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Intelligent bridge monitoring system operational status assessment using analytic network-aided triangular intuitionistic fuzzy comprehensive model

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Abstract
The extensive construction of bridge health monitoring (BHM) systems has made it challenging for the authorities to manage them centrally. The reliable operational status of BHM systems is vital to obtaining accurate monitoring data and evaluating the condition of bridges. To evaluate the operational status of these systems, this study established an assessment model that integrates the triangular intuitionistic fuzzy analytic network process (TIFANP) and the triangular intuitionistic fuzzy comprehensive evaluation (TIFCE) method. Firstly, an evaluation index system was established for the operational status of a BHM system. Factors such as system stability, data reliability, system maintenance, early warning, and human-computer interaction were comprehensively considered. Secondly, the evaluation indicator weights were assigned using TIFANP. The system evaluation rating levels were divided into four grades, and the membership and non-membership functions of the evaluation indicators for these rating levels were constructed based on TIFCE. Finally, the effectiveness of the proposed method was verified based on a case study. This is the first time that an operational status assessment method suitable for in-service BHM systems has been proposed. The results show that the TIFANP better accounts for the relationships for non-independence and interactions among the evaluation indicators. Hesitations in the decision-making process were quantified, making the weight allocations more accurate. The proposed method outperforms other comparison methods and can be used to evaluate the operational status of BHM systems in a more scientific and objective manner.

Keywords: Bridge health monitoring, monitoring system operational status assessment, triangular intuitionistic fuzzy comprehensive evaluation, triangular intuitionistic fuzzy analytic network process

1. INTRODUCTION

1.1. Literature review

With the extension of service years, bridges inevitably suffer from performance deterioration under the coupling effects of environment and load[1,2]. The bridge health monitoring (BHM) system has been extensively established to ensure the security of bridges[3]. The functionalities of BHM systems have been progressively implemented[4], including real-time monitoring, intelligent early warning, and scientific assessment. Recently, the number of BHM systems has increased significantly, making it technically challenging for authorities to manage and evaluate the operational status of BHM systems. Due to long-term outdoor deployment, sensor failures[5], system instability[6], and abnormal monitoring data[7] can occasionally occur in BHM systems. Scholars have invested substantial energy into the assessment of bridge conditions based on BHM[8-10]; besides, the accuracy of bridge health diagnoses will be directly affected if the BHM system is suboptimal[11]. Therefore, the assessment of the BHM operational status has garnered increasing attention from bridge engineers and management authorities.

Relevant research on assessing the operational status of structural health monitoring (SHM) systems has been conducted[12-16]. At the acceptance stage, the reliability of BHM systems could be verified through consistency comparisons of the simulation and experimental data with the data of the BHM system. For example, Ye *et al.* evaluated the effectiveness of jacket platform SHM by comparing actual SHM data with finite element analysis simulation results[17]. Dal *et al.* analyzed the trends in dynamic and static data changes in a SHM system by applying external interventions to verify the reliability of the SHM system data[18]. Janapati *et al.* examined the effectiveness of acoustic SHM techniques for damage detection using both numerical calculations and experimental data[19]. These studies mainly focused on the effectiveness of the initial stage of system construction, neglecting the impact of long-term service on system operation. The operational status of the BHM system evolves progressively with the extension of its service life. To evaluate the operational status of a BHM system in service, Li *et al.* proposed a sensor fault detection method to diagnose of multiple sensor faults by using the relationship between the generalized likelihood ratio and the correlation coefficient[20]. Fan *et al.* introduced a method for the accurate classification and localization of anomaly monitoring data based on a convolutional neural network[21]. Li *et al.* developed a sensor anomaly signal detection method based on a two-segment deep convolutional neural network improving the recognition accuracy of abnormal signal patterns in a BHM system[22]. The aforementioned studies emphasized operational status diagnosis and abnormal sensor data detection. The evaluation perspective has been relatively singular and lacks a comprehensive consideration of the operational status of BHM systems.

With the extends of service life of the BHM system, environmental factors and load variations will lead to a decrease in sensor online rate, performance degradation of system, increased failure rate, and more frequent maintenance demands. The management demands of BHM systems cannot be adequately addressed merely through foundational validity assessments at implementation stage and runtime abnormal data detection.

Regarding the comprehensive evaluation of BHM systems during the process of long-term operation, Xin *et al.* developed a BHM evaluation model based on the Delphi, analytic hierarchy process (AHP), Grey relations analysis and Fuzzy integrated evaluation (DHGF) method to assess the performance of new BHM systems[23]. The model considers indicators related to the design, construction process, operation, and maintenance of BHM systems were considered. However, it is not fully applicable to BHM systems in long-term operation; additionally, it does not account for the non-independence of the evaluation index and the fuzzy information in the decision-making process. In summary, the operational status of in-service BHM systems is seldom reported, and there is an urgent need to establish a comprehensive evaluation model for the operational status of BHM systems.

The operational status of BHM systems is a multi-criterion comprehensive evaluation problem. However, interdependence and domination relationships often arise among the evaluation indicators during the system assessment process. Additionally, hesitation frequently occurs when distributing indicator weights, making it difficult to obtain definitive results[24,25]. To address this problem, Zhang *et al.* allocated indicator weights based on the triangular intuitionistic fuzzy analytic network process (TIFANP) and constructed a comparison matrix based on triangular intuitionistic fuzzy numbers (TIFNs), where the interactions among indicators were considered[26]. Through the interval from the lower limit (the most probable value) to the upper limit, fuzzy opinions in the decision-making process are more precisely described by TIFNs; this allows for a comprehensive consideration of actual attributes of each indicator; the logical relationships among multiple evaluation indicators, and their mutual influence can be comprehensively considered[27]. In addition, due to the strong ambiguity of some evaluation indicators, it is difficult to express them with accurate numerical values while quantifying the influence degree of each indicator on the evaluation grade; therefore, some differences exist between the opinions in the decision-making process and the actual situation. Pertinently, Zhang *et al.* proposed the triangular intuitionistic fuzzy comprehensive evaluation (TIFCE) model to quantify the influence of each indicator across different levels; this model uses membership and non-membership functions to describe ambiguous information in the decision-making process[26]. It represents not only the extent to which an element belongs to a set, but also considers the extent to which an element does not belong to a set due to subtle deviations in decision-making opinions; thus, the deviation of decision-making opinions caused by the ambiguous information of non-quantitative indicators is quantified. Hesitation and opinion deviations in the decision-making process of system assessment can be effectively addressed using the TIFANP and TIFCE models. Due to their improved performance, these models have been widely applied in tank floor corrosion assessments and marine supply chain management[24,28]. However, they have rarely been reported in the domain of BHM system operational status evaluation.

1.2. Contribution

Due to the aforementioned engineering requirements and the limitations of existing methods, this paper proposes a novel operational status assessment model for BHM systems. The model combines the TIFANP and TIFCE methods. Firstly, a three-layer comprehensive evaluation index system was established to assess the core elements of the system's operational status. Secondly, the logical relationships and mutual influences among the evaluation indicators were analyzed, and the index weights, reflecting the actual attributes, were assigned using TIFANP. Then, a calculation method for quantitative evaluation indicators was proposed, along with a linguistic evaluation term for qualitative indicators. Finally, the membership and non-membership functions of each evaluation indicator were constructed for the evaluation rating level. The final assessment results were obtained through comprehensive qualitative and quantitative analysis based on TIFCE. The main contributions of this paper in comparison with the extant literature are summarized as follows:

(1) This is the first time a hierarchical index system and evaluation criteria have been proposed for the operational status assessment of BHM systems. The system effectiveness, maintenance, early warning, and the convenience of human-computer interaction design were all considered. Quantitative calculation methods are proposed for key indicators, while other indicators that cannot be quantitatively analyzed are expressed using linguistic terms. The established index system is meticulous and accurate, scientific, comprehensive, and operable. It effectively reflects the operational status of BHM systems.

(2) The TIFANP was used to address the logical relationships and mutual influences among the evaluation indicators. Hesitation in the decision-making process was considered when assigning the weights of each indicator. TIFCE was employed to construct the membership functions. Differences between the decision opinion and the actual situation caused by the difficulty of quantifying calculation in the decision-making process, were expressed in the form of non-membership functions. The integration of TIFANP and TIFCE quantifies differences due to hesitation, deviation, and uncertainty in the decision-making process. It also resolves the problem of converting linguistic terms to TIFNs and exact values is solved when information is lacking for decision-making.

This paper is organized as follows. Section 2 presents the theoretical background of this paper. Section 3 presents the construction of the indicators for operational status evaluation of BHM system and introduces the specific process of the proposed method. Specific case study is shown in Section 4. A comparative analysis is presented in Section 5, and conclusions are drawn in Section 6.

2. THEORETICAL BACKGROUND

2.1. TIFNs

TIFNs are complex intuitionistic fuzzy numbers that have the advantages of both triangular fuzzy numbers and intuitionistic fuzzy sets; they effectively handle the correlations and uncertainties between attributes. Approximating complex fuzzy information with simple rule forms, at the same time, the core characteristics of the information are preserved. It provides more accurate solutions for complex decision-making problems. In this way, multi-attribute evaluation problems with more ambiguity can be well resolved.

Assuming that domain X is a non-empty set, the TIFN A on X can be expressed as:

$$A = \left\langle [(a,b,c);\mu_A],[(a',b,c'),\nu_A] \right\rangle \tag{1}$$

where $\mu_A(x)$ and $\nu_A(x)$ are the membership and non-membership functions of element x in domain X, respectively, which belongs to A. $\mu_A(x)$ and $\nu_A(x)$ satisfy $\mu_A(x)$: $X \rightarrow [0, 1]$, $x \in X \rightarrow \mu_A(x) \in [0, 1]$, $\nu_A(x)$: $X \rightarrow [0, 1]$, $x \in X \rightarrow \nu_A(x) \in [0, 1]$, and $x \in X$, $0 \leq \mu_A(x) + \nu_A(x) \leq 1$. $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$ denotes the hesitancy degree of element x belonging to A. $0 \leq \pi_A(x) \leq 1$ for any x.

The membership functions can be expressed as[29]:

$$\mu_A(x) = \begin{cases} \dfrac{\mu(x-a)}{b-a}, & a \leq x \leq b \\ \mu\,, & x=b \\ \dfrac{\mu(c-x)}{c-b}, & b \leq x \leq c \\ 0, & x<a', x>c' \end{cases} \tag{2}$$

Non-membership functions can be expressed as[29]:

$$\nu_A(x)=\begin{cases}\dfrac{b-x+\nu(x-a)}{b-a}, & a\le x\le b\\ \nu, & x=b\\ \dfrac{x-b+\nu(c-x)}{c-b}, & b\le x\le c\\ 1, & x<a',x>c'\end{cases} \tag{3}$$

where μ is the maximum membership degree and ν is the minimum non-membership degree of set A, respectively.

