omega_2\omega_2^T \end{bmatrix} = \begin{bmatrix} \omega_1\omega_1^T \\ \omega_2\omega_2^T \end{bmatrix} \tag{16}$$

④ The optimal combination coefficients a_1 and a_2 are obtained via Formula (16). The normalization process

TABLE 3 Digital features of the cloud model.

Level	I			II			III			IV		
The digital feature	Ex	En	H_e	Ex	En	H_e	Ex	En	H_e	Ex	En	H_e
S_1	0.1	0.0333	0.01	0.25	0.0167	0.01	0.4	0.0333	0.01	1.75	0.4167	0.01
S_2	1.5	0.5	0.01	4	0.3333	0.01	7.5	0.8333	0.01	12.5	0.8333	0.01
S_3	0.15	0.05	0.01	0.65	0.1167	0.01	3	0.6667	0.01	7.5	0.8333	0.01

is obtained as $a_1^* = \frac{a_1}{(a_1+a_2)}$ and $a_2^* = \frac{a_2}{(a_1+a_2)}$. Then, based on game theory, the comprehensive weight ω can be obtained as:

$$\omega = a_1^* \omega_1^T + a_2^* \omega_2^T \tag{17}$$

2.2 Normal cloud model

The cloud model is defined as x, E, D, which is assumed to be a common quantitative set. The E is the domain, where $x \in E$, and D is the qualitative conception in the domain E. For the random research object x, a random number exists with a stable tendency $u(x) \in [0,1]$. Then, $u(x)$ is called the membership degree of x corresponding to D or the definitive degree. The distribution of the definitive degree in the domain E is called the membership cloud. If x meets $x \sim N(Ex, En'^2)$, and $En' \sim N(En, He^2)$, and $u(x)$ can be expressed as:

$$u(x) = \exp\left[-\frac{(x-Ex)^2}{2En'^2}\right] \tag{18}$$

where the distribution definitive degree $u(x)$ in the domain E is called the normal cloud or Gauss cloud. The expectation Ex, entropy En, and hyperentropy H_e are applied to represent digital features in the cloud model.

The Ex represents the point of a particular conception in the domain, En reflects the accepting range of the conception, and H_e demonstrates the uncertainty of the entropy with a magnitude reflecting the thickness of the cloud drop. These values are expressed as:

$$Ex = \frac{c^+ + c^-}{2} \tag{19}$$

$$En = \frac{c^+ - c^-}{6} \tag{20}$$

$$H_e = k_1 \tag{21}$$

where c^+ and c^- are the upper and lower bounds corresponding to the grade standard of the specific index, respectively. The hyperentropy H_e can select a proper constant k, set as 0.01 in the investigation.

3 Engineering example

3.1 Engineering background

The dam is located in Tianer County, Guangxi Province, China (Figure 1), and is a roller-compacted concrete gravity dam. All parts of the dam body with roller-compacted concrete conditions are roller-compacted concrete, while the others are standard concrete (Figure 2). The height of the dam body is 178 m, the maximum bottom width is 80 m, and the elevation of the dam top is 2160 m. As the dam began to operate, as many as 35 cracks appeared in the downstream surface. Most cracks are horizontal and distributed primarily at 2510–2570 m and few cracks or no obvious features are at other positions. The influence of these cracks on the dam's strength, stability, and safe operations is of great concern. So, 10 typical fractures were selected for evaluation. Their monitoring data are shown in Table 1.

4 Established assessment model

4.1 Constructed index system

Many factors affect the occurrence of concrete dam fractures; three evaluation indexes (width (S_1), length (S_2), and depth (S_3) of fracture) are selected as the assessments to simplify the calculations. According to the relevant references (Zhou et al., 2012), the three evaluation indexes are classified into four levels in Table 2. These are level I (slight), level II (common), level III (serious), and level IV (very serious).

4.2 Constructed evaluation frame

A flowchart of the assessment frame is plotted in Figure 3. Its calculative process is listed as follows:

1) Determining the evaluation index and corresponding classification.
2) Determining the weighting coefficients using the game method according to Eqs 1–17.
3) The characteristic parameters Ex, En, and H_e in the cloud model are calculated based on Eqs 19–21.

