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ARTICLE

A Feasibility Study of a Comprehensive Evaluation Method for Bridge Static and Dynamic Performance Based on Trend Analysis of Monitoring Data

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ABSTRACT: To fully leverage structural health monitoring data for bridge condition assessment, this study proposes a comprehensive evaluation method that integrates static and dynamic indicators using monitoring data, and demonstrates its feasibility through a short-term monitoring-based trend analysis on a newly built bridge. First, based on statistical principles, the Weibull distribution is employed to extract the dead-load component from static monitoring data. Building upon this, a static performance evaluation method is established by incorporating spatial uniformity and trend non-uniformity coefficients. Subsequently, spectral analysis is performed on the main girder acceleration data to extract fundamental frequency information and apply temperature correction, establishing a method for assessing the bridge's dynamic performance. Finally, considering the nonlinear impact of single-indicator deterioration on overall bridge performance, variable weight theory is introduced to construct a static-dynamic integrated assessment model that accounts for indicator equilibrium. Using actual monitoring data from an arch bridge as an example, the bridge's static, dynamic, and comprehensive scores in the second month after opening were 95.11, 96.21, and 95.66, respectively. Over the following months, all scores remained around 94 points with a gradual decline, confirming the bridge's good condition and the effectiveness of the proposed comprehensive assessment method for short-term monitoring-based trend analysis. The findings indicate that minor fluctuations in evaluation scores stem from uncertainties in the assessment process, primarily related to traffic randomness, environmental effects, and residual data processing errors. This method enables unified dimensional quantification and trend tracking of a bridge's static and dynamic performance without requiring bridge closure, providing a quantitative basis for performance comparison and maintenance decision-making during the service phase.

KEYWORDS: Structural health monitoring; static performance; dynamic performance; dead load effect; variable-weight theory; trend analysis

1 Introduction

To ensure the structural integrity and operational safety of bridges, particularly long-span bridges, health monitoring systems are typically installed to continuously track service conditions, loads, structural responses, and displacements [1]. Bridge health monitoring data are characterized by large volume, multi-source heterogeneity, and low-frequency, high-noise patterns. Consequently, assessing bridge conditions and issuing anomaly alerts based on this data remains a significant challenge within the industry [2].

Extensive research has been conducted globally on data mining for bridge health monitoring. In structural damage identification, models based on static and dynamic monitoring indicators have been developed, with their effectiveness validated through laboratory experiments [3]. Recently, artificial intelligence methods have been widely applied to bridge structural damage identification, demonstrating significant improvements in accuracy [4,5]. Compared with the extensive research on structural damage identification, studies on bridge condition assessment based on monitoring data remain relatively limited. Previous work has evaluated the safety margin of bridge structures using static monitoring data while considering the time-varying evolution of structural performance [6,7]. However, no comprehensive assessment method has been developed that simultaneously accounts for both static and dynamic structural performance to evaluate deterioration trends.

This paper conducts trend analysis of structural parameters under complex service conditions based on static and dynamic monitoring data. Considering the spatial characteristics of evaluation indicators, it separately assesses the static and dynamic performance of bridge structures. Finally, by applying variable weight theory, it proposes a comprehensive bridge structure evaluation method that integrates static and dynamic performance.

Recent research in bridge structural health monitoring has focused on practical monitoring systems and data analysis methods that turn large-scale measurements into useful condition information. Studies have shown that detailed analysis of multi-sensor data can directly support the assessment of component performance and deterioration in real bridges, making this data-driven approach a valuable tool for informing maintenance decisions [8,9]. Among these approaches, digital-twin (DT) frameworks have recently been adopted to combine multi-sensor data with physics-based models or trained surrogates for condition estimation and full-field response prediction [10]. When a calibrated virtual replica of the bridge can be built and continuously updated, DT-based methods are quite effective—they allow for scenario simulation and parameter inference [11]. However, developing and maintaining an online DT model often requires extra effort in modeling, calibration data, and computational resources. Such resources are not always available in routine practice [12]. In this context, the proposed variable-weight method offers a lightweight alternative. It works directly at the indicator level, merging static and dynamic monitoring indicators into a single, interpretable score. This approach does not rely on a fully updated DT model, making it well-suited for practical applications where quick scoring and trend tracking are needed—especially when a full DT system is still under development.