In this paper, the centroid method was adopted to defuzzify the TIFNs. If μ = 1 and ν = 0 (i.e., A = [(a, b, c), (a', b, c')]), its crisp values can be calculated as[30,31]:

$$\overline{X}=\frac{(c'-a')(c'+a'+b)+(c-a)(c+a+b)}{3(c'-a')+3(c-a)} \tag{4}$$

2.2. TIFANP

As an extension of triangular intuitionistic fuzzy set theory, TIFANP offers a systematic approach to handle complex network structures characterized by element interdependencies. The relative influence degree (RID) of each indicator is determined through the indirect dominance degree, and the cluster comparison matrix and indicator comparison matrix are established. The logical relationships among indicators and their degree of mutual influence are taken into account in the TIFANP, meanwhile, TIFNs are used instead of the normal 1-9 scale to represent the RID and participating in the calculation of eigenvectors. The typical structure of the TIFANP is shown in Figure 1.

2.3. TIFCE

TIFCE has the ability to evaluate multiple attributes of FCE. It replaces the fuzzy set with a triangular intuitionistic fuzzy set, and the uncertainty in the decision-making process is expressed in the form of non-membership functions. Membership functions and non-membership functions are essential tools for TIFCE to handling fuzzy information. Membership functions describe the degree to which an element belongs to a fuzzy set; their range is between 0 and 1, representing a continuous transition from “completely not belonging” to “completely belonging”. Non-membership functions, on the other hand, describe the degree to which an element does not belong to a fuzzy set. Similar to membership functions, their values range from 0 to 1, indicating a transition from “completely belonging” to “completely not belonging”. Therefore, TIFCE can more effectively quantify the assessment results[32].

3. CONSTRUCTION OF TIFANP-TIFCE MODEL

3.1. Overview of the proposed method

The flowchart of the proposed operational status evaluation method of BHM systems is shown in Figure 2. Firstly, the critical factors for evaluating the operational status of the BHM system are determined, and the hierarchical index system and indicator set of the BHM operational status are established. Secondly, the degrees of interaction among the indicators are defined, and the weights of the indicators are determined using the TIFANP. Then, the membership and non-membership functions are constructed between each indicator and the evaluation target using TIFCE. Finally, the final operational status evaluation grade of the BHM system is obtained through the comprehensive weight and evaluation matrix.

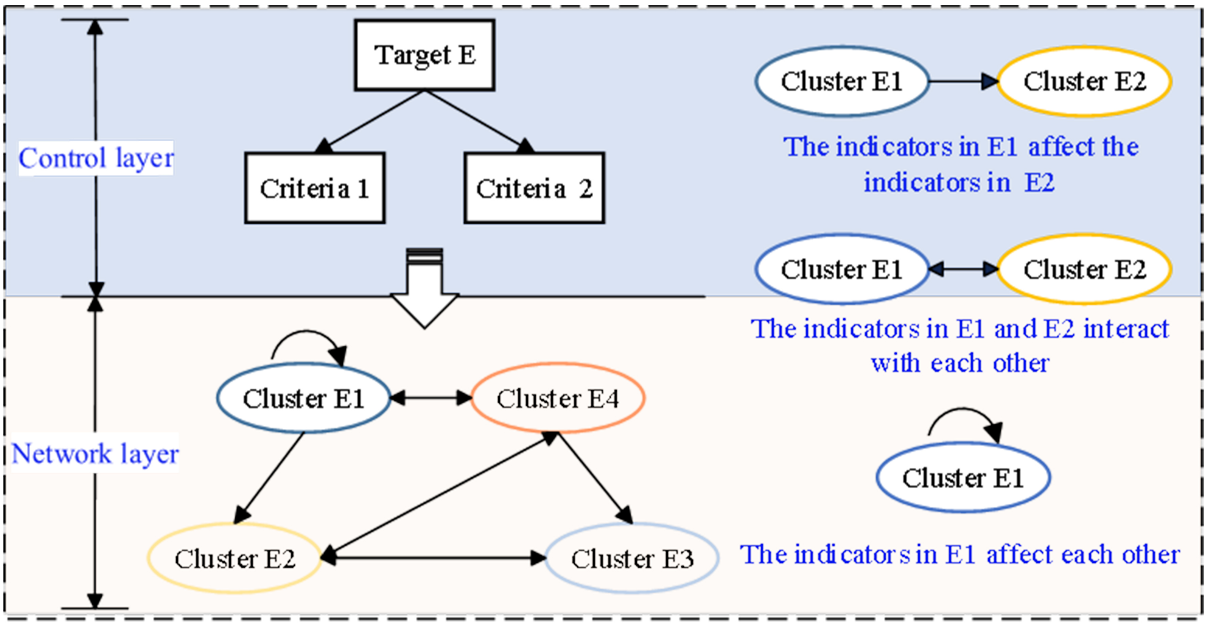

Figure 1. Typical structure of TIFANP. TIFANP: Triangular intuitionistic fuzzy analytic network process.

3.2. Construction of the index system

First, based on the principles of scientific rigor, comprehensiveness, and feasibility, identify the factors influencing the operational state of the BHM system.

From the perspective of designers, real-time performance, continuity, and accuracy are expected of a BHM system; these can be reflected through indicators of mean no-failure rate, sensors online rate, data accuracy, data integrity and data consistency[33]. From the perspective of managers, a BHM system is expected to accurately predict structural abnormalities, making threshold settings and accuracy of early warnings as suitable evaluation indicators[34]. Additionally, system maintenance plays a crucial role in ensuring the functionality of system, leading to the selection of timeliness of troubleshooting, timeliness of alarm confirmation and timeliness of report uploads as another evaluation indicator[35]. From the perspective of users, the smoothness of system operation plays a critical role in judgment during warning events. Therefore, interface layout, operational response time has been chosen as an evaluation criterion[36].

Subsequently, a hierarchical indicator system was established, as illustrated in Figure 3.

As shown in Figure 3, each cluster $E_i = (E_1, E_2, \ldots, E_n)$ contains several nodes E_{ik}, and all the indicators ultimately make up the indicator set. In the proposed hierarchical evaluation index system, the factors influencing the operational status of the system are considered in four categories: system effectiveness, system maintenance, early warning and human-computer interaction.

3.3. Allocation of relative weights

Each evaluation indicator has a distinct degree of influence on the system operational status; therefore, an accurate weight is assigned to each indicator.

Step 1: Establish an analytical network structure.
Utilizing the predefined indicator sets, consider the interactions among elements in a complex system, and analyze the relationships between different clusters and each indicator within each cluster[37].

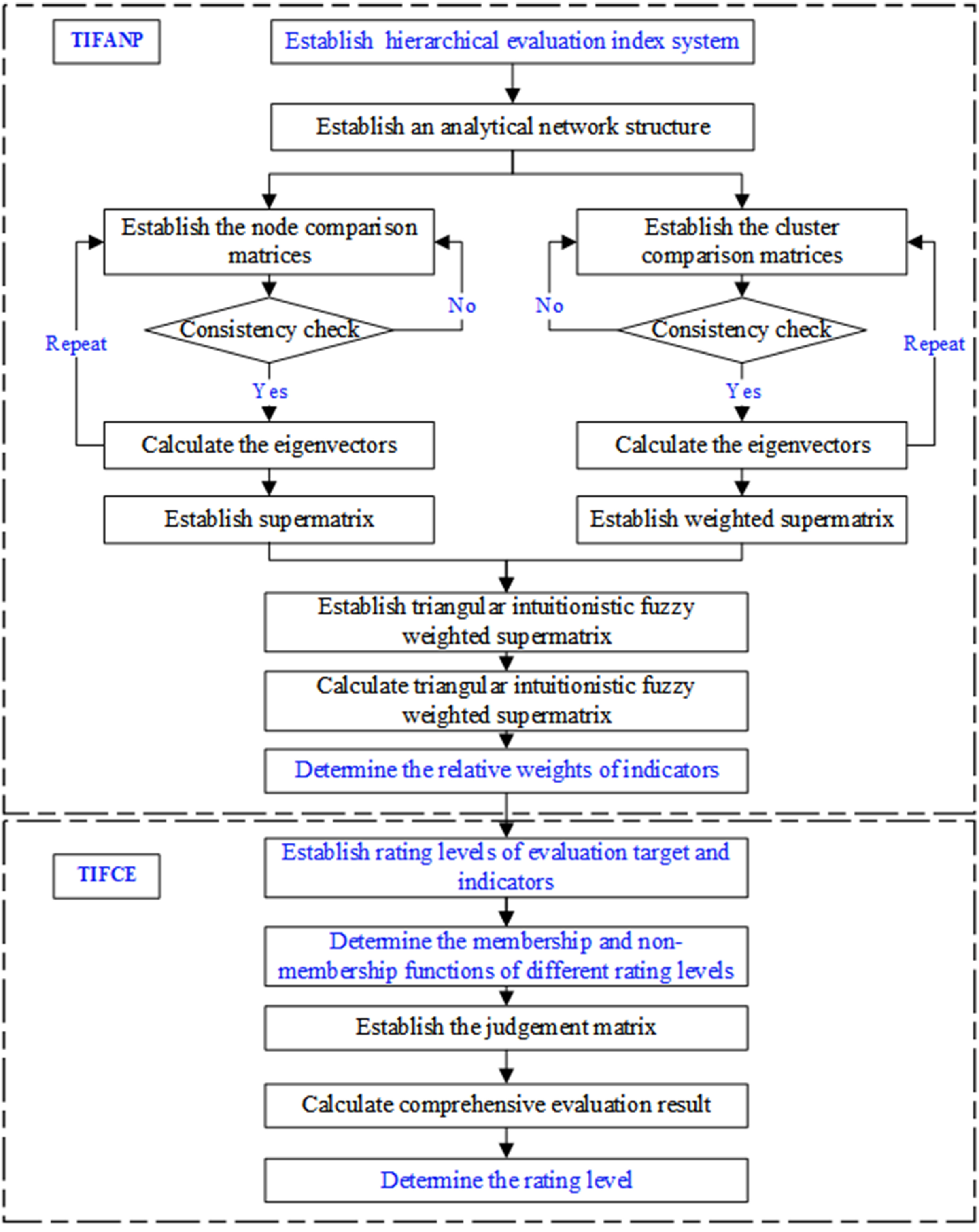

Figure 2. The holistic structure of the proposed method.

