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Hydropower unit health assessment based on a combination weighting and improved fuzzy comprehensive evaluation method

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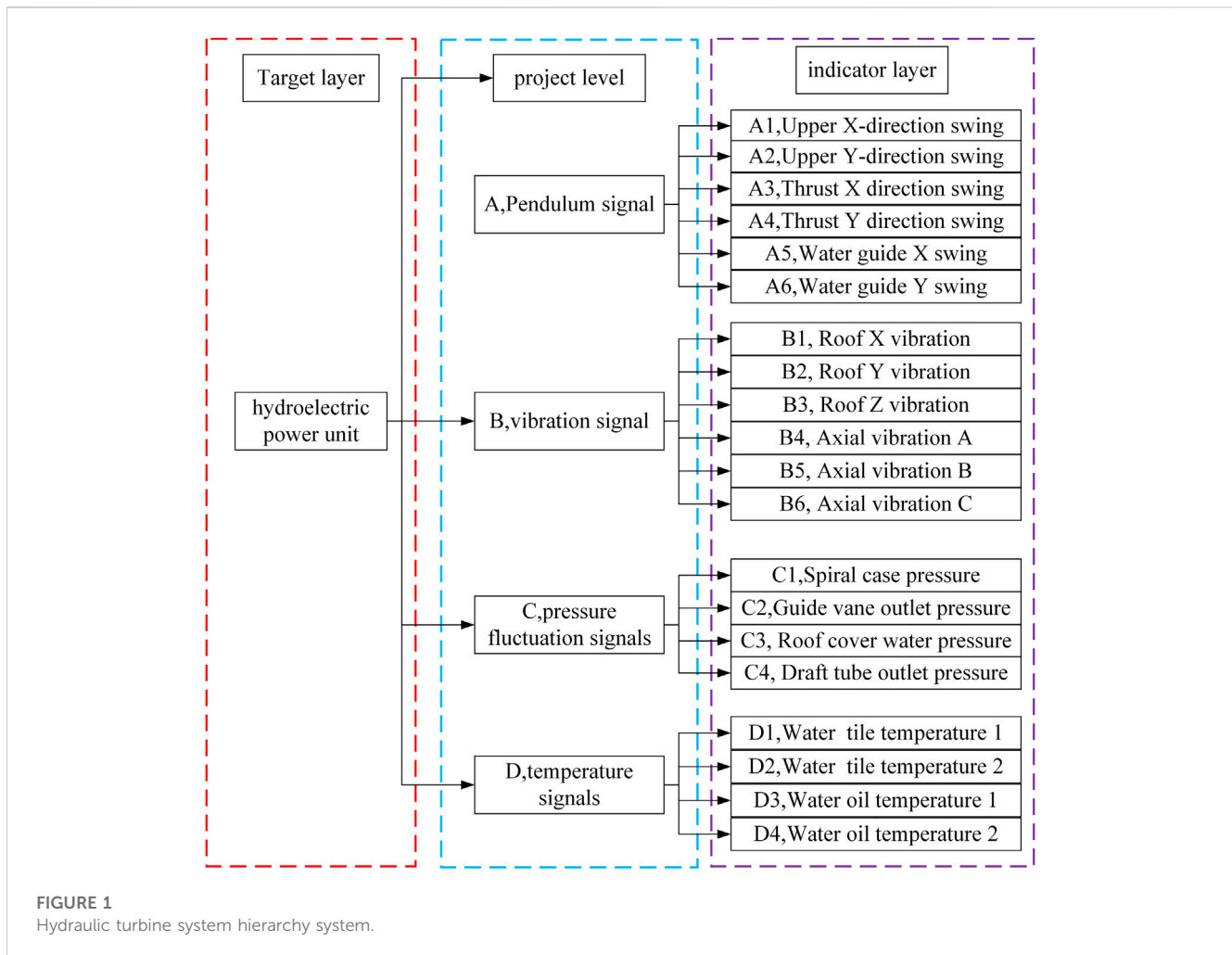
The health state of hydroelectric power generation units is of great significance to ensure the stability and economy of safe operation of the power grid. In order to address the challenges in existing assessment methods of the insufficient reliability of the evaluation of multi-complex systems and the inability to reflect anomalies of a single index. A state evaluation model based on combination weighting and improved fuzzy comprehensive evaluation method is accordingly proposed. First, a hierarchical analysis system is constructed based on actual monitoring indicator data from the hydropower unit. Optimal comprehensive and indicator weights are subsequently obtained for each indicator level using a combination of the improved hierarchical analysis and CRITIC method through game theory. Next, the industry guidelines and regulations are difficult to effectively determine the limit values of each index of the unit, and they do not fully take into account the actual situation of the unit itself and the huge amount of accumulated historical health data. To address this issue. The Gaussian threshold method was proposed to determine the limit values of the monitoring data for each indicator, which more accurately determines the indicator thresholds as well as their standard values. The degradation degree of the hydroelectric unit can be calculated by comparing the real-time monitoring data with these limits. Finally, the combined weights of dynamic change and the fuzzy evaluation matrix are used to obtain the state evaluation matrix reflecting the condition of the turbine. The proposed approach is validated using the actual monitoring data and operating conditions for case study hydroelectric station, The results show that the improved evaluation method has an optimal evaluation effect.

KEYWORDS

health assessment, hydropower unit, game theory, fuzzy hierarchical analysis, combination weighting, CRITIC method, theory of variation

1 Introduction

Hydroelectric power generation is the most common renewable energy source and a critical means to reduce CO₂ emission (Awan et al., 2023). With the adjustment of China's energy structure, hydropower generation has become an indispensable method for generating power, due to its excellent stability. Therefore, it is critical to fully utilize the



power generation functionality of hydraulic turbine sets to ensure the safe and stable operation of the power grid. This requires highly reliable hydroelectric generator sets, which can be ensured by evaluating the health state of hydropower units through monitoring and analyzing their parameters to assess whether there is any anomaly or potential risk of unit failure. This allows unit faults to be discovered in a timely manner and appropriate repair and maintenance procedures to be implemented, improving dependability and stability while extending service life. Thus, the steady operation of the power system and the quality of the power supply can be ensured (Zeng et al., 2023).

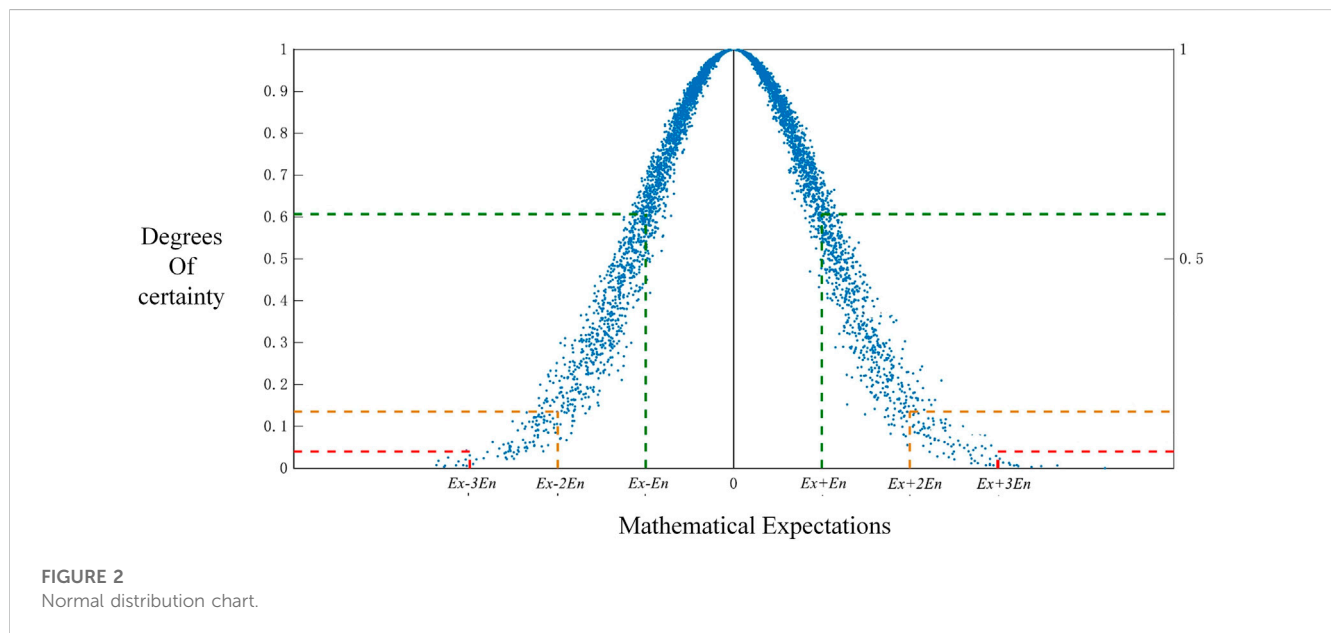
The main elements of the comprehensive condition assessment of hydropower units combine the structural system of the equipment with the distribution of measurement points, Extracting and constructing correlation indicators that reflect the operational health state, and integrating the performance indicators to make a holistic and global evaluation of the system health state. In recent years, as the concept of condition maintenance continues to advance, The power industry has successively established comprehensive condition detection systems, A wealth of measurement point information provides data support for the overall evaluation of the health state of the equipment, Condition assessment theory and techniques have also developed considerably, Commonly used condition evaluation methods include hierarchical

analysis (Ge et al., 2020), cluster analysis (Hu et al., 2019), fuzzy comprehensive evaluation (Fang et al., 2016), grey system theory (Huang et al., 2022), etc.