In addition, recent studies on balanced cantilever bridges have shown that multi-source data fusion combined with dynamic characteristics measurement can enhance structural state perception and model updating. These methods typically focus on heterogeneous data integration, dynamic-feature extraction, and model-assisted interpretation of bridge behavior [13]. In contrast, the present study adopts a lightweight indicator-level fusion strategy that directly converts static and dynamic monitoring data into a unified performance score. Thus, the proposed method is better suited for rapid engineering screening and trend tracking under limited monitoring and modeling resources, while DT-based or multi-source fusion approaches are more advantageous for high-fidelity diagnosis, simulation, and prediction.

2 Comprehensive Evaluation Method for Bridge Static and Dynamic Performance

The comprehensive assessment process for static and dynamic performance proposed in this paper is illustrated in Fig. 1. For bridge structure static monitoring data, analyze the correlation between monitoring data and temperature, establish a quantitative correlation model, and obtain the high-frequency components of the data after eliminating temperature effects. After data preprocessing and extraction of the high-frequency components from the monitoring data, the response value corresponding to the peak of the probability density function is taken as the theoretical dead load component and used as the evaluation index. In principle, take the index value in the as-built state as the reference sequence (if the data are unavailable, monitoring data from the initial operation period may be used as an engineering approximation), and perform uniformity assessment and non-uniformity correction based on the deviation from the reference sequence to obtain the bridge structure static performance evaluation results. For dynamic monitoring data, dynamic indicators such as fundamental frequency are derived using the Fourier transform, incorporating temperature correction. Dynamic performance is evaluated by comparing against the as-built dynamic indicators as the baseline. Based on the static and dynamic performance assessments, the comprehensive evaluation result for the bridge structure is calculated using variable weight theory.

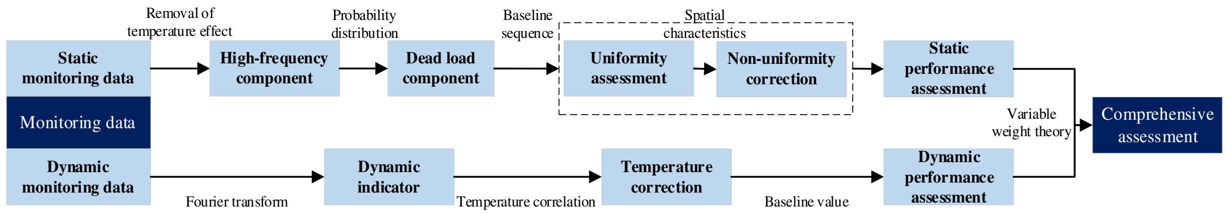


Figure 1: Integrated assessment process for bridge static and dynamic performance.

2.1 Static Performance Evaluation Method

2.1.1 Extraction of Dead Load Components from Static Monitoring Data

A well-defined load environment facilitates the assessment of bridge condition. However, the complexity of bridge operational conditions results in diverse components within the monitoring signals collected by sensors, including permanent load effects, live load effects, temperature effects, and noise. Given the inherent uncertainty of live loads and temperature variations, directly evaluating the acquired monitoring signals yields suboptimal results due to the random nature of load influences. Therefore, it is necessary to conduct in-depth data mining on the monitoring signal components to extract structural response signals corresponding to stable load conditions as the primary basis for structural condition assessment, thereby enhancing the reliability of bridge condition evaluation results. Some field investigations on cracking pathologies provide empirical evidence that local cracking and deterioration can lead to stiffness loss, stress redistribution, and measurable changes in static response fields [14]. Based on the objective principle that structural damage—whether cumulative or sudden—causes the redistribution of permanent stresses within the structure, the characteristics and extent of such permanent stress redistribution can thus be employed to assess the structural condition [15,16].