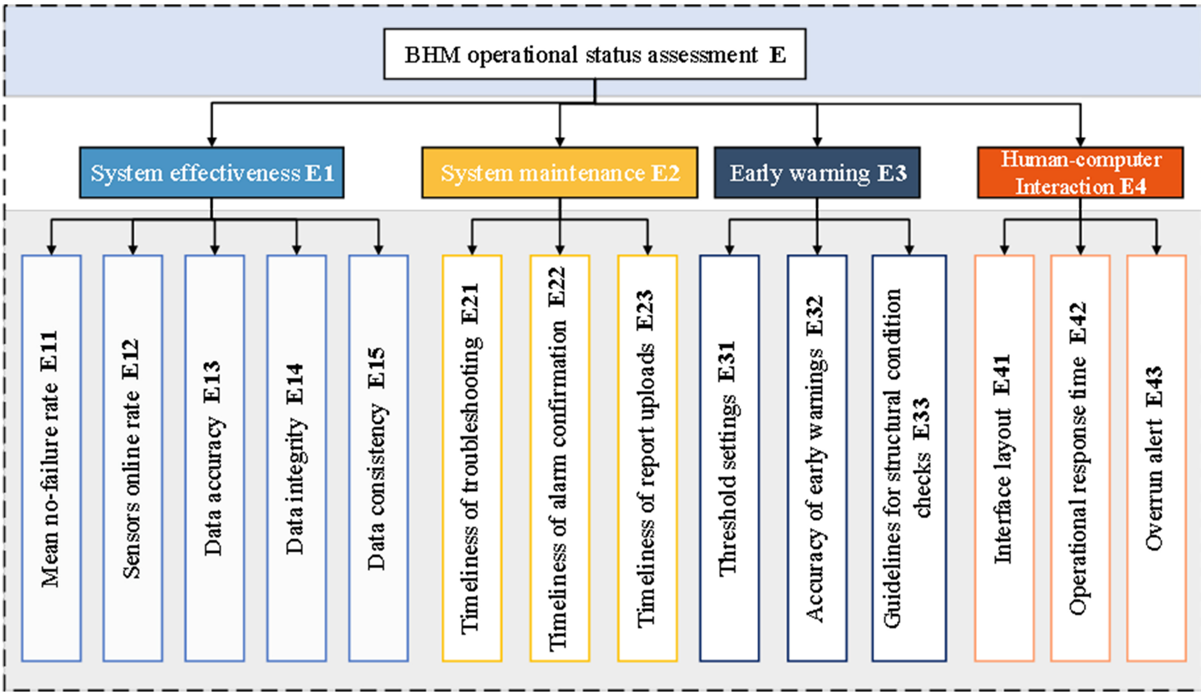

Figure 3. Hierarchical evaluation index system of BHM operational status. BHM: Bridge health monitoring.

Step 2: Establish a triangular intuitionistic fuzzy comparison matrix.
In this study, TIFNs are utilized to represent the RIDs in place of conventional precise numerical values. For example, "essential or strong importance" can be expressed as $\left\langle [(5 - \Delta\mu, 5, 5 + \Delta\mu); \mu], [(5 - \Delta\nu, 5, 5 + \Delta\nu); \nu] \right\rangle$, where $\Delta\mu$ and $\Delta\nu$ are termed the fuzzy factors corresponding to the degrees of membership and non-membership, respectively. To simplify the calculation, let $\mu = 1$, $\nu = 0$, $\Delta\mu = 1$, $\Delta\nu = 1.5$. Table 1 presents the linguistic scales and their associated TIFNs used to describe the RID.

Table 2 illustrates the cluster comparison matrix and the node comparison matrix, which is derived from the analysis of indirect dominance relationships.

According to Equation (4), all of the w_{ik} values are clarified into a clear set of values $w_{ij}^{'}$, and all of the $w_{ij}^{'}$ values can be calculated as follows:

$$W_{ij} = \begin{bmatrix} w_{i1}^{(j1)} & \cdots & w_{i1}^{(jl)} \\ \cdots & \cdots & \cdots \\ w_{il}^{(j1)} & \cdots & w_{il}^{(jl)} \end{bmatrix} \tag{5}$$

where the column vectors of W_{ij} are the vectors of the RID of $E_{i1}, E_{i2}, \ldots, E_{il}$ in the E_i relative to $E_{j1}, E_{j2}, \ldots, E_{jl}$ in E_j. If there is no influence, $W_{ij} = 0$.

Step 3: Consistency check.
To avoid logical mistakes in the judgment matrix and achieve a higher level of reliability of the model, it is necessary to perform a consistency check of the judgment matrix.

Table 1. Linguistic scales and their corresponding TIFNs to describe the relative importance degree between two indicators

Importance degree	Scale	TIFN
Equal importance	1	[(1, 1, 2), (1, 1, 2.5)]
Weak importance	3	[(2, 3, 4), (1.5, 3, 4.5)]
Essential or strong importance	5	[(4, 5, 6), (3.5, 5, 6.5)]
Demonstrated importance	7	[(6, 7, 8), (5.5, 7, 8.5)]
Extreme importance	9	[(8, 9, 9), (7.5, 9, 9)]
Intermediate value between two adjacent comparisons	2, 4, 6, 8	[(1, 2, 3), (1, 2, 3.5)], [(3, 4, 5), (2.5, 4, 5.5)], [(5, 6, 7), (4.5, 6, 7.5)], [(7, 8, 9), (6.5, 8, 9)]
Reciprocals	-	If the importance of A relative to B is $[(a, b, c), (a', b, c')]$, then B relative to A is $[(\frac{1}{c}, \frac{1}{b}, \frac{1}{a}), (\frac{1}{c'}, \frac{1}{b}, \frac{1}{a'})]$

TIFNs: Triangular intuitionistic fuzzy numbers.

Table 2. Node comparison matrix

D_{jk}	$D_{i1}D_{i2}...D_{il}$	Normalized eigenvectors
D_{i1}	$I_{11}I_{12}...I_{1l}$	$w_{i1}^{(jk)}$
D_{i2}	$I_{21}I_{22}...I_{2l}$	$w_{i2}^{(jk)}$
$\vdots$	$\vdots$	$\vdots$
D_{il}	$I_{i1}I_{i2}...I_{il}$	$w_{il}^{(jk)}$

The consistency index can be calculated by

$$CI = \frac{\lambda_{\max} - n}{n-1}$$

where $\lambda_{\max}$ is the maximum eigenvalue of the judgment matrix, n is the order of the matrix.

Then, the consistency ratio can be calculated as

$$CR = \frac{CI}{RI}.$$

where RI represents the random index, which has a unique value determined by the order of judgment matrix[18]. If RI is less than 0.1, the judgment matrix could be considered to have satisfactory consistency.

Step 4: Establish a weighted supermatrix.
The supermatrix S can be constituted by all W_{ij}:

$$S = \begin{bmatrix} W_{11} & \cdots & W_{1j} \\ \vdots & \ddots & \vdots \\ W_{i1} & \cdots & W_{ij} \end{bmatrix} \tag{6}$$

Similarly, the weighted supermatrix A_W can be constituted by all the eigenvectors a_{ij}:

$$A_W = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \tag{7}$$

The weighted supermatrix can be calculated by

$$\overline{S} = \sum_{i=1}^{m} \sum_{j=1}^{m} a_{ij} W_{ij} \tag{8}$$

Step 5: Calculate the limit supermatrix.
Through limit processing of the weighted supermatrix, the resultant steady-state matrix $\overline{S}^{\infty}$ (limit supermatrix) can be derived as follows:

$$\overline{S}^{\infty} = \lim_{N \to \infty} \left(\frac{1}{N} \right) \sum_{k=1}^{n} \overline{S}^{k} \tag{9}$$

Step 6: Determine the relative weight of each indicator.
The column vectors of a limit supermatrix represent the final relative weight vectors of the indicators.

3.4. Establishment of the rating levels

The E_{ik} obtained in Section 3.2 constitutes a set of indicators. For ease of calculation, the indicator set can be recorded as $e = \{e_1, e_2, \ldots, e_n\}$, and the value of each indicator can be denoted as a number in the range [1-100] for the purpose of assessment.

The set of rating levels contains all the possible assessment results for the operational status of the BHM system. In this study, a 4-level TIFN was used to classify the system rating levels, i.e., $Y = (y_1, y_2, y_3, y_4)$. Similar to the TIFANP where $\mu = 1$ and $\nu = 0$, $\Delta\mu = 5$ and $\Delta\nu = 10$ in TIFCE. The rating levels of the BHM system operational status are divided into I, II, III, and IV, i.e., $V = (90, 75, 60, 20)^T$. The system evaluation level divisions and the corresponding TIFNs are shown in Table 3.

3.5. Establishment of the membership and non-membership functions

The membership and non-membership functions of the index are established for each rating level are shown in Figure 4. Specifically, $\mu(x)$ shows the membership function, while $\nu(x)$ illustrates the corresponding non-membership function. Figure 4 presents the relationship between the membership and non-membership degrees as the indicator scores change across different levels.

3.6. Comprehensive evaluation results

Assume that all the values of indicators are $(x_1, x_2, \ldots, x_n)$. According to the membership and non-membership functions of each indicator and rating level, the judgment matrix can be expressed as follows:

$$R = (\mathrm{r_{ij}})_{mn} = \begin{bmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & \ddots & \vdots \\ r_{n1} & \cdots & r_{nm} \end{bmatrix} = \begin{bmatrix} (\mu_{11}, \nu_{11}) & \cdots & (\mu_{1m}, \nu_{1m}) \\ \vdots & \ddots & \vdots \\ (\mu_{n1}, \nu_{n1}) & \cdots & (\mu_{nm}, \nu_{nm}) \end{bmatrix} \tag{10}$$

where r_{ij} represents the value x_i of indicator e_i for the membership and non-membership functions of rating level y_i.

Table 3. The linguistic terms and corresponding TIFNs of the operational status of BHM systems

Evaluation level	Linguistic term	Score level	TIFN
I	Excellent	[90, 100]	[(85, 90, 95), (80, 90, 100)]
II	Good	[75, 90]	[(70, 75, 80), (65, 75, 90)]
III	Fair	[60, 75]	[(55, 60, 65), (50, 60, 70)]
IV	Poor	[20, 60]	[(15, 20, 25), (10, 20, 30)]

Level I: excellent. The BHM system is operating in optimal condition, requiring only regular routine checks. Level II: good. The BHM system is operating effectively, but there may be potential risks. Occasional specialized inspections are recommended. Level III: Fair. The performance of the BHM system is suboptimal; specialized inspections should be conducted. Level IV: Poor. The BHM system has significant issues and fails to provide effective monitoring. A major overhaul is necessary. TIFNs: Triangular intuitionistic fuzzy numbers; BHM: bridge health monitoring.