In terms of calculating the weights, hierarchical analysis, as a classic system analysis method, is widely used in risk assessment, resource allocation, equipment evaluation and other fields due to its clear structure, hierarchical nature and adaptability to complex systems (Zhang H. et al., 2020; Liu et al., 2022; Cai et al., 2023; Zhu et al., 2023). Yucesan and Kahraman (2019) use hierarchical analysis for risk assessment of hydropower plants to help ensure grid security and prevent economic losses. Zeng et al. (2023) used hierarchical analysis and fuzzy integrated evaluation method to assess water resources pollution and proposed risk level evaluation, A hierarchical analysis is a traditional analysis method comprising a simple hierarchical structure (Ma et al., 2020). However, this method has several drawbacks: 1) It is extremely difficult to test the consistency of judgement matrices 2) the assignment of indicators relies too much on the experience of experts and is not objective enough. The fuzzy hierarchical analysis method (Doz et al., 2023) used in this paper not only retains the advantages of hierarchical analysis, but also adds a fuzzy consistency matrix, which ensures the consistency of the judgement matrix and solves the problem of the difficulty of checking whether the judgement matrix is

TABLE 1 Meaning of affiliation values used to compare indicators on a scale of 0.1–0.9.

Scale	Description
0.5 Equally important	Equally important
0.6 Slightly important	One element is slightly more important than the other
0.7 Significantly important	One element is significantly more important than the other
0.8 Much more important	One element is much more important than the other
0.9 Extremely important	One element is more extremely important than the other
0.1, 0.2, 0.3, 0.4	Compare element a_i with element a_j to obtain the judgment r_{ij} , then obtain the judgment as $r_{ji} = 1 - r_{ij}$



consistent. Also, due to its lack of objectivity, this paper applies the CRITIC method (Krishnan et al., 2021; Wen et al., 2022) to calculate its objective weights through historical health samples. However, subjective weights or objective weights cannot fully represent the weights of the indicator, in order to allocate the rationality of the weights, the method of game theory (Li H. et al., 2022; Li et al., 2023) is introduced to calculate the optimal weights, so as to make its weight allocation more reasonable.

Although fuzzy theory has made many advances in equipment condition evaluation, there are still some limitations in its research and application in the field of hydropower units: 1) It is difficult to determine the indicator limit value, and when using the affiliation function, it is necessary to calculate the indicator degradation degree according to the indicator limit value. 2) It fails to consider the influence of the unit's own operating conditions well. Hydropower units in different operating conditions, some state parameters such as pendulum, temperature, etc., there will be a big difference, the general use of uniform regulations to calculate the state of deterioration degree lack of reasonableness: 3) indicators of deterioration degree of different intervals and affiliation function of the mapping of the different evaluation state of the relationship between the lack of effective explanation. Geng and Liang (2022) proposed the degradation degree of hydropower units and applied

the principle of maximum affiliation to determine the condition of the units, providing scientific guidance for the evaluation of the health of hydropower generators. Li C. et al. (2022) constructed a hierarchical index system for transmission lines and combined it with the triangular-semi-trapezoidal affiliation function in fuzzy theory, Second, the mapping relationship between the different degradation degree intervals and evaluation states of the affiliation function lacks effective and reasonable explanation. Therefore, to evaluate the unit health state more accurately, the Gaussian threshold method (Zhang et al., 2022; Paialung et al., 2023) can be used to determine the indicator limit value. This study accordingly proposed an improved adaptive fuzzy comprehensive evaluation model for hydropower units that combines the Gaussian threshold method with the fuzzy comprehensive evaluation method to achieve a more effective and reliable evaluation of unit status.

To address to the shortcomings of current hydropower unit evaluation research, an adaptive fuzzy evaluation model that integrates the game theory-based combination of assignment with an improved fuzzy comprehensive evaluation is proposed in this paper. Based on the structure of the research object and the distribution of measurement points, the fuzzy hierarchical analysis method is used to construct the unit hierarchy system (Tian et al., 2020; Xia et al., 2020) and calculate the subjective

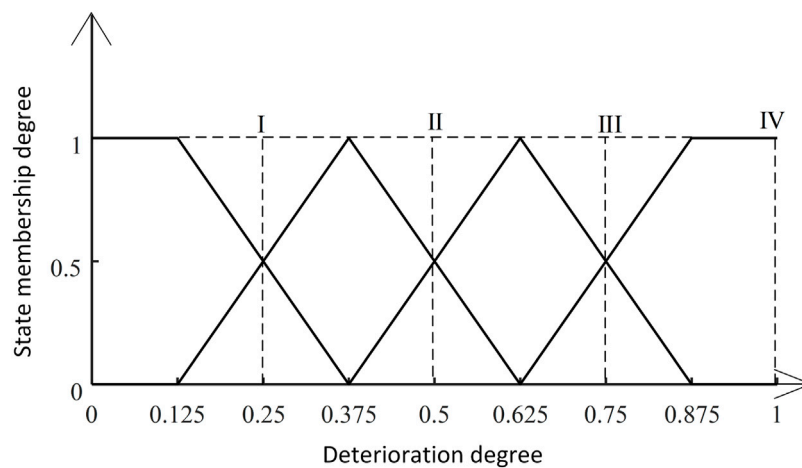


FIGURE 3
Improved triangle-semi-trapezoid affiliation function graph.

TABLE 2 Hydroelectric unit condition evaluation table.

Evaluated state	Status description
Good	The monitoring values of each parameter are far from the thresholds or within the standard values, the maintenance cycle can be extended appropriately
Qualified	Monitoring data for each parameter is within the permissible range and not as far from the threshold as in good condition
Attention	Monitoring data deviate from the normal operating value, the trend is close to the standard limit, but does not exceed the standard limit
Abnormal	Monitoring data seriously exceeds the standard limit, should immediately arrange for shutdown maintenance

weights for indicator parameters. The objective weights of each indicator are calculated by the CRITIC method based on historical monitoring data, and the corresponding optimal objective and subjective weights are subsequently calculated using game theory. Then, the state affiliation of each indicator is determined according to the improved comprehensive evaluation model to determine the unit state. In the final results, it is found that in the hydropower unit indicator evaluation system, the influence of the weight of the bottom indicator on the overall evaluation results is weakened with the increase of the number of transmission layers, which is similar to the phenomenon of the disappearance of the gradient of the neural network. Therefore, this paper proposes a variable weighting algorithm (Fu et al., 2017) with a penalty factor that can adaptively adjust the weight of the indicator according to the operating state of the indicator, and applies it through the case study and verifies its optimal evaluation effect by comparing the improved method with other methods without improvement.

2 Safety evaluation system for hydropower units

Due to the complex structure of hydropower units, the need to monitor many parts, the need to monitor many parts, and the differences in the types of measurement points between different power plants and unit models, a hydropower unit evaluation system can be constructed using division by components or division

according to monitoring signals. The latter approach was applied in this study. The monitoring signals for a hydraulic turbine system can be divided into pendulum, vibration type, pressure pulsation, and temperature type signals. In order to reflect the real operation of the unit and determine the reliability of the evaluation method, this study constructed a hierarchical analysis system according to the type of monitoring signals (Zhang et al., 2023), taking Unit 4 of a power plant as an example. This hydropower unit was divided into the three layers shown in Figure 1.

A goal layer, project layer, and indicator layer. The project layer consists of the four monitoring signal types: pendulum, vibration, pressure pulsation, and temperature. The indicator layer comprises the different measurement points under each of the four signals, comprehensively reflecting the operation status of the hydropower unit.

3 Combinatorial empowerment via game theory

How to scientifically and reasonably determine the weights of indicators for the evaluation of hydropower units has a significant impact on the evaluation structure. Currently, the commonly used evaluation methods include subjective and fuzzy methods. If the calculation process is complicated and inaccurate, no traditional evaluation method will lead to acceptable solution. In such cases, need for improvement of the capacity of the single assessment

TABLE 3 Correspondence between indicator boundary values and unit states.

State	Boundary values				
	μ	$\mu + \sigma$	$\mu + 2\sigma$	$\mu + 3\sigma$	$\mu + 4\sigma$
Good	100%	50%	0	0	0
Qualified	0	50%	50%	0	0
Attention	0	0	50%	50%	0
Abnormal	0	0	0	50%	100%
Degradation	0	0.25	0.5	0.75	1

methodology to address practical problems. Therefore, this study combined a game theory weight determination method with the subjective weights of the fuzzy hierarchical analysis method and the

objective weights of the CRITIC method to obtain the two optimal weight vectors through game aggregation.