Currently, extensive research exists on temperature effect separation methods, with existing approaches achieving computational accuracy sufficient for engineering applications [17,18]. Previous studies indicate a significant correlation between static monitoring data and temperature, typically exhibiting linear relationships [1,19]. Although more sophisticated nonlinear or time-lag-integrated models can better characterize thermal effects, their performance gains are often marginal, whereas linear models are more straightforward to implement and interpret in engineering applications. The linear approximation is sufficiently accurate for monthly statistical evaluation and practical temperature correction, striking a favorable balance between robustness, interpretability, and computational simplicity. This paper proposes employing a quantitative correlation model between monitoring data and temperature to eliminate temperature effects from the monitoring data, thereby isolating the high-frequency components.

Currently, the simplest method to obtain dead-load components is to close the bridge, thereby eliminating vehicle load influences. Structural response signals collected during the closure period are unaffected by vehicular loads. However, for large bridges located at critical junctions of transportation networks, bridge closures incur substantial economic losses and social impacts. Consequently, it is necessary to investigate methods for extracting dead-load components under random vehicular traffic loads.

This paper employs a statistical approach to extract dead-load components under random vehicle loads. The method first fits monitoring data using the Weibull extreme value distribution model, defining the value corresponding to the maximum probability density function as the theoretical dead-load component. The method's validity was verified using cable force monitoring data. By selecting 22 cables as test subjects and comparing the constant load cable force values calculated by this method with those monitored during bridge closure periods, the findings indicate that the relative errors of most estimated constant-load cable forces are within 10%, meeting the requirements for engineering applications [20–22].

2.1.2 Static Performance Evaluation Method Considering Spatial Characteristics

Generally, static monitoring data originate from multiple spatial measurement points, forming sequential arrays. For instance, it is common to monitor bridge deflection at the 1/4 span, midspan, and 3/4 span locations. Data from these points exhibit spatial correlation, necessitating consideration of spatial characteristics during processing.

Uniformity and non-uniformity are commonly used to characterize sequence arrays. The uniformity coefficient represents the average distance of sequence indicators from the baseline, while the non-uniformity coefficient indicates the degree of fluctuation around the baseline. The geometric interpretations of these coefficients are illustrated in Fig. 2.

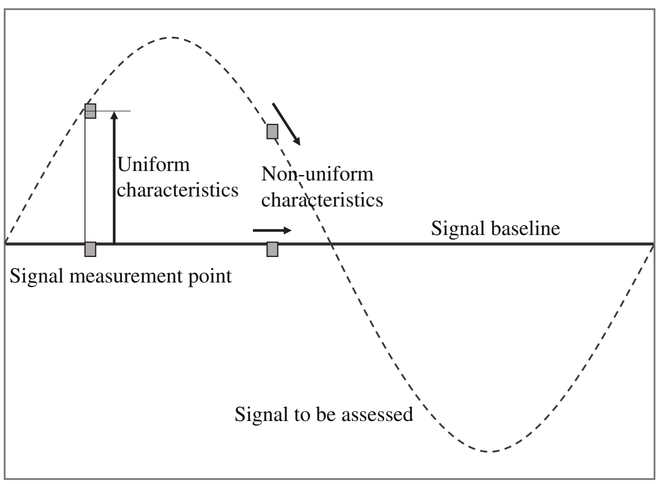


Figure 2: Uniformity and non-uniformity characteristics of sequence arrays.

For static monitoring sequence arrays, evaluate their uniformity and non-uniformity to assess the static performance of bridge structures. The specific process is as follows:

(1) Determination of Reference Sequence

First, establish the reference sequence. Typically, the monitoring indicator values corresponding to the bridge completion are selected as the baseline. For example, the dead load profile indicator for the stiffener beam: the as-built bridge profile represents the optimal geometry calculated to place the bridge structure in its best condition. Therefore, the closer the measured sequence indicator values are to the reference values, the better the technical condition of the bridge structure. Sequence indicators are generally evaluated based on the degree of deviation from the baseline. If the as-built baseline is unavailable, a stabilized period in early service can be used as the reference.