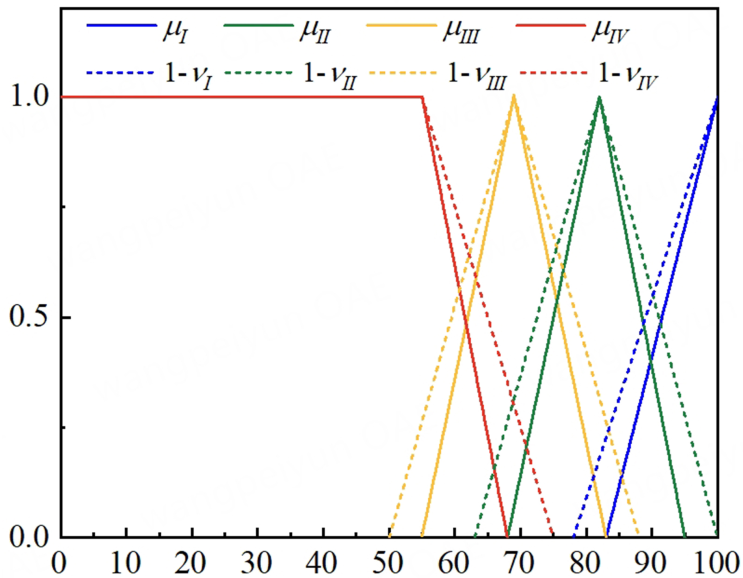

Figure 4. Membership and non-membership functions of each rating level.

The results of the comprehensive assessment can be calculated as follows:

$$B = T(X, R) = XR = \left[\left(b_1^{\mu}, b_1^{\nu}\right)\left(b_j^{\mu}, b_j^{\nu}\right)\left(b_m^{\mu}, b_m^{\nu}\right)\right] \tag{11}$$

$$\left(b_j^{\mu}, b_j^{\nu}\right) = \left(\sum_{i=1}^{n}\left(W^i \bullet \mu_{ij}\right), \sum_{i=1}^{n}\left(W^i \bullet \nu_{ij}\right)\right), j = 1, 2, .., m \tag{12}$$

where W^i is the relative weight of the indicator. According to the principle of maximum membership, the comprehensive evaluation result is b_j^{μ}, $j = 1, 2, \ldots, m$, and the corresponding evaluation grade is y_j.

To facilitate comparison, a crisp value of TIFCE can be converted from the calculation result as follows:

$$TIZ = \frac{\sum_{j=1}^{m}\left(b_j^{\mu} \bullet V_j\right)}{\sum_{j=1}^{m} b_j^{\mu}} = \left[\left(a_{TIZ}, b_{TIZ}, c_{TIZ}\right), \left(a'_{TIZ}, b'_{TIZ}, c'_{TIZ}\right)\right] \tag{13}$$

$$Z=\frac{\left(c_{TIZ}^{'}-a_{TIZ}^{'}\right)\left(c_{TIZ}^{'}+a_{TIZ}^{'}+b_{TIZ}^{'}\right)+\left(c_{TIZ}-a_{TIZ}\right)\left(c_{TIZ}+a_{TIZ}+b_{TIZ}\right)}{3\left(c_{TIZ}^{'}-a_{TIZ}^{'}\right)\left(c_{TIZ}-a_{TIZ}\right)} \tag{14}$$

where TIZ is the score of the operational status of the BHM system expressed by a TIFN, Z is the score of the operating status of the BHM system after TIFN deblurring, and V_j is the TIFN of the system rating level j.

4. CASE STUDY

The operational status of the BHM system plays a vital role in the subsequent structural status assessment. In this section, a specific model is constructed using the proposed method for the operational status evaluation of BHM systems.

4.1. Background of a cable-stayed BHM system

The analysis focused on a BHM system of cable-stayed bridges with a total span length of 1,001 meters. The BHM system integrates a network of 288 measurement points, which capture various parameters including environmental temperature, humidity, vehicle load, *etc.* The arrangement of measurement points is illustrated in Figure 5.

4.2. Comprehensive evaluation

4.2.1. Analytical network structure of the index system

According to the hierarchical evaluation index system constructed in Section 3.2, the hierarchical evaluation index system of the operational status of BHM systems was divided into four clusters, and the interactions among the indicators were further analyzed. Taking the mean no-failure rate as an example, the mean no-failure rate of the system affects the sensors online rate, data integrity, and other indicators; it is also affected by the timeliness of troubleshooting indicator. Table 4 shows the relationships among the influencing indicators. According to the data in Table 4, a network analysis structure of the BHM system's operational status was constructed, as shown in Figure 6.

4.2.2. Allocate the relative weights of indicators

A comparison matrix was systematically developed for each cluster and corresponding node. As an example, the comparison matrix for the cluster of E_1 is shown in Table 5. The Supplementary Materials provides comprehensive details of the comparison matrix for both cluster and node, enabling a thorough examination of the respective datasets.

After the consistency check, a TIFANP weighted matrix was constructed using the eigenvalues calculated from each judgment matrix, as shown in Table 6.

Using Equations (5) and (6), the TIFANP supermatrix, weighted supermatrix, and limit supermatrix were calculated. The supermatrix was constructed using all of the node comparison matrices, as shown in Table 7.

The stable limit-weighted supermatrix was calculated using Equation (9), as shown in Table 8. The weighted supermatrix of the TIFANP model can be found in the Supplementary Materials.

Table 4. The influencing relationships among indicators

Assessment indicators	Influenced indicators
E_{11}	E_{12}, E_{14}, E_{32}, E_{33}
E_{12}	E_{11}, E_{12}, E_{22}, E_{23}
E_{13}	E_{14}, E_{15}, E_{31}, E_{32}, E_{41}, E_{43}
E_{14}	E_{11}, E_{13}, E_{21}, E_{23}, E_{32}, E_{33}
E_{15}	E_{11}, E_{13}, E_{31}, E_{32}
E_{21}	E_{11}, E_{12}, E_{13}, E_{14}, E_{15}, E_{32}, E_{33}, E_{41}
E_{22}	E_{21}, E_{23}, E_{31}, E_{33}
E_{23}	E_{21}, E_{22}, E_{31}, E_{32}, E_{43}
E_{31}	E_{13}, E_{15}, E_{22}, E_{23}, E_{32}, E_{33}
E_{32}	E_{14}, E_{15}, E_{21}, E_{22}
E_{33}	E_{41}, E_{43}
E_{41}	E_{42}, E_{43}
E_{42}	E_{32}, E_{33}
E_{43}	E_{22}, E_{23}

Table 5. Cluster comparison matrix of E_1

E_1	E_1	E_2	E_3	E_4
E_1	[(1, 1, 2)(1, 1, 2.5)]	[(1, 1, 2)(1, 1, 2.5)]	[(1, 2, 3)(1, 2, 3.5)]	[(1, 2, 3)(1, 2, 3.5)]
E_2	$[(\frac{1}{3}, \frac{1}{2}, 1)(\frac{1}{3.5}, \frac{1}{2}, 1)]$	[(1, 1, 2)(1, 1, 2.5)]	$[(\frac{1}{3}, \frac{1}{2}, 1)(\frac{1}{3.5}, \frac{1}{2}, 1)]$	$[(\frac{1}{3}, \frac{1}{2}, 1)(\frac{1}{3.5}, \frac{1}{2}, 1)]$
E_3	$[(\frac{1}{3}, \frac{1}{2}, 1)(\frac{1}{3.5}, \frac{1}{2}, 1)]$	[(1, 2, 3)(1, 2, 3.5)]	[(1, 1, 2)(1, 1, 2.5)]	[(1, 1, 2)(1, 1, 2.5)]
E_4	$[(\frac{1}{3}, \frac{1}{2}, 1)(\frac{1}{3.5}, \frac{1}{2}, 1)]$	[(1, 2, 3)(1, 2, 3.5)]	[(1, 1, 2)(1, 1, 2.5)]	[(1, 1, 2)(1, 1, 2.5)]

Table 6. The weighted matrix of the TIFANP model

	E_1	E_2	E_3	E_4
E_1	0.3264	0.1934	0.2400	0.2400
E_2	0.2863	0.2863	0.2863	0.1412
E_3	0.2251	0.1081	0.2993	0.2592
E_4	0	0.4612	0.2694	0.2694

TIFANP: Triangular intuitionistic fuzzy analytic network process.

The normalized weight distribution of BHM system operational status indicators is represented by the column vectors derived from the limit supermatrix, as depicted in Figure 7. The weight of the data accuracy indicator is higher than that of the other indicators because the accuracy of the system data is affected by more indicators and also directly affects more other indicators, so a higher proportion was assigned.

Keep the influence relationships in Table 4 unchanged, and increase the influence level by one degree (e.g., changing “Weak importance” to “Essential” or “Strong importance”). The resulting limit supermatrix is provided in the Supplementary Materials. As a result, the disparity between the higher and lower weights increases, demonstrating that the computed weights are affected by the degree of importance assigned to the criteria. Specifically, as the influence level of an indicator rises, its corresponding computed weight becomes larger. Therefore, selecting an appropriate influence level is crucial for obtaining reasonable weights.