3.1 Fuzzy hierarchical analysis method

The fuzzy hierarchical analysis method has been widely used as a basis for quantifying evaluation indicators and selecting an optimal solution. It combines a fuzzy consistency matrix with a hierarchical analysis, retaining the advantages of the latter while overcoming its fuzziness in the judgment matrix to ensure consistency and functionality more to imitate the human decision-making.

The fuzzy complementary matrix of hydropower unit evaluation indicators can be established by comparing the evaluation indicators r_i and r_j to determine and quantitatively express the importance of one factor over the other. The fuzzy relationship affiliation degree

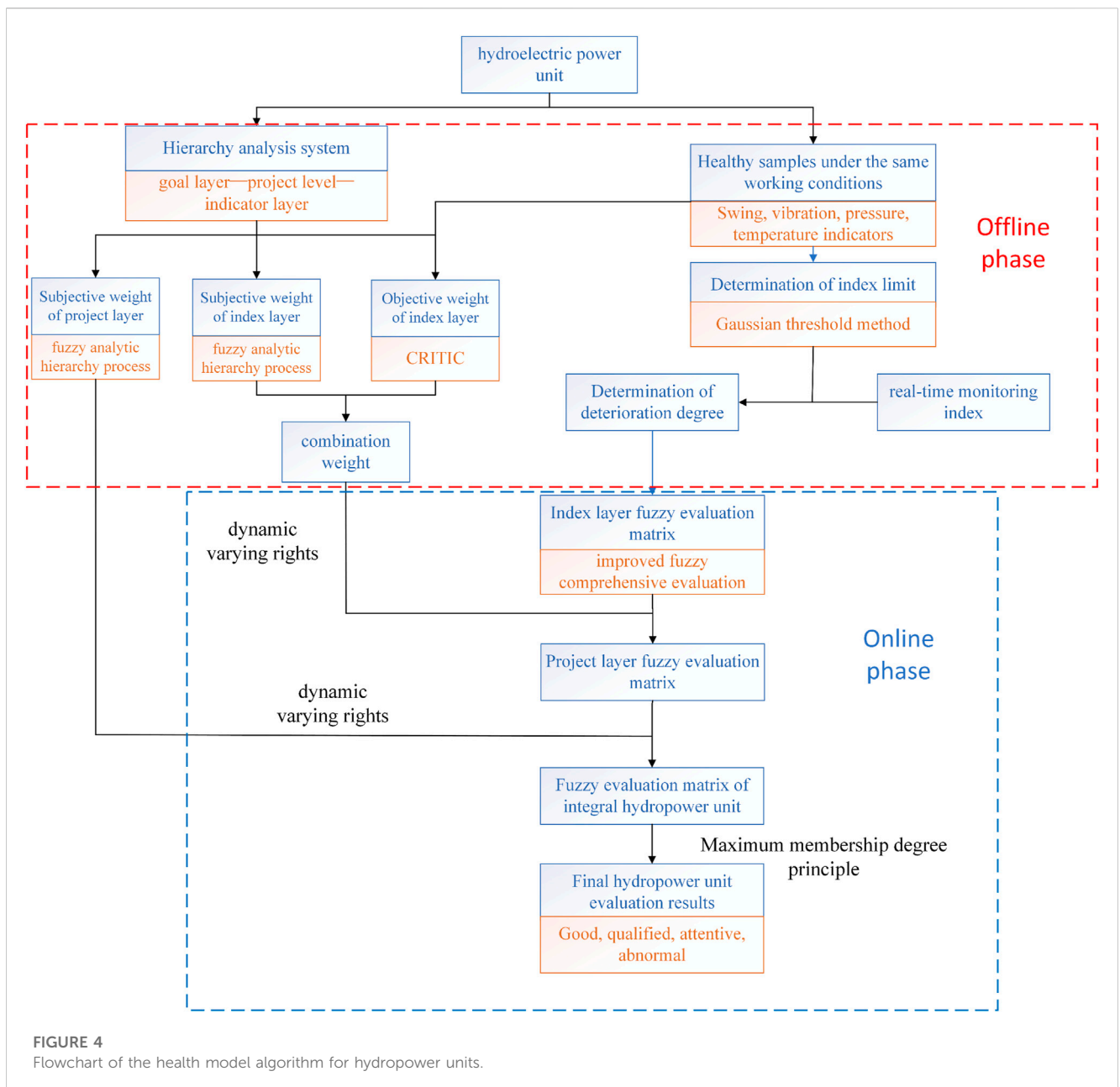


FIGURE 4 Flowchart of the health model algorithm for hydropower units.

TABLE 4 Project layer weighting table.

Indicator	Subjective weights	Objective weights	Portfolio empowerment
Pendulum	(1/6,1/6,1/6,1/6,1/6,1/6)	(0.156,0.163,0.142,0.165,0.217,0.157)	(0.161,0.165,0.154,0.166,0.192,0.162)
Vibration	(1/6,1/6,1/6,1/6,1/6,1/6)	(0.172,0.108,0.111,0.209,0.211,0.189)	(0.169,0.137,0.140,0.189,0.187,0.178)
Pressure	(0.30,0.30,0.233,0.167)	(0.274,0.231,0.192,0.312)	(0.287,0.266,0.213,0.234)
Temperature	(0.283,0.283,0.217,0.217)	(0.267,0.293,0.202,0.238)	(0.273,0.289,0.208,0.230)

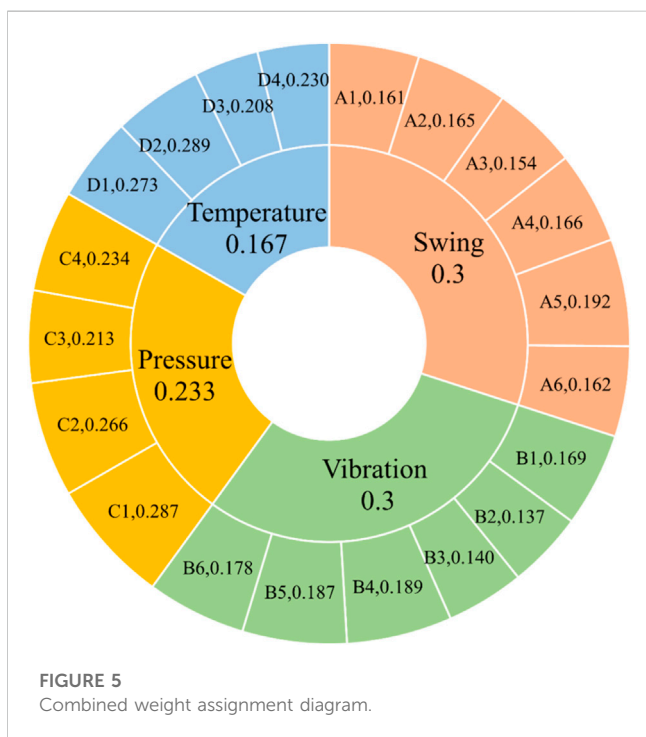


FIGURE 5 Combined weight assignment diagram.

between these two indicators, a_{ij} , is quantitatively described on a scale of 0.1–0.9, with the meaning of each interval in this range expressed in Table 1. Thus, the fuzzy complementary judgment matrix of the evaluation indicators for hydropower units is expressed as $A = (a_{ij})_{n \times n}$ which satisfies $0 \leq a_{ij} \leq 1$ and $a_{ij} + a_{ji} = 1$, where:

$$a_{ii} = 0.5 (i = 1, 2, \dots, n)$$

$$a_{ij} + a_{ji} = 1 (i, j = 1, 2, \dots, n);$$

As shown in Table 1, $a_{ii} = 0.5$ indicates that each factor is equally important; $a_{ij} \in [0.1, 0.5]$ indicates that factor x_j is more important than x_i ; and $a_{ij} \in [0.5, 0.9]$ indicates that factor x_i is more important than x_j . For the last case, the fuzzy consistency matrix performs a summation operation for each row of the fuzzy judgment matrix as follows:

$$r_i = \sum_{j=1}^n a_{ij} \tag{1}$$

The matrix transformation conducted according to Eq. 1 yields the fuzzy judgment matrix $E = (e_{ij})_{n \times n}$, which is consistent, as follows.

$$e_{ij} = \frac{r_i - r_j}{2n} + 0.5 \tag{2}$$

where e_{ij} is the consistency-processed value of a_{ij} in the i th row and j th column of matrix E and r_i is the value from the fuzzy complementary matrix $A = (a_{ij})_{n \times n}$. The value of the row-by-row summation of the weight of each indicator i , $w_i = (w_1, w_2, w_3, \dots, w_n)$ is subsequently obtained from the matrix $E = (e_{ij})_{n \times n}$ as follows:

$$w_i = \frac{2 \sum_{j=1}^n e_{ij} - 1}{n(n-1)} \tag{3}$$

3.2 CRITIC method

The CRITIC method is an objective weighting method that uses the quantity of information for each indicator to calculate the value of its weight. This represents a superior method compared to entropy weighting or the coefficient of variation when the information describing each indicator to be evaluated is provided by varying intensities and conflicts with that describing other indicators. Indeed, the CRITIC method determines the weights not only by taking the variability of the indicator information as a premise, but also by combining the correlation between indicators, thereby preventing subjective factors from having an outsized effect and causing the results to deviate from objective reality.