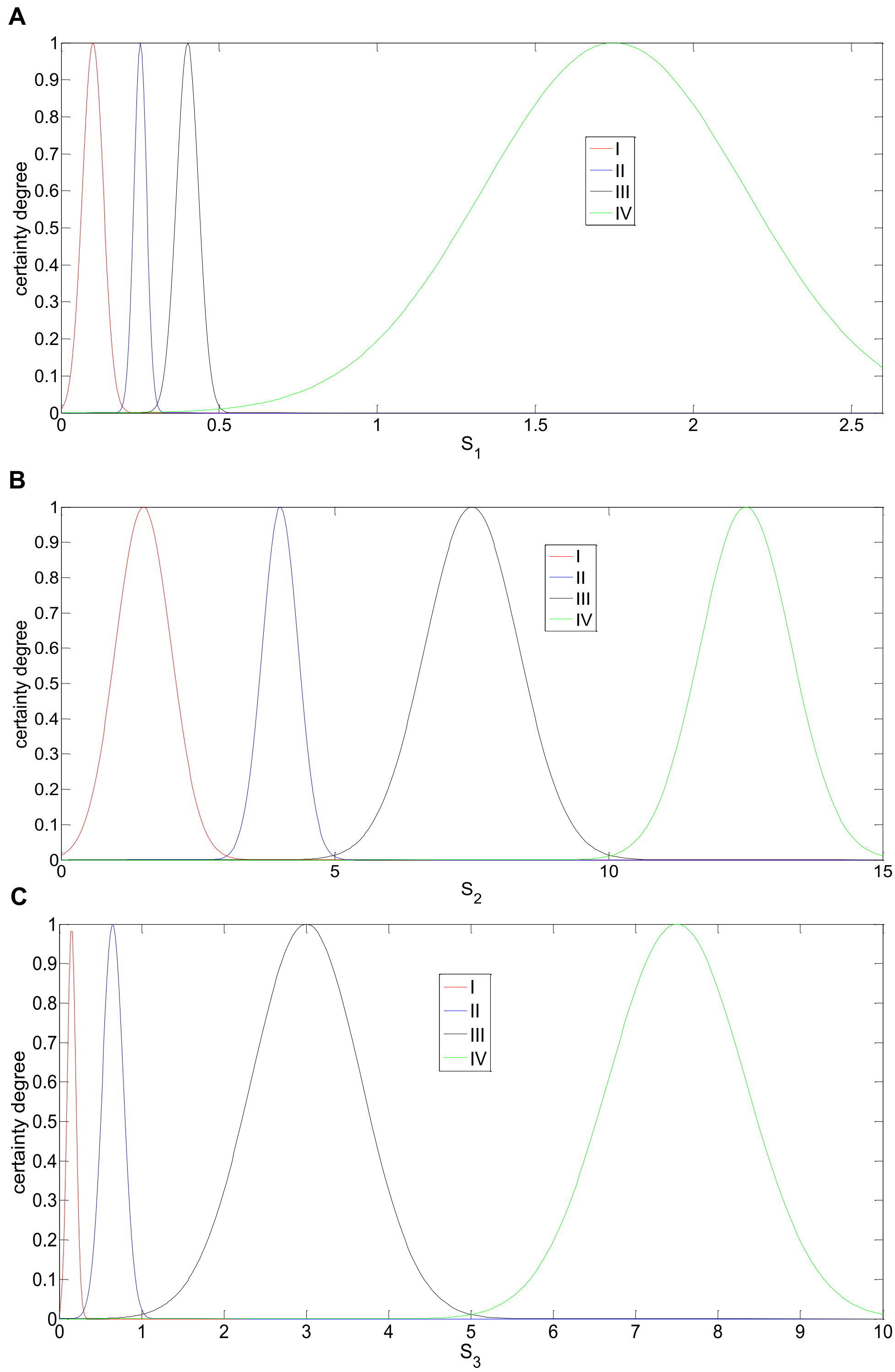

FIGURE 4
Cloud of each assessment index: **(A)** The width of fracture S1 **(B)** The length of fracture S2 **(C)** The depth of fracture S3.