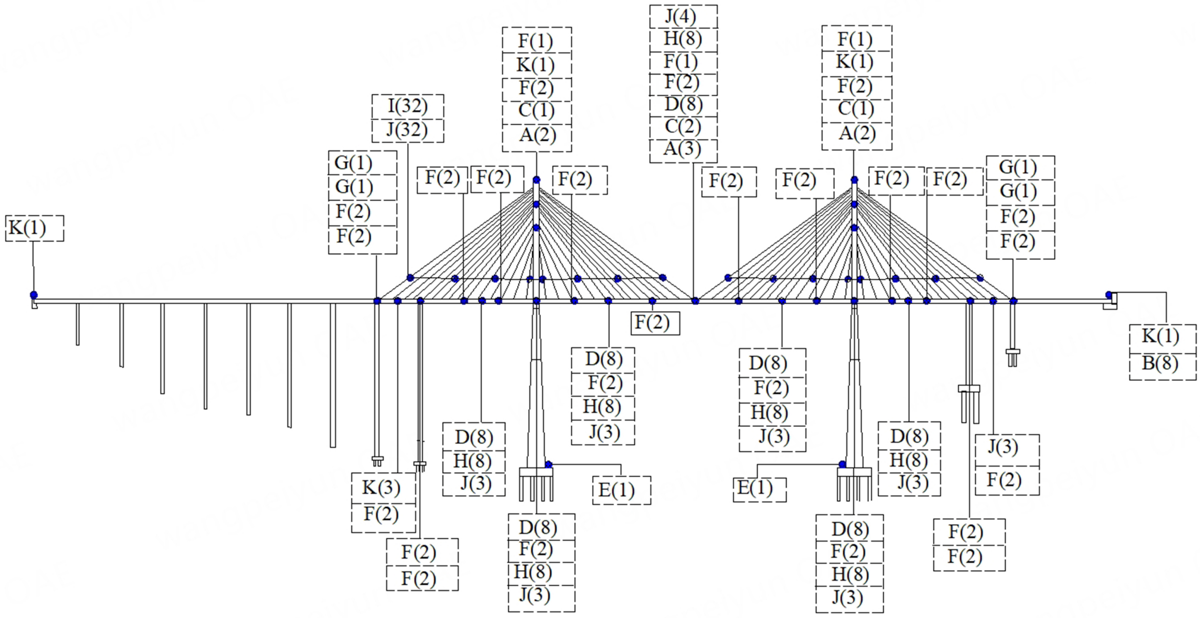

Figure 5. Longitudinal layout of the bridge measuring points of a long-span cable-stayed bridge. Note: the number of sensors is given in parentheses: (A) Ambient temperature and humidity; (B) Vehicle load; (C) Wind load; (D) Structural temperature; (E) Earthquake; (F) Displacement; (G) Angle of rotation; (H) Strain; (I) Cable tension; (J) Vibration; (K) Video.

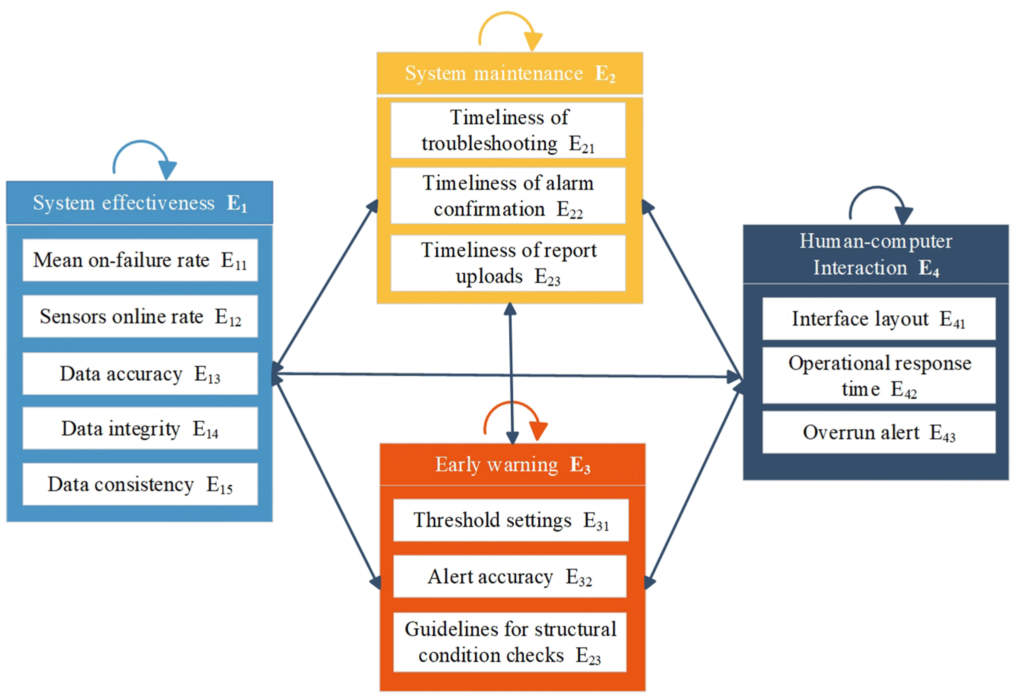

Figure 6. Network analysis structure diagram of BHM system operational status. BHM: Bridge health monitoring.

4.2.3. Establish the rating levels

In this paper, evaluation criteria for each index are proposed, as shown in Table 9; the calculation methods for quantitative indicators are synchronously defined:

Table 7. The supermatrix of the TIFANP model

	E_{11}	E_{12}	E_{13}	E_{14}	E_{15}	E_{21}	E_{22}	E_{23}	E_{31}	E_{32}	E_{33}	E_{41}	E_{42}	E_{43}
E_{11}	0.000	0.500	0.000	0.500	0.000	0.000	0.000	0.000	0.000	0.647	0.353	0.000	0.000	0.000
E_{12}	0.353	0.647	0.000	0.000	0.000	0.000	0.353	0.647	0.000	0.000	0.000	0.000	0.000	0.000
E_{13}	0.000	0.000	0.000	0.353	0.647	0.000	0.000	0.000	0.737	0.263	0.000	0.263	0.000	0.737
E_{14}	0.647	0.000	0.353	0.000	0.000	0.263	0.000	0.737	0.000	0.737	0.263	0.000	0.000	0.000
E_{15}	0.647	0.000	0.000	0.353	0.000	0.000	0.000	0.000	0.737	0.263	0.000	0.000	0.000	0.000
E_{21}	0.185	0.133	0.271	0.271	0.133	0.000	0.000	0.000	0.000	0.737	0.263	0.000	0.000	0.000
E_{22}	0.000	0.000	0.000	0.000	0.000	0.353	0.000	0.647	0.647	0.000	0.353	0.000	0.000	0.000
E_{23}	0.000	0.000	0.000	0.000	0.000	0.647	0.353	0.000	0.353	0.647	0.000	0.000	0.000	0.000
E_{31}	0.000	0.000	0.353	0.000	0.647	0.000	0.353	0.647	0.000	0.789	0.211	0.000	0.000	0.000
E_{32}	0.000	0.000	0.000	0.647	0.353	0.353	0.647	0.000	0.000	0.000	0.000	0.000	0.000	0.000
E_{33}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.647	0.000	0.353
E_{41}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.353	0.647
E_{42}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.353	0.647	0.000	0.000	0.000
E_{43}	0.000	0.000	0.000	0.000	0.000	0.000	0.789	0.211	0.000	0.000	0.000	0.000	0.000	0.000

TIFANP: Triangular intuitionistic fuzzy analytic network process.

(1) Average no-failure rate

The average no-failure rate can be defined as

$$P_1 = \frac{\sum_{i=1}^{n} t_i}{\sum_{i=1}^{n} r_i}$$

where t_i is the normal working time of the unit i, r_i is the abnormal working time of the unit i, and n is the total number of units in the data acquisition.

(2) Sensors online rate

The sensors online rate can be defined as

Table 8. The limit supermatrix of the TIFANP model

	E_{11}	E_{12}	E_{13}	E_{14}	E_{15}	E_{21}	E_{22}	E_{23}	E_{31}	E_{32}	E_{33}	E_{41}	E_{42}	E_{43}
E_{11}	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
E_{12}	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079
E_{13}	0.116	0.116	0.116	0.116	0.116	0.116	0.116	0.116	0.116	0.116	0.116	0.116	0.116	0.116
E_{14}	0.118	0.118	0.118	0.118	0.118	0.118	0.118	0.118	0.118	0.118	0.118	0.118	0.118	0.118
E_{15}	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
E_{21}	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084
E_{22}	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078
E_{23}	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
E_{31}	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087
E_{32}	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058
E_{33}	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040
E_{41}	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039
E_{42}	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017
E_{43}	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056

TIFANP: Triangular intuitionistic fuzzy analytic network process.

$$P_2 = \sum_{i=1}^{n} (1 - \frac{t_i}{T}) \times 100\%$$

(3) Data integrity

The data integrity is calculated as follows:

$$P_3 = \left(1 - \frac{\sum_{i=1}^{p} t_i}{P \times T} \right) \times 100\%$$

where P_3 represents the rate of data integrity, p represents the count of faulty measurement points, t_i denotes the duration of failure for the i-th measurement point (in terms of days), P stands for the total number of measurement points, and T indicates the evaluation period (in terms of days).

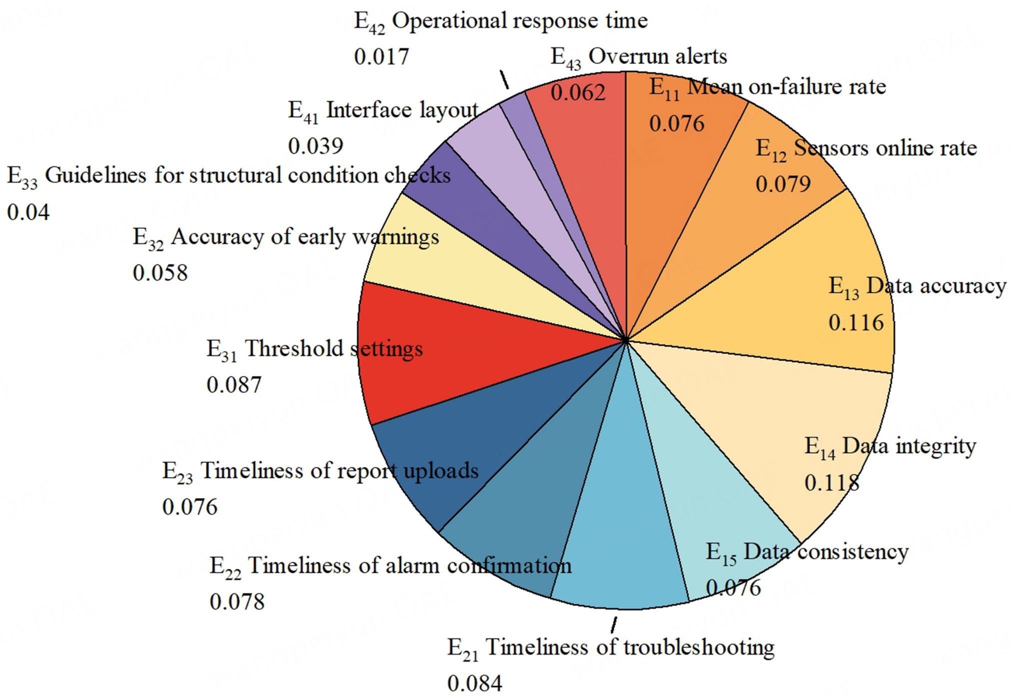

Figure 7. Weight distribution of each indicator.

(4) Timeliness of troubleshooting
When the percentage of the eigenvalues of each sensor is less than 70% of the total number of sensors, and the troubleshooting duration is more than 6 h, the system is judged to be faulty. If the faulty system is not fixed within 72 h, it is judged that the fault is not promptly fixed.