Indicator dissimilarity is generally expressed as a standard value that represents the volatility of the indicator; the greater the volatility, the greater the indicator dissimilarity. Conflict between two different indicators is expressed in terms of correlation; the greater the conflict, the smaller the correlation.

Generally, CRITIC method modeling is conducted using the following steps.

- (1) Dimensionless processing

Considering the inconsistency in the scale of the data for each indicator, dimensionless processing is first conducted on each indicator to remove the influence of such inconsistency on the evaluation results. When there are many objects to be evaluated, standardization can be used for this task as follows:

$$y_i = (x_i - x_0) / s \tag{4}$$

where x_i is the sample mean for each indicator, x_0 is the actual variable value, and s is the standard value.

- (2) Calculate indicator dissimilarity

TABLE 5 Indicator limits and monitoring values at considered moments.

Indicator	Lower limit value	Upper limit value	Monitoring values					
			Base value	Moment A	Moment B	Moment C	Moment D	Moment E
A1 (µm)	99.29	131.95	115.62	111.65	118.33	119.17	108.23	103.87
A2 (µm)	96.94	128.00	112.47	120.40	117.53	118.24	116.58	117.92
A3 (µm)	516.60	697.10	606.08	568.18	570.37	561.27	566.79	550.59
A4 (µm)	473.21	637.14	555.17	541.10	538.85	521.13	567.13	555.95
A5 (µm)	170.77	278.47	224.62	200.05	228.11	287.72	331.47	316.27
A6 (µm)	138.96	253.2	196.08	178.98	164.58	172.05	233.46	232.77
B1 (µm)	20.84	31.53	26.18	27.51	22.54	24.50	28.682	20.84
B2 (µm)	21.41	30.93	26.17	25.64	28.58	27.53	30.76	25.26
B3 (µm)	0.56	2.18	1.37	1.645	0.684	1.347	0.973	1.304
B4 (µm)	97.82	161.01	129.41	132.45	248.05	298.32	417.65	471.01
B5 (µm)	81.82	153.36	117.59	104.05	197.60	246.99	372.00	413.36
B6 (µm)	79.61	158.44	119.02	105.58	207.60	270.31	381.94	458.43
C1 (kPa)	0.56	1	0.78	0.69	0.65	0.596	0.557	0.549
C2 (kPa)	0.20	0.21	0.205	0.206	0.203	0.205	0.203	0.203
C3 (kPa)	0.34	0.35	0.345	0.345	0.345	0.345	0.345	0.345
C4 (kPa)	0.136	0.265	0.20	0.194	0.182	0.174	0.172	0.212
D1 (°C)	44.49	63.234	53.87	52.58	52.64	50.77	59.19	57.234
D2 (°C)	46.326	64.932	55.62	51.43	53.21	51.32	57.33	58.32
D3 (°C)	41.03	59.56	50.30	49.00	49.15	50.17	59.92	59.56
D4 (°C)	40.13	59.66	49.90	48.32	48.46	51.22	58.35	59.32

The CRITIC method uses the standard deviation to express the variability between indicators as follows:

$$S_j = \sqrt{\frac{\sum_{i=1}^n (x_{ij} - \bar{x}_j)^2}{n - 1}} \tag{5}$$

where \bar{x}_j is the mean value of each indicator. The larger the standard deviation, the greater the difference between the indicator values, the more information is provided among them, and the greater their assessment strength, suggesting that they should be given higher weights.

(3) Calculate indicator conflict

Indicator conflict is expressed in terms of the correlation coefficient as follows:

$$E_j = \sum_{i=1}^n (1 - r_{ij}) \tag{6}$$

where r_{ij} denotes the Pearson correlation coefficient (Edelmann et al., 2021) between indicators i and j

(4) Calculate quantity of information

The quantity of information is determined by:

$$V_j = S_j \times E_j \tag{7}$$

(5) Calculate the objective weights

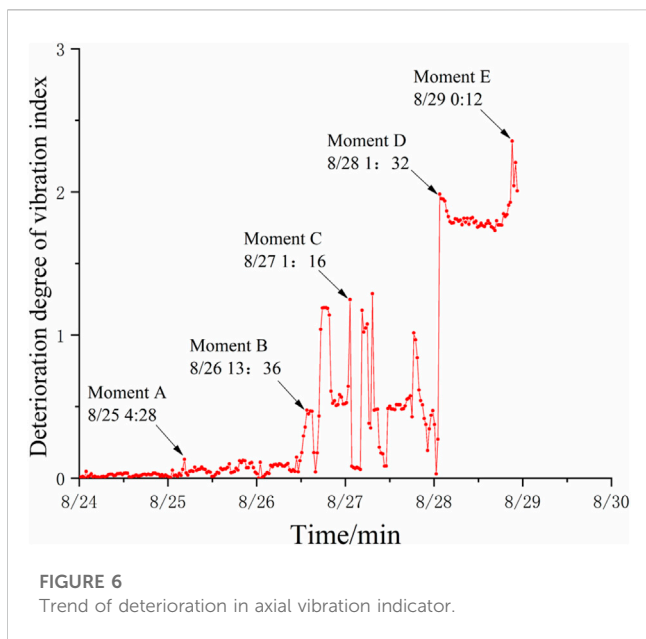
The objective weight of the j indicator W_j is given by

$$W_j = \frac{V_j}{\sum_{j=1}^n V_j} \tag{8}$$

and $W = (W_1, W_2, \dots, W_n)^T$ is the indicator objective weight vector.

3.3 Portfolio empowerment based on game theory

Game theory provide a mathematical method for investigating how to make decisions and maximize benefits when there are multiple struggling or competing individuals in a group. When used in subjective-objective combination weight calculations, game theory can apply weighting to the combinations between indicators and determine weights that deviate the least from each basic value,



thereby ensuring that the calculated values match the actual situation. This “portfolio empowerment” method is conducted as follows.

- (1) Employ the game theory concept of outlier minimization to find the optimal weights w_k^* as follows:

$$w_k^* = \min \left\| \sum_{k=1}^n a_k w_k^T \right\|_2 \quad (9)$$

where k represents the number of approaches (thus, the number of weights obtained) and w_i is the matrix of the weights obtained for each approach.

- (2) Normalize the obtained $(\alpha_1, \alpha_2, \dots, \alpha_q)$ to derive a_k^* as follows:

$$\begin{pmatrix} w_1 w_1^T & \dots & w_1 w_k^T \\ \vdots & \ddots & \vdots \\ w_k w_1^T & \dots & w_k w_k^T \end{pmatrix} \begin{pmatrix} \alpha_1 \\ \vdots \\ \alpha_k \end{pmatrix} = \begin{pmatrix} w_1 w_1^T \\ \vdots \\ w_k w_k^T \end{pmatrix} \quad (10)$$

$$a_k^* = \frac{\alpha_k}{\sum_{k=1}^n \alpha_k} \quad (11)$$

- (3) Assign a combination of weights to obtain the combined weight of the evaluation indicators as w^* :

$$w^* = \sum_{k=1}^n a_k^* w_k^T \quad (12)$$

and the combined weight vector is $w = (w_1, w_2, \dots, w_n)$.

4 Improved fuzzy comprehensive evaluation method

The indicator monitoring volume limits determined using regulation guidelines are not clear and do not consider the actual operating conditions of the hydropower unit. However, the indicator thresholds obtained from historical indicator monitoring data can accurately reflect the unit status. Therefore,

to evaluate the health state of the hydropower unit more accurately, the indicator limits are determined from these data using the Gaussian threshold method.

4.1 Determination of the indicator limits using Gaussian thresholds

The indicator data from a hydropower unit include random measurement errors and exhibit obvious normal distribution characteristics (Zheng et al., 2017; Zhang S. et al., 2020), as shown in Figure 2. For normally distributed unit monitoring indicators $V_i = \{V_i(1), V_i(2), \dots, V_i(t) \dots, V_i(m)\}$, the probability that an indicator value falls in the range $[\mu - 3\sigma, \mu + 3\sigma]$, where μ is the optimal value of the indicator, is 99.74% and the probability it falls outside this range is 0.26%. Thus, the interval $[\mu - 3\sigma, \mu + 3\sigma]$ can be considered the normal operation limit of an indicator and the interval $[\mu - 4\sigma, \mu + 4\sigma]$ can be considered its overall, where:

$$u = \text{mean}(V_i) = \frac{1}{m} \sum_{i=1}^m V_i(t) \quad (13)$$

$$\sigma = \sqrt{\frac{1}{m} \sum_{i=1}^m (V_i(t) - \mu)^2} \quad (14)$$

4.2 Determination of degradation

The degradation degree when using indicators for which larger values are better is expressed as:

$$g = \begin{cases} 1 & x_i < a \\ \frac{\beta - x_i}{\beta - a} & a < x_i < \beta \\ 0 & x_i > \beta \end{cases} \quad (15)$$

where g is the degradation degree, x_i is the measured value of the indicator, β is the optimal value of the indicator, a is the lower limit of the indicator, and $a < \beta$.