(2) Single-Point Indicator Scoring

Through numerical simulation calculations, the impact of a certain percentage reduction in the early warning indicator on the structural response is determined, establishing the most unfavorable relative distance from the baseline. Generally, when the relative distance from the baseline exceeds ±40%, the structure is deemed to have reached an unacceptable state, resulting in a score of 0 for that indicator [23]. However, with the operation of the bridge, it is recommended to update the threshold accordingly based on specific needs. Using the above assessment limits as a reference, linear interpolation is employed to calculate the score for individual position indicators, yielding:

$$y_i = \begin{cases} \dfrac{x_i - 0.6x_i^0}{x_i^0 - 0.6x_i^0} \times 100, & 0.6x_i^0 < x_i < x_i^0; \\ \dfrac{1.4x_i^0 - x_i}{1.4x_i^0 - x_i^0} \times 100, & x_i^0 < x_i < 1.4x_i^0; \\ 0, \quad x_i \le 0.6x_i^0, & x_i \ge 1.4x_i^0 \end{cases} \tag{1}$$

where y_i takes values within the range [0, 100], x_i represents the measured value corresponding to the sequence indicator at position i, and x_i^0 denotes the baseline value at that position.

(3) Uniformity Assessment

Based on the single-point indicator scores, the uniformity variation score U is calculated by a weighted summation as follows:

$$U = \sum_{i=1}^{n} \omega_i y_i \tag{2}$$

where $y_i \in [0, 100]$ is the score of the indicator at location i, and ω_i is the corresponding weight. In the original form, equal weights $\omega_i^0 = 1/m$ can be used. To avoid diluting localized but critical anomalies by simple averaging, we further adopt a variable-weight scheme to adaptively update ω_i according to the single-point scores:

$$\omega_i = \frac{\omega_i^0 \left(\alpha_u + (1-\alpha_u)\frac{y_i}{100}\right)}{\sum_{j=1}^{m} \omega_j^0 \left(\alpha_u + (1-\alpha_u)\frac{y_j}{100}\right)}, 0 \le \alpha_u \le 1 \tag{3}$$

where α_u denotes the factor equilibrium coefficient, whose value adjusts the weighting effect of the variable-weight model. From a structural safety perspective, this paper adopts $\alpha_u = 0.2$ for calculations, which is suitable for general engineering applications.

(4) Non-Uniformity Coefficient

The non-uniformity coefficient measures the degree of fluctuation of an ordinal array around a baseline, emphasizing the trend of variation in the sequence array. Correlation is adopted as the measure of non-uniformity to assess the consistency of trends between two sets of sequence indicators. Considering the requirement for order preservation, slope correlation is adopted as the non-uniformity coefficient indicator, calculated as follows:

$$r = \frac{1}{n-1} \sum_{i=1}^{n-1} \left[1 + \left|\frac{x_i}{x_{i+1}} - \frac{x_i^0}{x_{i+1}^0}\right|\right]^{-1} \tag{4}$$

Mechanically, this formulation is intended to distinguish between two typical situations. Under global and relatively uniform changes, such as a nearly uniform temperature effect or a globally distributed stiffness variation, the response sequence tends to shift or scale as a whole while preserving its overall spatial shape; in this case, the slope pattern remains similar to the baseline, and the coefficient stays high. In contrast, under localized or non-uniform changes, such as local stiffness reduction, bearing deterioration, or connection abnormality, the spatial response profile is more likely to become distorted in a local region, causing the slope pattern to deviate from the baseline and the coefficient to decrease. Therefore, the slope-correlation coefficient should be interpreted as a data-driven indicator of spatial pattern consistency rather than a direct physical parameter.