The timeliness of troubleshooting can be constructed as below:

$$P_4 = (1 - \frac{n}{N}) \times 100\%$$

where P_4 is the rate of promptly addressed faults in the past year, n is the number of faults not addressed promptly in the past year, and N indicates the total number of faults that occurred in the past year.

(5) Timeliness of alarm confirmation
The timeliness of alarm confirmations within one year is evaluated. When a second-level warning is not confirmed within 48 h or a third-level warning is not confirmed within 24 h, it is judged that the alarm is not promptly confirmed.

The timeliness of alarm confirmation can be calculated as follows:

$$P_5 = \sum_{i=1}^{2} P_{5i} \times a_i$$

where P_5 is the number of promptly confirmed alarms, P_{5i} is the score of the i-th level of the rate of promptly confirmed alarms, and a_i is the weight of the i-th level of the rate of promptly confirmed alarms (0.4 for the second level and 0.6 for the third level). The i-th level for the timeliness of alarm confirmation

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Table 9. The rating criteria of the indicators for the operational status of BHM systems

Indicator/score		I [90-100]	II [75-90]	III [60-75]	IV [0-60]
System effectiveness	Mean no-failure rate	$P_1 \geq 99\%$	$95\% < P_1 \leq 99\%$	$90\% < P_1 \leq 95\%$	$P_1 \leq 90\%$
	Sensors online rate	$90\% \leq P_2 \leq 100\%$	$75\% < P_2 < 95\%$	$60\% \leq P_2 < 75\%$	$P_2 < 60\%$
	Data accuracy	The data of the system are in excellent agreement with the theoretical calculations	The data of the system are in good agreement with the theoretical calculations	The data of the system are basically in agreement with the theoretical calculations	The data of the system are not in agreement with the theoretical calculations
	Data integrity	$95\% \leq P_3 \leq 100\%$	$90\% \leq P_3 < 95\%$	$85\% \leq P_3 < 90\%$	$P_3 < 85\%$
	Data consistency	The associative relationship between symmetrical and closely located sensors of the same type is extremely clear and reasonable	The associative relationship between symmetrical and closely located sensors of the same type is clear and reasonable	The associative relationship between symmetrical and closely located sensors of the same type is basically clear and reasonable	The associative relationship between symmetrical and closely located sensors of the same type is not clear and reasonable
System maintenance	Timeliness of troubleshooting	$90\% \leq P_4 \leq 100\%$	$75\% \leq P_4 < 90\%$	$60\% \leq P_4 < 75\%$	$P_4 < 60\%$
	Timeliness of alarm confirmation	$90\% \leq P_5 \leq 100\%$	$75\% \leq P_5 < 90\%$	$60\% \leq P_5 < 75\%$	$P_5 < 60\%$
	Timeliness of report uploads	$90\% \leq P_6 \leq 100\%$	$75\% \leq P_6 < 90\%$	$60\% \leq P_6 < 75\%$	$P_6 < 60\%$
Early warning	Threshold settings	The three-level thresholds for all monitoring items are extremely accurate	The three-level thresholds for all monitoring items are accurate	The thresholds at all levels are basically accurate	The thresholds at all levels deviate from the requirements of the specification
	Accuracy of early warnings	The alarms for structural safety demonstrate exceptional precision, exhibiting a near-zero false positive rate in its warning outputs	The structural safety alarm exhibits high precision, with false alarm probabilities maintained within statistically acceptable thresholds	The structural safety alarm generates intermittent false positives, exerting a measurable yet non-critical influence on operational efficacy	The structural safety alarm demonstrates suboptimal reliability, with statistically significant false alarm rates
	Guidelines for structural condition checks	The system can provide exact bridge inspection guidelines and management measures based on the structural condition assessment and overrun conditions	The system can provide correct bridge inspection guidelines and management measures based on the structural condition assessment and overrun conditions	Sometimes the system can provide bridge inspection guidelines and management measures based on the structural condition assessment and overrun conditions	There are no relevant bridge inspection guidelines or management measures when the monitoring data and analysis results are exceeded
Human-computer interaction	Interface layout	The interface demonstrates an optimally designed layout with logically organized elements, enabling intuitive visualization of dynamic data variations	The interface exhibits a well-structured layout with logically organized elements, enabling intuitive visualization of dynamic data changes	The interface exhibits suboptimal layout organization, compromising both visual clarity and the accurate representation of dynamic data changes	The interface's spatial arrangement lacks intuitive coherence, hindering effective data interpretation and user interaction
	Operational response time	The response time of the system's software operations is less than 2 s, and the response time of data queries is less than 3 s	The response time of the system's software operations is within 2-3 s, and the response time of data queries is within 3-5 s	The response time of the system's software operations is within 3-10 s, and the response time of data queries is within 5-15 s	The response time of the system's software operations is more than 10 s, and the response time of data queries is more than 15 s
	Overrun alerts	It has a variety of overrun reminder methods, such as color changes, pushed messages, SMS prompts, sound and light alarm, *etc.*, and the overrun reminder is extremely obvious	It has a comparatively diverse overrun reminder methods, such as color changes, pushed messages, SMS prompts, sound and light alarm, *etc.*, and the overrun reminder is comparatively obvious	The overrun reminder is comparatively less obvious	There is no overrun reminder, or the overrun reminder method is not obvious

where P_2 is the online rate of the sensor, n represents the aggregate count of sensors in the system. T is the range of inquiry time, and t_i is the offline time for the i-th sensor within the range of the query time. BHM: Bridge health monitoring; SMS: short message service.

can be calculated as follows:

$$P_{5i} = \sum_{i=1}^{2}(1-\frac{n_i}{N_i})\times 100\%$$

where n_i is the number of times that a first-level alarm has not been promptly confirmed in the past year, and N_i is the total number of times that the i-th level alarm has occurred in the past year.

(6) Timeliness of report upload

The timeliness of the report within 1 year is evaluated. If one of the following conditions is met, the report is not promptly uploaded:

① The quarterly reports are not uploaded within 30 days after the end of the quarter.

② The annual report was not uploaded by the end of February of the following year.

③ A special matters report was not uploaded within 15 days after the incident was processed.

The timeliness of report upload is defined as

$$P_6 = \sum_{i=1}^{3} P_{6i} \times b_i$$

where P_6 is the timeliness of report uploads, P_{6i} is the score of the i-th level of report upload timeliness, and b_i is the weight of the i-th level of the report upload timeliness (0.2 for quarterly reports, 0.5 for annual reports, and 0.3 for special incident reports). The i-th level timeliness of report upload is calculated as

$$P_{6i} = \sum_{i=1}^{3}(1-\frac{n_i}{N_i})\times 100\%$$

where n_i is the number of times that i-th level reports were not promptly uploaded in the past year, and N_i is the total number of i-th level reports in the past year.

4.2.4. Establish the membership and non-membership functions

According to the TIFNs, the membership and non-membership functions of the rating level are written as follows:

For Level *I*:

$$\mu_I(x) = \begin{cases} 0.0588x - 4.88 & 83 \le x \le 100 \\ 0 & x < 83 \end{cases}$$

$$\nu_I(x) = \begin{cases} -0.0455x + 4.55 & 78 \le x \le 100 \\ 1 & x < 78 \end{cases}$$

For Level *II*:

$$\mu_{II}(x) = \begin{cases} 0.0714x - 4.8548 & 68 \le x < 82 \\ -0.0769x + 7.3058 & 82 < x \le 95 \\ 0 & x < 68 \end{cases}$$

$$\nu_{II}(x) = \begin{cases} -0.0526x + 4.3132 & 63 \le x < 82 \\ 0.0556x - 4.5592 & 82 < x \le 100 \\ 1 & x < 63 \end{cases}$$

For Level *III*:

$$\mu_{III}(x) = \begin{cases} 0.0714x - 3.9266 & 55 \le x < 69 \\ -0.0714x + 5.9266 & 69 < x \le 83 \\ 0 & x < 55 \end{cases}$$

$$\nu_{III}(x) = \begin{cases} -0.0526x + 2.6294 & 50 \le x < 69 \\ 0.0526x - 3.6294 & 69 < x \le 88 \\ 1 & x < 50 \end{cases}$$

For Level *IV*:

$$\mu_{IV}(x) = \begin{cases} -0.0769x + 5.2295 & 55 \le x \le 68 \\ 0 & x < 55 \end{cases}$$

$$\nu_{IV}(x) = \begin{cases} 0.05x - 2.75 & 55 \le x \le 75 \\ 1 & x < 55 \end{cases}$$

4.2.5. Comprehensive evaluation result

The construction of the comparison matrix requires specific indicator values. In this study, a long-span cable-stayed BHM system was taken as an example. Compared with the rating criteria for each indicator in Table 9, the scores of each index are x = (92, 92, 94, 84, 88, 92, 81, 86, 83, 92, 87, 93, 89, 89), by integrating the membership and non-membership functions outlined in Section 4.2.4, the judgment matrix could be systematically derived as follows:

$$R=\begin{bmatrix}(0.5296,0.3640) & (0.2310,0.5560) & (0.0000,0.0000) & (0.0000,0.0000)\\(0.5296,0.3640) & (0.2310,0.5560) & (0.0000,0.0000) & (0.0000,0.0000)\\(0.6472,0.2730) & (0.0772,0.6672) & (0.0000,0.0000) & (0.0000,0.0000)\\(0.0592,0.7280) & (0.8462,0.1112) & (0.0000,0.0000) & (0.0000,0.0000)\\(0.2944,0.5460) & (0.5386,0.3336) & (0.0000,0.0000) & (0.0000,0.0000)\\(0.5296,0.3640) & (0.2310,0.5560) & (0.0000,0.0000) & (0.0000,0.0000)\\(0.0000,1.0000) & (0.9286,0.0526) & (0.1432,0.6312) & (0.0000,0.0000)\\(0.1768,0.6370) & (0.6924,0.2224) & (0.0000,0.0000) & (0.0000,0.0000)\\(0.0004,07735) & (0.9231,0.0556) & (0.0000,0.0000) & (0.0000,0.0000)\\(0.5296,0.3640) & (0.2310,0.5560) & (0.0000,0.0000) & (0.0000,0.0000)\\(0.2356,0.5915) & (0.6155,0.2780) & (0.0000,0.0000) & (0.0000,0.0000)\\(0.5884,0.3185) & (0.1541,0.6116) & (0.0000,0.0000) & (0.0000,0.0000)\\(0.3532,0.5005) & (0.4617,0.3892) & (0.0000,0.0000) & (0.0000,0.0000)\\(0.3532,0.5005) & (0.4617,0.3892) & (0.0000,0.0000) & (0.0000,0.0000)\end{bmatrix}$$

According to the relative weights and judgment matrix R obtained in Section 4.2.2, using Equations (11) and (12), the comprehensive assessment results were calculated:

$$B=T(X,R)=XR=\left[(0.3334,0.5334)(0.4880,0.3703)(0.0111,0.0490)(0,0)\right]$$

$$\text{TIZ}=\frac{\sum_{j=1}^{m}\left(b_j^{\mu}\bullet V_j\right)}{\sum_{j=1}^{m}b_j^{\mu}}=\left[(75.81,80.81,85.81),(70.81,80.81,90.81)\right]$$

$$Z=80.98$$

Based on the range of the four evaluation grades outlined in Table 3, it can be concluded that the BHM system falls into the "*II*" evaluation grade. This indicates a "good" status; the BHM system is operating effectively, but there may be potential risks. Occasional specialized inspections are recommended.