The degradation degree when using indicators for which smaller values are better is given by:

$$g = \begin{cases} 0 & x_i < a \\ \frac{x_i - \beta}{\beta - a} & a < x_i < \beta \\ 1 & x_i > \beta \end{cases} \quad (16)$$

where $\beta < a$.

4.3 Improved fuzzy comprehensive evaluation method

When establishing the safety evaluation model for a hydropower unit in use, most of the risk evaluation indicators have randomness, fuzziness, and other uncertainties. The fuzzy comprehensive evaluation method has unique advantages for solving such problems. Fuzzy comprehensive evaluation is based on fuzzy

TABLE 6 Fuzzy evaluation matrix of hydropower station system at each moment.

Moment	Indicator	Evaluation matrix at the indicator level	Result	Target level evaluation matrix after weighting change	Result change
A	Pendulum	$(0.760,0.240,0,0)^T$	Good	$(0.576,0.424,0,0)^T$	Good
	Vibration	$(0.673,0.327,0,0)^T$	Good		
	Pressure	$(0.781,0.219,0,0)^T$	Good		
	Temperature	$(0.594,0.406,0,0)^T$	Good		
B	Pendulum	$(0.081,0.531,0.231,0.243)^T$	Qualified	$(0.190,0.266,0.331,0.213)^T$	Attention
	Vibration	$(0.121,0.138,0.452,0.289)^T$	Attention		
	Pressure	$(0.521,0.260,0.219,0)^T$	Good		
	Temperature	$(0.494,0.306,0.2,0)^T$	Good		
C	Pendulum	$(0.150,0.201,0.449,0.200)^T$	Attention	$(0.051,0.042,0.410,0.497)^T$	Abnormal
	Vibration	$(0.006,0.045,0.284,0.712)^T$	Abnormal		
	Pressure	$(0.721,0.279,0,0)^T$	Good		
	Temperature	$(0.199,0.801,0,0)^T$	Qualified		
D	Pendulum	$(0.063,0.024,0.282,0.626)^T$	Abnormal	$(0.020,0.067,0.353,0.560)^T$	Abnormal
	Vibration	$(0.008,0.036,0.087,0.901)^T$	Abnormal		
	Pressure	$(0.572,0.427,0,0)^T$	Good		
	Temperature	$(0.258,0.418,0.324,0)^T$	Qualified		
E	Pendulum	$(0.081,0.031,0.472,0.424)^T$	Attention	$(0.050,0.086,0.243,0.621)^T$	Abnormal
	Vibration	$(0.005,0.006,0.034,0.954)^T$	Abnormal		
	Pressure	$(0.412,0.288,0.123,0.177)^T$	Good		
	Temperature	$(0.187,0.432,0.211,0.170)^T$	Qualified		

TABLE 7 Turbine system monitoring limits.

Monitoring volume	Lower value	Upper value
A1, A2 (um)	0	150
A3, A4 (um)	0	600
A5, A6 (um)	0	200
B1, B2, B3 (um)	0	70
B4, B5, B6 (um)	0	450
C1, C2, C3, C4 (kpa)	0	4
D1, D2, D3, D4 (°C)	25	75

mathematics and uses fuzzy relationship synthesis to quantify factors with unknown boundaries that are not easy to quantify, then comprehensively evaluate the system considering multiple factors. This approach is based on correlation theory, which converts a qualitative evaluation into a quantitative evaluation. This study accordingly adopted the fuzzy comprehensive evaluation method to evaluate and analyze the state of hydropower units.

The triangular/semi-trapezoidal membership function has been widely used in fuzzy comprehensive assessments due to its simple

distribution, and it provides results comparable to other more complex membership functions used in risk assessments and equipment evaluations. However, as the degradation values used in the traditional triangular/semi-trapezoidal affiliation function for equipment evaluation depend on expert experience, and the correspondence among different levels lacks explanation. To explain the rationality of the relationships corresponding to different evaluation levels, an improved triangular/semi-trapezoidal affiliation function was proposed for use in this study as shown in the diagram in [Figure 3](#).

The diagram shows that the hydropower unit can be classified into four states: I, II, III, and IV, representing good, qualified, attention, and abnormal conditions, respectively, corresponding to degradation degrees of 0.25, 0.50, 0.75, and 1, respectively. These four conditions can intuitively express hydropower unit health as defined in [Table 2](#).

Since the hydropower unit indicators exhibit normal distribution characteristics, as shown in [Figure 2](#), the hydropower unit states in [Table 2](#) were defined using the four indicator value intervals shown in [Table 3](#). These intervals are defined as $[\mu, \mu + 2\sigma]$, $[\mu + \sigma, \mu + 2\sigma]$, $[\mu + 2\sigma, \mu + 3\sigma]$, and $[\mu + 3\sigma, \mu + 4\sigma]$, where $[\mu]$, $[\mu + \sigma]$, $[\mu + 2\sigma]$, $[\mu + 3\sigma]$, and $[\mu + 4\sigma]$ are zone boundary values corresponding to degradation degrees of 0, 0.25, 0.5, 0.75, 0.1, respectively, $[\mu, \mu + 3\sigma]$

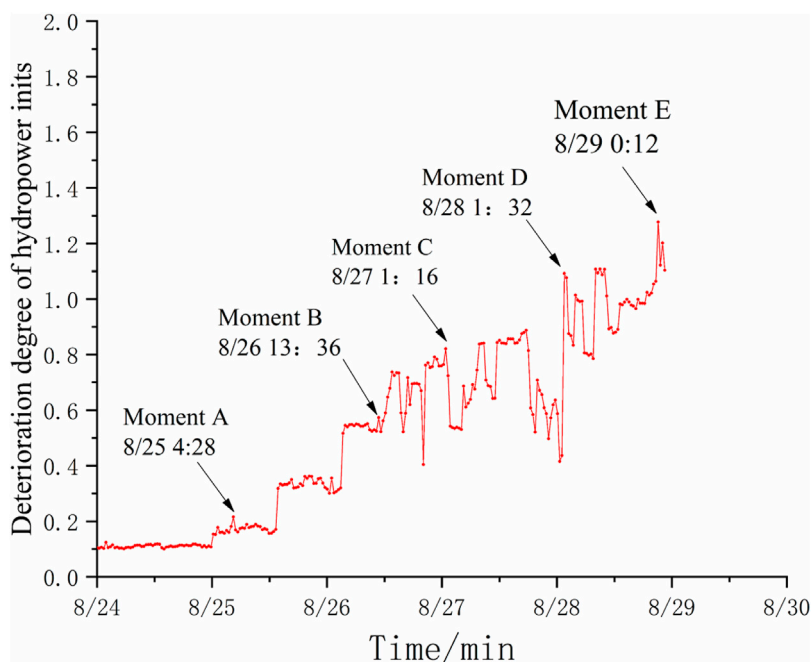


FIGURE 7
Comprehensive deterioration trend for the case study hydropower unit.

denotes the standard limits, and $[\mu, \mu + 4\sigma]$ denotes the overall limits.

According to the intervals defined in Table 3 and based on the triangular/semi-trapezoidal affiliation function in Figure 3, the expressions for the affiliation function were constructed as follows:

$$f_1 = \begin{cases} 1 & g < 0.125 \\ -4g + 1.5 & 0.125 < g < 0.375 \\ 0 & g > 0.375 \end{cases} \quad (17)$$

$$f_2 = \begin{cases} 0 & g < 0.125 \\ 4g - 0.5 & 0.125 < g < 0.375 \\ -4g + 2.5 & 0.375 < g < 0.625 \\ 0 & g > 0.625 \end{cases} \quad (18)$$

$$f_3 = \begin{cases} 0 & g < 0.375 \\ 4g - 1.5 & 0.375 < g < 0.625 \\ -4g + 3.5 & 0.625 < g < 0.875 \\ 0 & g > 0.875 \end{cases} \quad (19)$$

$$f_4 = \begin{cases} 0 & g < 0.625 \\ 4g - 2.5 & 0.625 < g < 0.875 \\ 1 & g > 0.875 \end{cases} \quad (20)$$

5 Case study example

5.1 Hydropower unit health assessment process

The following sequence was used to conduct the hydropower unit case study in this example (a flow chart of this process is provided in Figure 4).