4) Determining the membership degree of each assessment index when the characteristic parameters are instituted into Eq. 18.
5) The synthetic membership degree M of each level for different samples can be calculated according to Eq. 19.

$$M = \sum_{i=1}^{n} u_i \omega_i \tag{22}$$

6) The level corresponding to the maximum synthetic membership degree is determined as the final risk grade.

TABLE 4 Predicted results of the concrete dam fracture.

Sample No	The level of concrete dam fracture				Comprehensive assessment
	I	II	III	IV	
1	0.0209	0	0.1385	0	III
2	0	0.326	0.4375	0	III
3	0.0867	0.3385	0	0	II
4	0.2633	0	0.3385	0	III
5	0.0853	0.3747	0	0.1587	II
6	0.461	0	0.327	0	I
7	0.0029	0.0213	0.035	0	III
8	0.0519	0.0414	0.1587	0	III
9	0	0.2633	0.3013	0	III
10	0.2517	0	0.0569	0	I

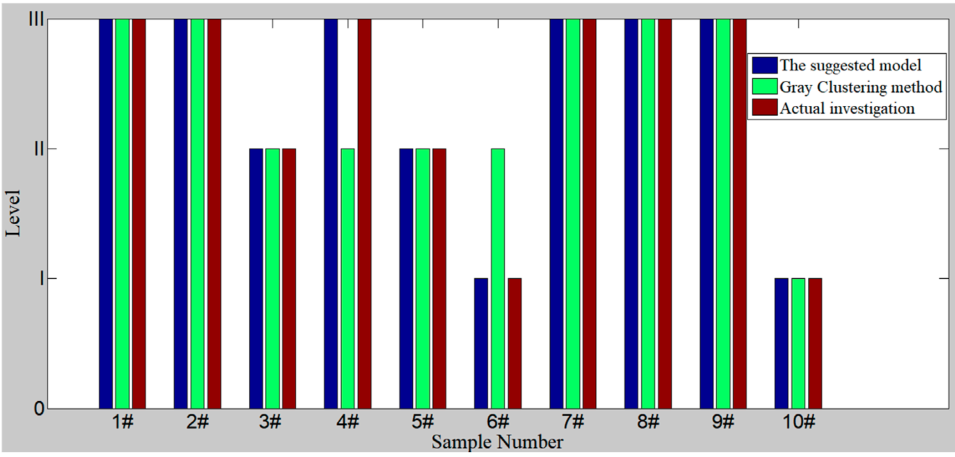

FIGURE 5
The comparison results of the three methods.

4.3 Determining index weight coefficients

1) Calculations of the weight coefficient ω_1 based on the entropy method.

According to Eqs 1–7 and in conjunction with Table 1, the corresponding weight coefficient can be calculated as:

$$\omega_1 = [0.1993 \quad 0.3561 \quad 0.4446]$$

2) Calculation of weight coefficient ω_2 based on the CRITIC method

Based on Eqs 8–10 and in conjunction with Table 1, the coefficients of correlation can be obtained as:

$$r = \begin{bmatrix} 1 & 0.3008 & 0.2026 \\ 0.3008 & 1 & 0.4328 \\ 0.2026 & 0.4328 & 1 \end{bmatrix}$$

According to Eq. 11, the standard deviation of different columns is obtained as:

$$\eta = (0.37 \quad 0.2907 \quad 0.3485)$$

Similarly, Eqs 12, 13 calculate the weights of each evaluation index as:

$$\omega_2 = (0.3962 \quad 0.2636 \quad 0.3403)$$

4) Calculation of combination weights.

Based on Eqs 14–17 and in conjunction with the weight sets ω_1 and ω_2, the combination weight ω is obtained as:

$$\omega = (0.2633 \quad 0.326 \quad 0.4107)$$

4.4 Determination of digital features in the normal cloud model

The classification standard of the normal cloud about seismic slopes is depicted in Table 3 based on Table 2 and in conjunction with Eqs 19–22. The characters of the cloud model corresponding to different indexes are calculated using the forward cloud generator, as plotted in Figure 4. The horizontal coordinates provide the magnitude of different variables. The vertical coordinates present the magnitude of the certainty degree. The sub-figure in Figure 4 includes four grades: I, II, III, and IV. The certainty degree of a given point at the state grade can be obtained when a certain variable is fixed.