4.2.6. Application to a BHM system of suspension bridge

A long-span suspension bridge has a total length of 1,650.5 meters. The main span of the bridge measures 1,120 meters, while the deck width is 22 meters. The structural design features a hybrid steel-concrete beam for the main girder and reinforced concrete for the main piers. This configuration ensures both durability and load-bearing capacity, making it a robust example of modern bridge engineering. Figure 8 is the measurement point layout diagram of its BHM system.

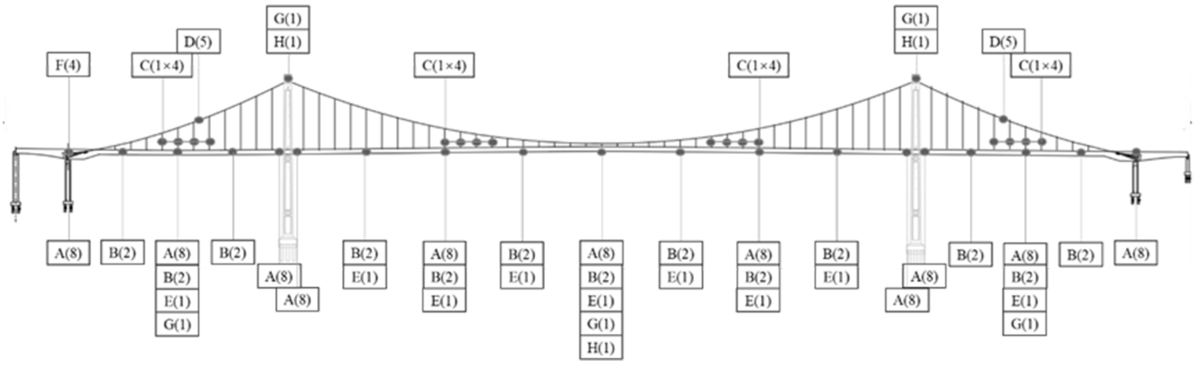

Figure 8. Longitudinal layout of monitoring points of a long-span suspension bridge. Note: the number of sensors is given in parentheses: (A) Displacement; (B) Cable tension; (C) Cable tension of sling; (D) Anchor strand force across the cable; (E) acceleration; (F) Vehicle load; (G) wind velocity; (H) temperature.

Compared with the rating criteria for each indicator in Table 9, the scores of each index are x = (96, 96, 94, 90, 86, 89, 90, 96, 98, 94, 97, 94, 96, 88), The calculation process is detailed in the Supplementary Materials, with the final evaluation result:

$$Z = 86.76$$

Based on the range of the four evaluation grades determined in Table 3, it can be concluded that the bridge monitoring system belongs to the evaluation grade "*II*", which indicates a "good" status; the BHM system is operating effectively, but there may be potential risks. Occasional specialized inspections are recommended.

5. COMPARISON AND DISCUSSION

5.1. Efficiency verification of TIFANP

To verify the reliability of the TIFANP in assigning the weights of each indicator, a comprehensive comparative analysis was performed to evaluate various weight assignment methodologies.

The comparative analysis of weight assignment methodologies, including TIFANP, AHP, analytic network process (ANP), and intuitive fuzzy analytic network process (IFANP), is illustrated in Figure 9. As depicted, a significant divergence is observed between the TIFANP and AHP approaches in determining indicator weights. For example, the AHP assigns a lower weight of 0.045 to indicator E_{11}, but the TIFANP assigns a higher weight of 0.076 to E_{11}. Similar differences are also reflected in indicators E_{12}, E_{21}, E_{42}, and E_{43}; this is due to the different mechanisms underlying the AHP and TIFANP methods. The AHP follows a hierarchical structure. The decision problem is broken down into multiple levels. Higher-level indicators influence lower-level ones, but there are no direct interactions between the lower-level indicators. Only the importance of two indicators is considered in the AHP when determining the weight. TIFANP uses a network structure, the interdependence and dominance of indicators at the same level are more flexibly considered. Considering the actual attributes of the indicators, the weights obtained by the TIFANP are more consistent with the importance that decision-makers place on the indicators; therefore, the TIFANP is more appropriate than the AHP for weight assignment.

In the case of the same comparison matrix, the weights derived from the ANP, IFANP, and TIFANP exhibit notable similarities. This convergence arises from their shared foundational logic, which involves the analysis of the mutual influence degree of indicators. At the same time, the TIFANP, IFANP, and ANP also reflect some differences, such as in the indicators E_{11} and E_{32}, due to the fact that when hesitation occurs in

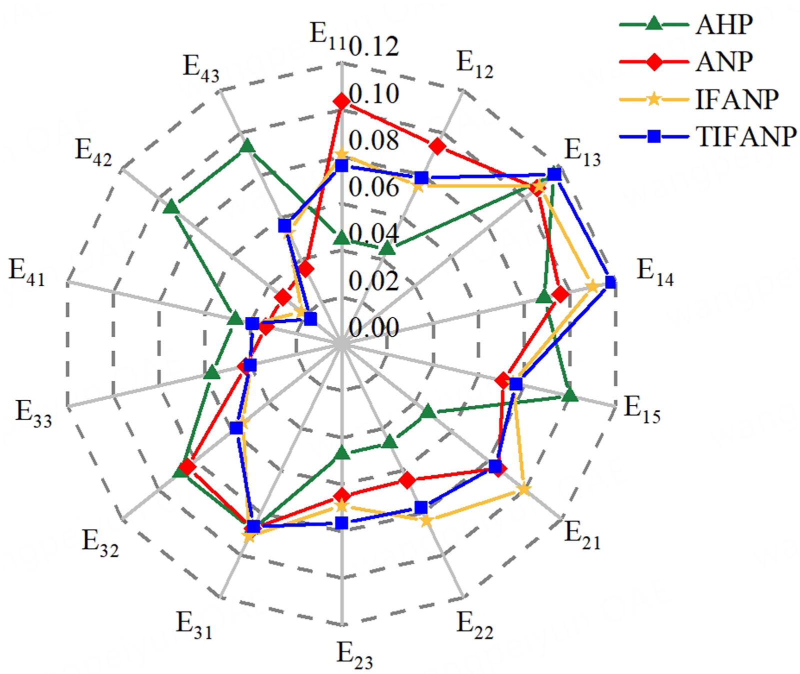

Figure 9. Comparative evaluation of weight assignment methodologies: AHP, ANP, IFANP, and TIFANP. AHP: Analytic hierarchy process; ANP: analytic network process; IFANP: intuitive fuzzy analytic network process; TIFANP: triangular intuitionistic fuzzy analytic network process.

the decision-making process, the traditional ANP completely relies on subjective judgment, and the IFANP and TIFANP obtain quantitative hesitation information through TIFNs. The weights derived from the IFANP and TIFANP are almost identical; the difference between the indicators is within 0.01 because both the IFANP and TIFANP quantify the hesitation information implicitly in the decision-making process, so the results are more accurate than the traditional ANP. The main difference between the TIFANP and the IFANP is that the TIFANP further introduces triangular fuzzy numbers to quantify the hesitation implied in the opinions of decision makers, which is more accurate than the IFANP in the method of quantifying uncertainty.

In summary, the TIFANP approach introduced in this study demonstrates superior reliability in determining indicator weights compared to alternative methodologies.

5.2. Efficiency of the TIFANP-TIFCE model

Based on the weights determined using the TIFANP, this section discusses the efficiency of the TIFANP-TIFCE method using different membership function construction methods.

The comparison of the assessment results obtained using the same indicator weights and different membership function construction methods, i.e., TIFANP-TIFCE, TIFANP-FCE, and the TIFANP-gray clustering method, are shown in Table 10. As can be seen in Table 10, the results of the rating level obtained using TIFANP-TIFCE are consistent with those obtained using other comprehensive evaluation methods under the same weight, which proves the effectiveness of the method. The scores of the TIFANP-grey clustering method and TIFANP-FCE are slightly higher than those of TIFANP-TIFCE, because the TIFANP-grey clustering method and TIFANP-FCE only consider the membership degree of the indicators to the system rating level. On this basis, TIFANP-TIFCE further considers the difference between the

Table 10. Result comparison of different membership function construction methods

Evaluation method	TIFANP-TIFCE	TIFANP-FCE	TIFANP-gray clustering
Rating level	II	II	II
Result	80.98	82.73	82.15

TIFANP: Triangular intuitionistic fuzzy analytic network process; TIFCE: triangular intuitionistic fuzzy comprehensive evaluation; FCE: fuzzy comprehensive evaluation.

decision-making opinion and the actual situation, which is caused by the difficulty of quantifying the calculation of some indicators in the decision-making process, i.e., the non-membership degree of the evaluation indicators to the system rating grade. Therefore, the evaluation results of TIFANP-TIFCE are more realistic and plausible.

6. CONCLUSIONS

To determine the operational status of BHM systems, this paper proposes a novel assessment method based on TIFANP-TIFCE. A comprehensive case study was performed on a long-span cable-stayed BHM system and a suspension BHM system to validate the efficacy of the proposed method. The conclusions of this study can be summarized as follows.

(1) The operational status evaluation of BHM systems represents a complex, multi-dimensional assessment that involves analyzing various interrelated indicators. For the first time, this paper proposes a multi-level evaluation index system, which is satisfactory and can well reflect the operational status of BHM systems in service.

(2) The mutual influence relationships of dependence and domination among indicators are comprehensively considered by the TIFANP, and the hesitation frequency of decision-makers during the evaluation process is effectively addressed. The weights obtained using the TIFANP are more accurate than those of the traditional AHP and ANP.