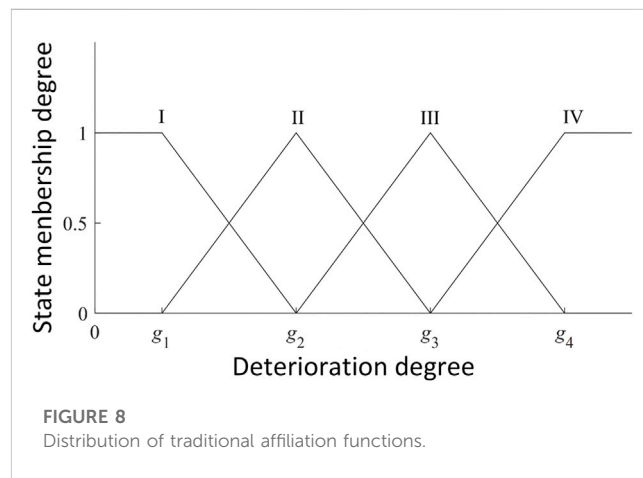


FIGURE 8
Distribution of traditional affiliation functions.

- 1) According to the actual situation of the case study hydropower plant unit structure and the arrangement of measurement points, a hierarchical analysis system was constructed by dividing the unit into a target layer, project layer, and indicator layer. Historical health data describing the oscillation, vibration, pressure, and temperature indicators—included in the project layer—were obtained under the same working conditions used in the example calculation.
- 2) Next, a fuzzy hierarchical analysis was employed to determine the subjective weights of the items in the project and indicator layers. The historical health data were inserted into the CRITIC method to determine the objective weights for the items in the indicator layer, and the optimal comprehensive weights were

TABLE 8 Evaluation results of the state of each moment based on the traditional fuzzy evaluation method.

Moment	Indicator	Evaluation matrix at the indicator level	Result	Evaluation matrix under traditional fuzzy evaluation	Result
A	Pendulum	$(0.693,0.307,0,0)^T$	Good	$(0.91,0.09,0,0)^T$	Good
	Vibration	$(1,0,0,0)^T$	Good		
	Pressure	$(0.99,0.01,0,0)^T$	Good		
	Temperature	$(0.95,0.05,0,0)^T$	Good		
B	Pendulum	$(0.42,0.58,0,0)^T$	Qualified	$(0.60,0.26,0.10,0.04)^T$	Good
	Vibration	$(0.32,0.16,0.37,0.15)^T$	Attention		
	Pressure	$(0.99,0.01,0,0)^T$	Good		
	Temperature	$(0.70,0.30,0,0)^T$	Good		
C	Pendulum	$(0.2,0.22,0.38,0.20)^T$	Attention	$(0.30,0.40,0.12,0.18)^T$	Qualified
	Vibration	$(0.17,0.16,0.24,0.42)^T$	Abnormal		
	Pressure	$(0.56,0.44,0,0)^T$	Good		
	Temperature	$(0.23,0.77,0,0)^T$	Qualified		
D	Pendulum	$(0.28,0.18,0.38,0.16)^T$	Attention	$(0.02,0.15,0.56,0.27)^T$	Attention
	Vibration	$(0.01,0.11,0.38,0.50)^T$	Abnormal		
	Pressure	$(0.57,0.43,0,0)^T$	Good		
	Temperature	$(0.26,0.42,0.32,0)^T$	Qualified		
E	Pendulum	$(0,0.1,0.47,0.43)^T$	Attention	$(0.16,0.23,0.35,0.26)^T$	Attention
	Vibration	$(0.005,0.006,0.034,0.954)^T$	Abnormal		
	Pressure	$(0.54,0.30,0.16,0)^T$	Good		
	Temperature	$(0.20,0.45,0.20,0.05)^T$	Qualified		

determined based on game theory principle by combining the subjective and objective weights.

- 3) The upper limit, lower limit, and benchmark value for each indicator were obtained using the Gaussian threshold method and the corresponding historical data based on the indicator operating limits and real-time monitoring values.
- 4) Using the improved adaptive fuzzy comprehensive evaluation method as the health evaluation model, the indicators were divided into four intervals corresponding to good, qualified, attention, and abnormal states. The degradation degree for each indicator was substituted into Eqs 17–20 to obtain the state affiliation for each indicator corresponding to the oscillation, vibration, pressure, and temperature, thereby obtaining the indicator layer fuzzy evaluation matrix.
- 5) The variable weight theory was subsequently applied to adjust the weight for each indicator, and the fuzzy evaluation matrix was weighted and calculated to obtain the fuzzy evaluation matrix for the project level of the hierarchy structure.
- 6) The fuzzy evaluation matrix for the entire hydropower unit system was derived using variable weight theory, and the final hydropower unit evaluation result was obtained according to the principle of maximum subordination.

5.2 Calculation of portfolio weights

The subjective project level weights included vibration, oscillation, pressure pulsation, and temperature indicators. The hierarchical analysis method was used to determine the weight of each indicator type. As the vibration, oscillation, and pressure pulsation indicators changed faster and were more sensitive to the state of the unit, the indicator importance was defined as vibration fault = oscillation fault > pressure pulsation fault > temperature fault. According to the 0.1–0.9 scale, the fuzzy judgment matrix for the project level was determined as follows:

$$C = (C_{ij}) = \begin{bmatrix} 0.5 & 0.5 & 0.7 & 0.9 \\ 0.5 & 0.5 & 0.7 & 0.9 \\ 0.3 & 0.3 & 0.5 & 0.7 \\ 0.1 & 0.1 & 0.3 & 0.5 \end{bmatrix}$$

And the fuzzy consistency matrix was obtained as

$$(E_{ij}) = \begin{bmatrix} 0.5 & 0.5 & 0.6 & 0.7 \\ 0.5 & 0.5 & 0.6 & 0.7 \\ 0.4 & 0.4 & 0.5 & 0.6 \\ 0.3 & 0.3 & 0.4 & 0.5 \end{bmatrix}$$

and subjective weights at the project level were (0.3, 0.3, 0.233, 0.167).

TABLE 9 Evaluation results of the state of each moment under constant weights.

Moment	Indicator	Evaluation matrix at the indicator level	Result	Target level evaluation matrix with unchanged weights	Result
A	Pendulum	$(0.63,0.30,0.07,0)^T$	Good	$(0.676,0.324,0,0)^T$	Good
	Vibration	$(0.53,0.47,0,0)^T$	Good		
	Pressure	$(0.98,0.02,0,0)^T$	Good		
	Temperature	$(0.51,0.49,0,0)^T$	Good		
B	Pendulum	$(0.28,0.701,0.02,0)^T$	Qualified	$(0.26,0.53,0.16,0.05)^T$	Qualified
	Vibration	$(0.09,0.33,0.50,0.1)^T$	Attention		
	Pressure	$(1,0,0,0)^T$	Good		
	Temperature	$(0.52,0.48,0.2,0)^T$	Good		
C	Pendulum	$(0.150,0.201,0.449,0.200)^T$	Attention	$(0.20,0.29,0.25,0.26)^T$	Qualified
	Vibration	$(0.006,0.045,0.284,0.712)^T$	Abnormal		
	Pressure	$(0.61,0.39,0,0)^T$	Good		
	Temperature	$(0.39,0.50,0.11,0)^T$	Qualified		
D	Pendulum	$(0.063,0.024,0.282,0.626)^T$	Abnormal	$(0.20,0.16,0.15,0.46)^T$	Abnormal
	Vibration	$(0.008,0.036,0.087,0.901)^T$	Abnormal		
	Pressure	$(0.572,0.427,0,0)^T$	Good		
	Temperature	$(0.258,0.418,0.324,0)^T$	Qualified		
E	Pendulum	$(0.08,0.43,0.37,0.12)^T$	Qualified	$(0.21,0.09,0.23,0.47)^T$	Abnormal
	Vibration	$(0.07,0.11,0.22,0.70)^T$	Abnormal		
	Pressure	$(1,0,0,0)^T$	Good		
	Temperature	$(0.20,0.52,0.18,0.10)^T$	Qualified		

The objective and subjective weights at the indicator level and the combination weights were subsequently obtained as shown in Table 4.

time. Note that all monitoring indicators considered in this example were minimum optimal (smaller is better) type indicators.

5.3 Determination of indicator limits

According to the case study unit model and its parameters, including operating head and rated speed, and other parameters, the oscillation, vibration, pressure pulsation, and temperature indicator limits were obtained by consulting international industry regulations, as well as power station regulations and guidelines. Then, the historical health indicator data and Gaussian threshold method has been applied to obtain the final weights of the oscillation, vibration, and pressure pulsation, and temperature indicators as shown in Figure 5.