The game theory combination weighting-normal cloud model is applied to evaluate the concrete dam fractures. The assessment results are depicted in Table 4. The hazard grade of the concrete dam fracture from Nos. 1–10 samples differ. The hazard level of concrete dam fractures at Nos. 1, 2, 4, 7, 8, and 9 samples is III and at Nos. 3s and 5 samples is I, and the remaining is I. Thus, the hazard level of the concrete dam fracture in most samples is significant, accounting for 60%. The remaining samples are light or common, accounting for 40%. So, necessary consolidation measurements should be taken for the Nos. 1, 2, 4, 7, 8, and 9 samples to prevent the concrete dam hazards. For example, grouting cracks could be performed. The other samples are considered safe.

The comparative results of the assessment model in Figure 5 indicate that the proposed method is consistent with the investigations for 10 different samples. Its accuracy reaches 100%, greater than the results from the Gray clustering method (80%) (LIANG et al., 2020). Therefore, estimating concrete dam fractures using the game theory combination weighting-normal cloud model is feasible. The proposed approach provides additional details for assessing concrete dam fractures. For example, the fracture length for the No. 5 sample is 11.5, belonging to level IV based on data in Table 2. In addition, the reliability distributions of the other indicators obtained using the proposed model belong to level III, indicating that the hazard level probability of the No. 5 sample at level III is greater than levels I, II, and IV. As a result, the hazard grade of the No. 5 sample is level III. Its hazard level is more likely to be level III than that of the No. 2 sample as the certain degree (0.3747) for level III is greater than the No. 2 sample (0.326). The results obtained using the proposed model accurately demonstrate the hazard level of concrete dam fractures and further determine the risk grade rankings for different samples at the same level.

5 Results and discussions

In comparison with the other traditional models, the fuzziness and randomness of evaluating the index are considered for the suggested model, and interval-oriented evaluation criteria are adopted. So, the suggested model improves the reliability of the assessment process and enhances the predictive accuracy of assessment results. So, in the future, it will have great application prospects in civil engineering.

However, some shortcomings still exist, for example, great calculative load and the neglected correlation among the indexes; these insufficiencies limit the development of the suggested method, but they still provide a new perspective for the hazard-level assessments of concrete dam fractures.

6 Conclusion

Considering the width (S_1), length (S_2), and depth (S_3) of fractures establishes a new evaluation method to assess the hazard level of concrete dam fractures based on the game theory combination weighting-normal cloud model. The weight coefficients for three different assessment indexes are first determined based on game theory combination weighting. Then, the certainty degrees for different indexes are calculated using the entropy normal cloud method. Finally, the comprehensive degree of concrete dam fractures is determined, and the hazard level is judged.

The proposed method assessed the hazard level of concrete dam fractures. The results obtained by the proposed method are consistent with actual investigations for 10 different samples. The method's accuracy reached 100%, which is greater than the results from the Gray clustering method (80%). The results give various hazard grades for the concrete dam fractures from Nos. 1–10 samples. The hazard level of concrete dam fracture at Nos. 1, 2, 4, 7, 8, and 9 samples is III, Nos. 3 and 5 samples is I, and the remaining is I. Thus, the hazard level of concrete dam fractures at most samples is significant, accounting for 60%. The remaining samples are considered light or common, accounting for 40%. So, the necessary consolidation measurements should be taken for Nos. 1, 2, 4, 7, 8, and 9 samples to reduce concrete dam risks. In addition, the reliability distributions of the other indicators obtained using the proposed model belong to level III, indicating that the hazard level probability of the No. 5 sample at level III is greater than levels I, II, and IV. The hazard grade of the No. 5 sample is level III, and its hazard level is more likely to be level III than that of the No. 2 sample as the certain degree (0.3747) for level III is greater than the No. 2 sample (0.326).

In total, the results from the proposed model accurately predict the hazard levels of concrete dam fractures and further determine the hazard grade ranking for different samples at the same level. The suggested method provides a new thought for the future of the hazard level of concrete dam fractures.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

W-WL: Data curation, Investigation, Writing–original draft. X-BG: Funding acquisition, Methodology, Writing–original draft. CY: Conceptualization, Supervision, Writing–review and editing. CZ: Formal Analysis, Validation, Writing–review and editing.

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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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