(3) By combining qualitative and quantitative evaluation, the influence of various indicators on the operational status of a BHM system is comprehensively considered. By integrating the complex indicators of the operational status of the BHM system, the membership degree function is constructed. While some indicators are difficult to quantify, the differences between the decision-making opinions and the actual situation are expressed through non-membership functions, and the evaluation results obtained are more authentic.

(4) Hesitation in the decision-making process is well addressed with the introduction of TIFNs, which solves the problem of conversion from linguistic terms to TIFNs and exact values when lacking information for decision-making, quantifying the deviation caused by hesitation and uncertainty in the decision-making process, and making the evaluation process more meticulous.

(5) A comparison analysis of the weights allocation by TIFANP, IFANP, ANP, and AHP is conducted. The results show that TIFANP outperforms other methods in handling the hesitant information and mutual influence relationship between indicators. Then, the differences of constructing membership functions between TIFCE and other methods were compared based on the weights obtained by TIFANP, the effectiveness of the non-membership functions of TIFCE in handling uncertain information are verified.

In this paper, some non-quantifiable indicators are included in the proposed indicator system, such as data consistency. Future research could focus on the development of methods for quantifying indicators.

DECLARATIONS

Authors' contributions

Made substantial contributions to conception and design of the study and performed data analysis and interpretation: Wang, C.; Tang, Q.; Wu, B.
Performed data acquisition and provided administrative, technical, and material support: Jiang, Y.; Xin, J.

Availability of data and materials

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Conflicts of interest

Jiang, Y. and Xin, J. are the Junior Editorial Board Members of the journal *Intelligence & Robotics*. They were not involved in any steps of editorial processing, notably including reviewer selection, manuscript handling, or decision-making. The other authors declare that there are no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

REFERENCES

1. Tang, Q.; Jiang, Y.; Xin, J.; Liao, G.; Zhou, J.; Yang, X. A novel method for the recovery of continuous missing data using multivariate variational mode decomposition and fully convolutional networks. *Measurement* **2023**, *220*, 113366. DOI
2. Xin, J.; Jiang, Y.; Zhou, J.; Peng, L.; Liu, S.; Tang, Q. Bridge deformation prediction based on SHM data using improved VMD and conditional KDE. *Eng. Struct.* **2022**, *261*, 114285. DOI
3. Xin, J.; Zhou, C.; Jiang, Y.; Tang, Q.; Yang, X.; Zhou, J. A signal recovery method for bridge monitoring system using TVFEMD and encoder-decoder aided LSTM. *Measurement* **2023**, *214*, 112797. DOI
4. Li, S.; Xin, J.; Jiang, Y.; Wang, C.; Zhou, J.; Yang, X. Temperature-induced deflection separation based on bridge deflection data using the TVFEMD-PE-KLD method. *J. Civil. Struct. Health. Monit.* **2023**, *13*, 781-97. DOI
5. Tang, Q.; Xin, J.; Jiang, Y.; Zhang, H.; Zhou, J. Dynamic response recovery of damaged structures using residual learning enhanced fully convolutional network. *Int. J. Str. Stab. Dyn.* **2025**, *25*, 2550008. DOI
6. Tang, Q.; Xin, J.; Jiang, Y.; Zhou, J.; Li, S.; Fu, L. Fast identification of random loads using the transmissibility of power spectral density and improved adaptive multiplicative regularization. *J. Sound. Vib.* **2022**, *534*, 117033. DOI
7. Tang, Q.; Xin, J.; Jiang, Y.; Zhou, J.; Li, S.; Chen, Z. Novel identification technique of moving loads using the random response power spectral density and deep transfer learning. *Measurement* **2022**, *195*, 111120. DOI
8. Morgese, M.; Wang, C.; Ying, Y.; Taylor, T.; Ansari, F. Stress–strain response of optical fibers in direct tension. *J. Eng. Mech.* **2023**, *149*, 04023037. DOI

9. Wang, C.; Ansari, F.; Wu, B.; Li, S.; Morgese, M.; Zhou, J. LSTM approach for condition assessment of suspension bridges based on time-series deflection and temperature data. *Adv. Struct. Eng.* **2022**, *25*, 3450-63. DOI
10. Morgese, M.; Wang, C.; Taylor, T.; Etemadi, M.; Ansari, F. Distributed detection and quantification of cracks in operating large bridges. *J. Bridge. Eng.* **2024**, *29*, 04023101. DOI
11. Peiris, A.; Sun, C.; Harik, I. Lessons learned from six different structural health monitoring systems on highway bridges. *J. Low. Freq. Noise. Vib. Act. Control.* **2020**, *39*, 616-30. DOI
12. Zhang, J.; Qian, K.; Luo, H.; et al. Process monitoring for tower pumping units under variable operational conditions: from an integrated multitasking perspective. *Control. Eng. Pract.* **2025**, *156*, 106229. DOI
13. Zhang, J.; Li, X.; Tian, J.; Jiang, Y.; Luo, H.; Yin, S. A variational local weighted deep sub-domain adaptation network for remaining useful life prediction facing cross-domain condition. *Reliab. Eng. Syst. Safe.* **2023**, *231*, 108986. DOI
14. Hu, K.; Chen, Z.; Kang, H.; Tang, Y. 3D vision technologies for a self-developed structural external crack damage recognition robot. *Automat. Constr.* **2024**, *159*, 105262. DOI
15. Wan, S.; Guan, S.; Tang, Y. Advancing bridge structural health monitoring: insights into knowledge-driven and data-driven approaches. *J. Data. Sci. Intell. Syst.* **2024**, *2*, 129-40. DOI
16. Tang, Y.; Qi, S.; Zhu, L.; Zhuo, X.; Zhang, Y.; Meng, F. Obstacle avoidance motion in mobile robotics. *J. Syst. Simul.* **2024**, *36*, 1-26. DOI
17. Ye, H.; Jiang, C.; Zu, F.; Li, S. Design of a structural health monitoring system and performance evaluation for a jacket offshore platform in East China Sea. *Appl. Sci.* **2022**, *12*, 12021. DOI
18. Dal Cin, A.; Russo, S. Evaluation of static and dynamic long-term structural monitoring for monumental masonry structure. *J. Civil. Struct. Health. Monit.* **2019**, *9*, 169-82. DOI
19. Janapati, V.; Kopsaftopoulos, F.; Li, F.; Lee, S. J.; Chang, F. Damage detection sensitivity characterization of acousto-ultrasound-based structural health monitoring techniques. *Struct. Health. Monit.* **2016**, *15*, 143-61. DOI
20. Li, L.; Liu, G.; Zhang, L.; Li, Q. Sensor fault detection with generalized likelihood ratio and correlation coefficient for bridge SHM. *J. Sound. Vib.* **2019**, *442*, 445-58. DOI
21. Fan, Z.; Huang, Q.; Ren, Y.; Ye, Q.; Chang, W.; Wang, Y. Cointegration based modeling and anomaly detection approaches using monitoring data of a suspension bridge. *Smart. Struct. Syst.* **2023**, *31*, 183-97. DOI
22. Li, S.; Jin, L.; Qiu, Y.; Zhang, M.; Wang, J. Signal anomaly detection of bridge SHM system based on two-stage deep convolutional neural networks. *Struct. Eng. Int.* **2023**, *33*, 74-83. DOI
23. Xin, J.; Wang, C.; Tang, Q.; Zhang, R.; Yang, T. An evaluation framework for construction quality of bridge monitoring system using the DHGF method. *Sensors* **2023**, *23*, 7139. DOI PubMed PMC
24. Azizi, M.; Hossein Zadeh, O.; Hajjarian, M. Theory and applications of the analytic network process: decision making with benefits, opportunities, costs, and risks (Translated to Persian). University of Tehran Press; 2015. https://www.researchgate.net/publication/359494836_Theory_and_Applications_of_the_Analytic_Network_Process_Decision_Making_with_Benefits_Opportunities_Costs_and_Risks_Translated_to_Persianfarsy. (accessed 18 Apr 2025).
25. Liao, H.; Mi, X.; Xu, Z.; Xu, J.; Herrera, F. Intuitionistic fuzzy analytic network process. *IEEE. Trans. Fuzzy. Syst.* **2018**, *26*, 2578-90. DOI
26. Zhang, Y.; Wang, S.; Liu, J.; Liu, D.; Li, T.; Wu, W. A corrosion assessment methodology based on triangular intuitionistic fuzzy comprehensive evaluation (TIFCE) with analytic network process (TIFANP): an application to external corrosion of the storage tank floor. *Expert. Syst. Appl.* **2024**, *238*, 121896. DOI
27. Atanassov, K. T. Intuitionistic fuzzy sets. *Fuzzy. Sets. Syst.* **1986**, *20*, 87-96. DOI
28. Sahin, B.; Soylu, A. Intuitionistic fuzzy analytical network process models for maritime supply chain. *Appl. Soft. Comput.* **2020**, *96*, 106614. DOI
29. Li, D. A note on “using intuitionistic fuzzy sets for fault-tree analysis on printed circuit board assembly”. *Microelectron. Reliab.* **2008**, *48*, 1741. DOI
30. Du, Y.; Wang, S.; Wang, Y. Group fuzzy comprehensive evaluation method under ignorance. *Expert. Syst. Appl.* **2019**, *126*, 92-111. DOI
31. Pei, Z.; Zheng, L. A novel approach to multi-attribute decision making based on intuitionistic fuzzy sets. *Expert. Syst. Appl.* **2012**, *39*, 2560-6. DOI
32. Sun, G.; Guan, X.; Yi, X.; Zhou, Z. Improvements on correlation coefficients of hesitant fuzzy sets and their applications. *Cogn. Comput.* **2019**, *11*, 529-44. DOI
33. Bień, J.; Kużawa, M.; Kamiński, T. Strategies and tools for the monitoring of concrete bridges. *Struct. Concr.* **2020**, *21*, 1227-39. DOI
34. Paul, D.; Roy, K. Application of bridge weigh-in-motion system in bridge health monitoring: a state-of-the-art review. *Struct. Health. Monit.* **2023**, *22*, 4194-232. DOI
35. Zinno, R.; Haghshenas, S. S.; Guido, G.; Vitale, A. Artificial intelligence and structural health monitoring of bridges: a review of the state-of-the-art. *IEEE. Access.* **2022**, *10*, 88058-78. DOI
36. López-Aragón, J.; Astiz, M. Some considerations about the incorporation of dynamic parameters in the structural health monitoring systems of bridges. *Appl. Sci.* **2024**, *14*, 33. DOI
37. Yu, J. R.; Shing, W. Fuzzy analytic hierarchy process and analytic network process: an integrated fuzzy logarithmic preference programming. *Appl. Soft. Comput.* **2013**, *13*, 1792-9. DOI