5.5 Unit condition assessment

During the evaluation of hydropower units, the serious deviation of a certain indicator or indicator type from its normal value often means that the feature of this indicator is abnormal and must be paid careful attention, or the system should be shut down for maintenance (Xu et al., 2016; Lin et al., 2020). However, as the weight value of a problematic indicator could be quite small in practice, the state of the response may not be reflected in the results for the entire hydropower unit. Therefore, an adaptive penalty factor algorithm was introduced to adjust the weight of each indicator according to its operating state as follows:

5.4 Determination of degradation degree

As shown in Table 5, the axial vibration class indicators exhibited the largest variation. Therefore, the axial vibration class degradation graph was obtained as shown in Figure 6, which identifies five moments representing the degradation trend over

$$w_i = \frac{\partial_k w_i}{\sum_{j=1}^n \partial_k w_i} \tag{21}$$

where $\partial_k = \{1,2,3,4\}$ is the penalty, defined according to the principle of maximum affiliation and the dynamics of the indicator state assessment results. In state 1, $\partial_k = \partial_1 = 1$, in state 2, $\partial_k = \partial_2 = 2$, etc. The project layer fuzzy evaluation matrix was constructed according

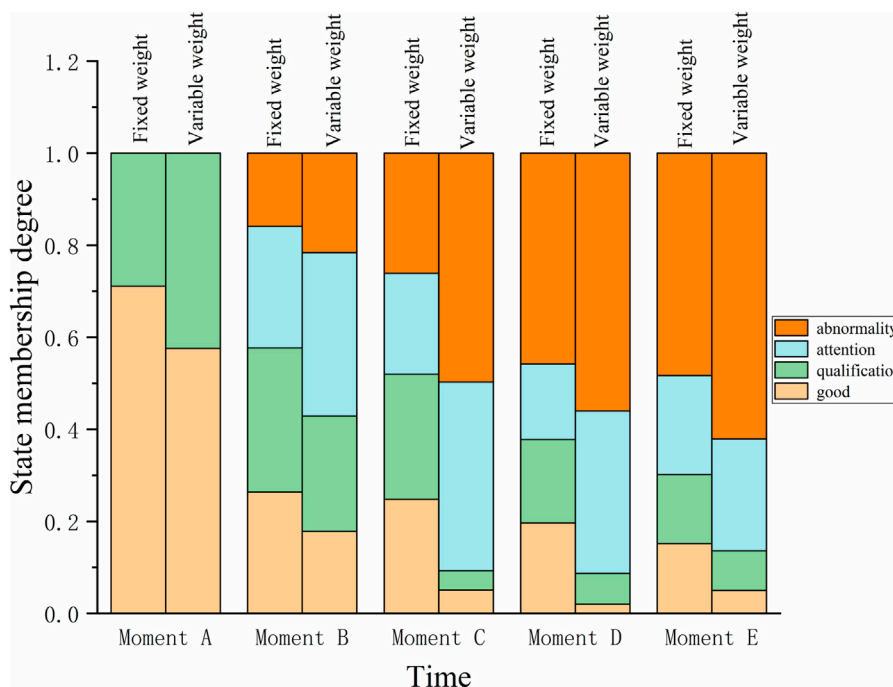


FIGURE 9 Comparison of the unit's operational condition assessment using variable and fixed weights.

to the variable weight theory and combined with the subjective weights of the project layer to obtain the overall fuzzy evaluation matrix.

The values of the indicators in Table 5 were substituted into Eq. 16 to obtain the deterioration degree for each indicator. These deterioration degrees were substituted into Eqs 17–20 to obtain the fuzzy evaluation matrix for each item level indicator as follows:

$$M_B = \begin{bmatrix} 0.623 & 0.377 & 0 & 0 \\ 0.588 & 0.412 & 0 & 0 \\ 0.313 & 0.687 & 0 & 0 \\ 0 & 0 & 0.548 & 0.452 \\ 0 & 0 & 0.652 & 0.348 \\ 0 & 0 & 0.631 & 0.369 \end{bmatrix}$$

As shown above, the weight of each indicator was reallocated using the variable weight theory. According to the principle of maximum subordination, the top vibrations in the X- and Y-directions are in state 1 (corresponding to penalty factor ∂_1), the top vibration in the Z-direction is in state 2 (corresponding to penalty factor ∂_2), and the axial vibrations A, B, and C are in state 3 (corresponding to penalty factor ∂_3). The vibration class indicator weights were combined into w_B and substituted into Eq. 4 to obtain the new vibration class weight vector as follows:

$$w' = (0.075, 0.061, 0.124, 0.252, 0.250, 0.238)$$

The vibration class fuzzy evaluation matrix was subsequently obtained based on the new vibration indicator weight vector as follows:

$$W_B = w_B' \cdot M_B = (0.121, 0.138, 0.451, 0.289)$$

The fuzzy evaluation matrices for the other indicator types have been obtained similarly, then the project level fuzzy evaluation matrix has been determined as follows:

$$M = \begin{bmatrix} 0.081 & 0.531 & 0.231 & 0.243 \\ 0.121 & 0.138 & 0.451 & 0.289 \\ 0.521 & 0.260 & 0.219 & 0 \\ 0.494 & 0.306 & 0.2 & 0 \end{bmatrix}$$

The new project layer weight vector has been obtained after the subjective weights of the project layer were weighted as $w' = (0.316, 0.474, 0.123, 0.087)$, and the final fuzzy evaluation matrix was given by $w' \cdot M = (0.190, 0.266, 0.331, 0.213)$.

According to the calculated fuzzy evaluation matrix, the weights of each indicator were reallocated using variable weight theory, giving the results shown in Table 6.

Furthermore, the comprehensive deterioration degree of the hydropower unit is plotted in Figure 7, which shows that the deterioration of the hydroelectric unit increased obviously from August 26, with abnormalities at C, D, and E. At the end of August, the vibration of the case study unit was reported to have been quite violent. After an accident probe of the site personnel, it was determined that the runner chamber steel plate fell off during this time period, leading to a hydraulic imbalance that would obviously change the vibration pendulum signal. Thus, the calculated deterioration degree is consistent with the reported reality.

6 Comparison of methods

In order to further validate the advantages of the proposed method for the health assessment of hydropower units, two sets of controlled experiments are designed in this section: fuzzy assessment based on traditional monitoring quantities and regulatory guidelines, fuzzy assessment based on constant-weighted Gaussian thresholds (You et al., 2022).

6.1 Comparison with traditional guideline protocol-fuzzy evaluation methods

This method is compared with the fuzzy evaluation method for hydropower units, which is based on traditional monitoring quantities and regulations. According to the unit type, working head, rated speed and other parameters, the upper and lower limit values of each measurement point of the hydraulic turbine system under steady state operation are determined by consulting the national standards and regulations and the guidelines of power plant regulations, as shown in Table 7.

It can be seen that all the monitored quantities are of the smaller and better type, therefore the degree of deterioration is calculated according to Eq. 16, as shown in the traditional plot of the membership function in Figure 8:

Where g_1, g_2, g_3, g_4 , correspond to (0.2, 0.4, 0.6, 0.8), respectively, as a comparison to evaluate the operating status of the turbine system A-E at each moment, corresponding to the actual monitoring values shown in Table 5, According to Table 5, the final state evaluation table under the traditional fuzzy evaluation method can be obtained as shown in Table 8:

Table 8 shows that the turbine system status and vibration indexes at C, D, and E time are still assessed as qualified or attention, but at this time, through the comprehensive deterioration diagram of the unit, it is obvious to see that there are abnormalities in the unit, and the evaluation results obviously cannot reflect the real state of the unit, in contrast, the evaluation results based on the combination of the assignment and the Gaussian threshold method of the state of the unit are more in line with the actual situation, and can be more real and effective. Reflecting the actual operating status of the unit.

6.2 Comparison with unweighted methods

According to the real-time evaluation status of each component in the unit hierarchical analysis system, the penalty factor is introduced to dynamically adjust the original weights of each component, so as to propose an adaptive variable weighting method. Compare it with the evaluation method using fixed constant weights to verify the advantages of introducing the variable weight theory. When using constant weights, the penalty factors in Eq. 21 are all 1, and the results are shown in Table 9.

Under the constant weighting mode, the evaluation status of the turbine system of the unit is qualified at two moments B and C. At this time, as shown in Figure 5, the vibration deterioration increases significantly and the evaluation results of vibration indexes at the two moments in Table 7 are attention and abnormality, respectively. In the case of a single category of indicators abnormal, but still the overall evaluation of the system as a qualified obviously does not match the actual situation. Figure 9 shows the difference between the evaluation results of the two methods more intuitively, and it can be seen that, Compared with the fixed constant weights, and conventional weights can not objectively reflect the serious deviation of indicators from the normal situation, so the introduction of variable weights theory can be based on the actual state of the unit to dynamically change the ratio of each component, highlighting the hidden equipment, variable weights mode of the unit's condition assessment results and the actual operating state of the unit is more in line with the actual operating state of the unit.

7 Conclusion

This study proposed a fuzzy comprehensive evaluation model using a combination of game theory assignment and the Gaussian threshold method to address difficulties associated with determining the indicator limits, the lack of reasonable correspondence between the degradation degree and the affiliation function, and the fact that indicator abnormality cannot be effectively reflected in the overall condition of the hydropower unit. The proposed model was confirmed to effectively and accurately reflect the operation of the case study example of unit 4 of a power station. The following conclusions were obtained by this study.

- (1) The use of fuzzy comprehensive hierarchical analysis overcomes the lack of consistency in the traditional fuzzy hierarchical analysis by using historical health monitoring data to determine the objective weights via the CRITIC method. This results in more reasonable objective weights that can be analyzed using game theory to obtain the optimal values.
- (2) Analysis of historical and real-time monitoring health indicator data can determine indicator limits using the Gaussian threshold method. When combined with the fuzzy comprehensive evaluation method, this results in a more accurate evaluation of the overall hydropower unit.
- (3) Since the indicator weights for the bottom layer of the hierarchy will continue to decay in the overall evaluation results as the number of transmission layers increases, the serious deviation of a certain indicator from its normal value may go unnoticed as it accounts for a relatively small portion of the overall unit state. The use of a variable weight algorithm effectively solves the problem of individual indicator anomalies.

Data availability statement

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

Author contributions

YK: Conceptualization, Methodology, Software, Writing-Original Draft, Writing-Review and Editing, Investigation QW: Revision and viewing of papers HX: Discontinuation of data supply has been thesis revision ZL: Assisted completion JL: Check the papers. All authors contributed to the article and approved the submitted version.

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.

Correction note

This article has been corrected with minor changes. These changes do not impact the scientific content of the article.

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References

- Awan, A., Kocoglu, M., Bandyopadhyay, A., Rej, S., and Altuntaş, M. (2023). A quantile-based analysis of the nexus between hydropower generation, trade and urbanization for China utilizing the EKC hypothesis. *Environ. Model. Assess.* 28, 843–857. doi:10.1007/s10666-023-09889-y
- Cai, F., Hu, Z., Jiang, B., Ruan, W., Cai, S., and Zou, H. (2023). Ecological health assessment with the combination weight method for the river reach after the retirement and renovation of small hydropower stations. *Water* 15 (2), 355. doi:10.3390/w15020355
- Doz, D., Felda, D., and Cotič, M. (2023). Demographic factors affecting fuzzy grading: a hierarchical linear regression analysis. *Mathematics* 11 (6), 1488. doi:10.3390/math11061488
- Edelmann, D., Móri, T. F., and Székely, G. J. (2021). On relationships between the Pearson and the distance correlation coefficients. *Statistics Probab. Lett.* 169, 108960. doi:10.1016/j.spl.2020.108960
- Fang, R., Wu, M., and Jiang, S. (2016). On-line status assessment of wind turbines based on improved fuzzy comprehensive evaluation method. *J. Intelligent Fuzzy Syst.* 31 (6), 2813–2819. doi:10.3233/jifs-169163
- Fu, L., Wei, Y., Fang, S., Zhou, X., and Lou, J. (2017). Condition monitoring for roller bearings of wind turbines based on health evaluation under variable operating states. *Energies* 10 (10), 1564. doi:10.3390/en10101564
- Ge, L., Li, Y., Zhu, X., Zhou, Y., Wang, T., and Yan, J. (2020). An evaluation system for HVDC protection systems by a novel indicator framework and a self-learning combination method. *IEEE Access* 8, 152053–152070. doi:10.1109/access.2020.3017502
- Geng, Q., and Liang, C. (2022). Turbine health evaluation based on degradation degree. *Energy Rep.* 8, 435–444. doi:10.1016/j.egy.2022.01.214
- Hu, A., Xie, N., and Zheng, M. (2019). Air quality evaluation based on grey clustering method: a case study of 74 cities in China. *J. Grey Syst.* 31 (2).
- Huang, X., Wang, Z., and Liu, S. (2022). Health status evaluation method of CNC machine tools based on grey clustering analysis and fuzzy comprehensive evaluation. *J. Intelligent Fuzzy Syst.* 42 (4), 4065–4082. doi:10.3233/jifs-212406
- Krishnan, A. R., Kasim, M. M., Hamid, R., and Ghazali, M. F. (2021). A modified CRITIC method to estimate the objective weights of decision criteria. *Symmetry* 13 (6), 973. doi:10.3390/sym13060973
- Li, C., Chen, X., Li, Z., Zhang, Y., Yue, K., Ma, J., et al. (2022b). Comprehensive evaluation method of transmission line operating status based on improved combination weighting evaluation model. *Energy Rep.* 8, 387–397. doi:10.1016/j.egy.2022.01.207
- Li, H., Chen, L., Tian, F., Zhao, L., and Tian, S. (2022a). Comprehensive evaluation model of coal mine safety under the combination of game theory and TOPSIS. *Math. Problems Eng.* 2022, 1–15. doi:10.1155/2022/5623282
- Li, X., Wang, J., and Sun, C. (2023). Safety evaluation of steel temporary beam service status based on the combination weighting-fuzzy model of game theory. *Math. Problems Eng.* 2023. doi:10.1155/2023/6271946
- Lin, K., Chen, H., Xu, C. Y., Yan, P., Lan, T., Liu, Z., et al. (2020). Assessment of flash flood risk based on improved analytic hierarchy process method and integrated maximum likelihood clustering algorithm. *J. Hydrology* 584, 124696. doi:10.1016/j.jhydrol.2020.124696
- Liu, G., Zhang, C., Zhu, Z., and Wang, X. (2022). Power quality assessment based on rough AHP and extension analysis. *Energy Eng.* 119 (3), 929–946. doi:10.32604/ee.2022.014816
- Ma, Y., Wei, J., Li, C., Liang, C., and Liu, G. (2020). Fuzzy comprehensive performance evaluation method of rolling linear guide based on improved analytic hierarchy process. *J. Mech. Sci. Technol.* 34, 2923–2932. doi:10.1007/s12206-020-0624-3
- Pailunga, P., and Corcoran, J. (2023). Damage detection in guided wave structural health monitoring using Gaussian process regression. *Struct. Health Monit.* 1, 147592172311593. doi:10.1177/14759217231159399
- Tian, D., Wang, Y., and Yu, T. (2020). Fuzzy risk assessment based on interval numbers and assessment distributions. *Int. J. Fuzzy Syst.* 22, 1142–1157. doi:10.1007/s40815-020-00837-6
- Wen, X., Nie, Y., Du, Z., and Huang, L. (2022). Operational safety assessment of straddle-type monorail vehicle system based on cloud model and improved CRITIC method. *Eng. Fail. Anal.* 139, 106463. doi:10.1016/j.engfailanal.2022.106463
- Xia, P., Hu, X., Wu, S., Ying, C., and Liu, C. (2020). Slope stability analysis based on group decision theory and fuzzy comprehensive evaluation. *J. Earth Sci.* 31, 1121–1132. doi:10.1007/s12583-020-1101-8
- Xu, X., Niu, D., Qiu, J., Wu, M., Wang, P., Qian, W., et al. (2016). Comprehensive evaluation of coordination development for regional power grid and renewable energy power supply based on improved matter element extension and TOPSIS method for sustainability. *Sustainability* 8 (2), 143. doi:10.3390/su8020143
- You, P., Liu, S., and Guo, S. (2022). A hybrid novel fuzzy MCDM method for comprehensive performance evaluation of pumped storage power station in China. *Mathematics* 10 (1), 71. doi:10.3390/math10010071
- Yucesan, M., and Kahraman, G. (2019). Risk evaluation and prevention in hydropower plant operations: a model based on Pythagorean fuzzy AHP. *Energy policy* 126, 343–351. doi:10.1016/j.enpol.2018.11.039
- Zeng, B., He, C., Mao, C., and Wu, Y. (2023). Forecasting China's hydropower generation capacity using a novel grey combination optimization model. *Energy* 262, 125341. doi:10.1016/j.energy.2022.125341
- Zhang, B., Yan, X., Liu, G., and Fan, K. (2022). Multi-source fault diagnosis of chiller plant sensors based on an improved ensemble empirical mode decomposition Gaussian mixture model. *Energy Rep.* 8, 2831–2842. doi:10.1016/j.egy.2022.01.179
- Zhang, H., Li, W., Miao, P., Sun, B., and Kong, F. (2020a). Risk grade assessment of sudden water pollution based on analytic hierarchy process and fuzzy comprehensive evaluation. *Environ. Sci. Pollut. Res.* 27, 469–481. doi:10.1007/s11356-019-06517-9
- Zhang, H., Xiu, B., Jiang, D., Zhuang, G., Zhang, Y., and Li, B. (2023). An evaluation method of health condition for wind turbine based on asymmetric proximity. *Front. Energy Res.* 11, 1111355. doi:10.3389/fenrg.2023.1111355
- Zhang, S., Xiang, M., Xu, Z., Wang, L., and Zhang, C. (2020b). Evaluation of water cycle health status based on a cloud model. *J. Clean. Prod.* 245, 118850. doi:10.1016/j.jclepro.2019.118850
- Zheng, K., Han, L., Guo, S., Wang, Z., Zhang, X., and Dong, X. (2017). Fuzzy synthetic condition assessment of wind turbine based on combination weighting and cloud model. *J. Intelligent Fuzzy Syst.* 32 (6), 4563–4572. doi:10.3233/jifs-169220
- Zhu, L., Wu, Z., and Huang, S. (2023). Assessment method of distribution network health level based on multivariate information. *Front. Energy Res.* 11, 1178631. doi:10.3389/fenrg.2023.1178631