(5) Static Performance Evaluation

The uniformity assessment results are adjusted based on the non-uniformity coefficient to obtain the static performance evaluation results for the bridge structure, serving as:

$$\begin{aligned} V &= r \times U = rg\sum_{i=1}^{n} y_i \omega_i \\ &= \sum_{i=1}^{n} \frac{rg y_i^{\alpha_f}}{\sum_{k=1}^{n} y_k^{\alpha_f}} \end{aligned} \tag{5}$$

2.2 Dynamic Performance Evaluation Method

Dynamic characteristic parameters are inherent properties of a structure that remain constant regardless of changes in the service environment. Consequently, dynamic parameters of bridge structures were among the earliest to be utilized in structural damage research, with common indicators including frequency, vibration modes, and modal parameters [24]. The primary parameter for direct monitoring of a bridge structure's dynamic performance is typically the acceleration signal. However, acceleration data is generally not directly employed for bridge structural condition assessment or damage identification; instead, Fourier transforms are commonly used to convert time-domain data into frequency-domain signals. Among these, the most representative frequency-domain dynamic indicator is the fundamental frequency of the structure. This paper also selects the fundamental frequency of bridge structures as an indicator for dynamic performance assessment.

Based on acceleration monitoring data, the Fourier transform is applied to obtain the spectrum of the monitoring data. The fundamental frequency information extracted from this spectrum serves as the indicator for evaluating the structural dynamic performance. Considering that the Fourier transform is a well-established signal processing method for extracting structural frequencies, further elaboration is omitted here.

Previous studies indicate that the fundamental frequency of bridge structures also varies with temperature, typically exhibiting a linear relationship [25]. Therefore, before utilizing the fundamental frequency for bridge structural assessment, it is necessary to establish the correlation between the bridge structure's fundamental frequency and temperature based on the data, followed by temperature correction of the fundamental frequency. The assessment of the bridge structure's dynamic performance is then conducted based on the corrected fundamental frequency.

Using the fundamental frequency of the bridge structure in its completed state as the reference value, the dynamic performance of the bridge structure is evaluated by comparing the deviation between the subsequent fundamental frequencies and this reference value. Specifically, using the fundamental frequency as the dynamic indicator, the dynamic performance is evaluated via Eq. (1). Additionally, it is important to note that during the Fourier transform process, errors in fundamental frequency extraction can easily occur due to the quality of the analysis data, leading to suboptimal results in the assessment of the bridge structure's dynamic performance. Therefore, selecting high-quality acceleration data is a critical step in the dynamic performance evaluation process.

2.3 Comprehensive Evaluation Method

The static and dynamic performance characteristics of bridge structures represent two aspects of their condition. To reflect the nonlinear impact of rapid degradation in a single aspect on the overall bridge performance, a variable-weight calculation method is introduced for comprehensive evaluation.

The variable-weight synthesis method adjusts the initial weights of evaluation indicators based on their scores, accounting for the influence of indicator balance. For instance, when a bridge's static performance deteriorates significantly, the weight assigned to static performance indicators increases. This reflects the nonlinear impact of rapid degradation in a single aspect on the bridge's overall performance.

In practical applications, variable-weight functions are typically not constructed directly. Instead, variable-weight formulas are derived by constructing balanced functions. Common equilibrium functions include sum-type and product-type equilibrium functions, where the product-type equilibrium function can be regarded as a special case of the sum-type equilibrium function. Therefore, this paper employs the variable-weight comprehensive model corresponding to the sum-type equilibrium function, which is commonly used in bridge evaluation [26]. The expression for the sum-type equilibrium function is:

$$B_{\sum}(\mathrm{Y}) = \sum_{j=1}^{n} y_j^{\alpha_f}, \left(0 \le \alpha_f \le 1\right) \tag{6}$$

where n represents the number of indicators, and α_f $(0 \le \alpha_f \le 1)$ denotes the factor equilibrium coefficient, whose value adjusts the weighting effect of the variable-weight model. When $\alpha_f < 0.5$, it indicates that evaluators exhibit lower tolerance for local defects; conversely, when $\alpha_f > 0.5$, it signifies greater tolerance for deficiencies in certain aspects. From a structural safety perspective, this paper adopts $\alpha_f = 0.2$ for calculations, which is suitable for general engineering applications. Based on the equilibrium function, the variable weight calculation formula can be derived as:

$$\omega_j(\mathbf{Y}) = \frac{\omega_j^{(0)} \dfrac{\partial B_{\sum}(\mathbf{Y})}{\partial y_j}}{\sum_{k=1}^{n} \omega_k^{(0)} \dfrac{\partial B_{\sum}(\mathbf{Y})}{\partial y_k}}, j = 1, 2, K, n \tag{7}$$

where ω_i^0 represents the initial weight. In this paper, the initial weights are distributed equally, i.e., $\omega_i^0 = \frac{1}{n}$. Substituting Eqs. (6) into (7) yields the simplified formula for calculating the variable weights:

$$\omega_i = \frac{y_i^{\alpha_f - 1}}{\sum_{k=1}^{n} y_k^{\alpha_f - 1}} \tag{8}$$

3 Case Study

3.1 Project Background

The main bridge of the background project is a two-span arch bridge with a span arrangement of (139 + 151 m). Thermometers and hygrometers are installed on the bridge to measure ambient temperature and humidity; acceleration sensors are used to monitor girder vibration; cable-mounted accelerometers are used for vibration-based cable-force identification; and image-based displacement meters are used to measure girder deflection. Their specific layout is illustrated in Fig. 3.

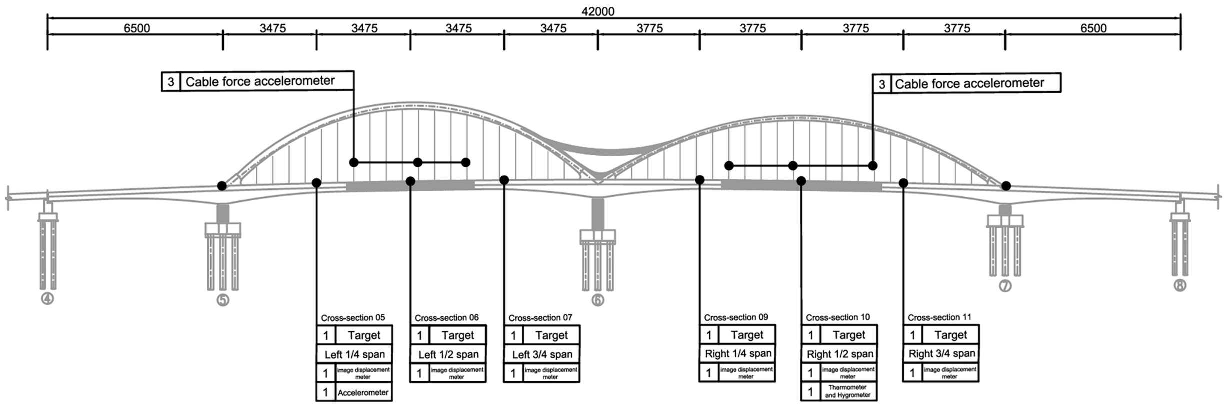


Figure 3: Case-study bridge sensor layout diagram.

3.2 Static Performance Evaluation

Using deflection and cable force monitoring data as the research subjects, the static performance of the case-study bridge is evaluated. Taking the deflection monitoring data from the left 1/4 span measurement points as an example, the specific calculation process is explained.

The sampling frequency of the deflection sensors is 10 Hz, and the collected raw data is shown in Fig. 4a. The hourly average of the deflection monitoring data is taken, and its correlation with temperature is shown in Fig. 4b. Linear regression was used to fit the relationship between deflection and temperature, yielding the quantitative correlation formula: $f(T) = -0.159956 \times T + 4.0275$ (cm). After removing the temperature effect from the raw deflection monitoring data, the high-frequency components are shown in Fig. 4c.

Based on the high-frequency deflection monitoring data collected from the left 1/4 span during the bridge's first month of operation, statistical analysis yielded the probability density function shown in Fig. 5. Fitting with the extreme value distribution model revealed a deflection value of 0.34 cm corresponding to the peak of the probability density. This value is considered the dead-load component of the deflection and will be used for subsequent static performance evaluations.

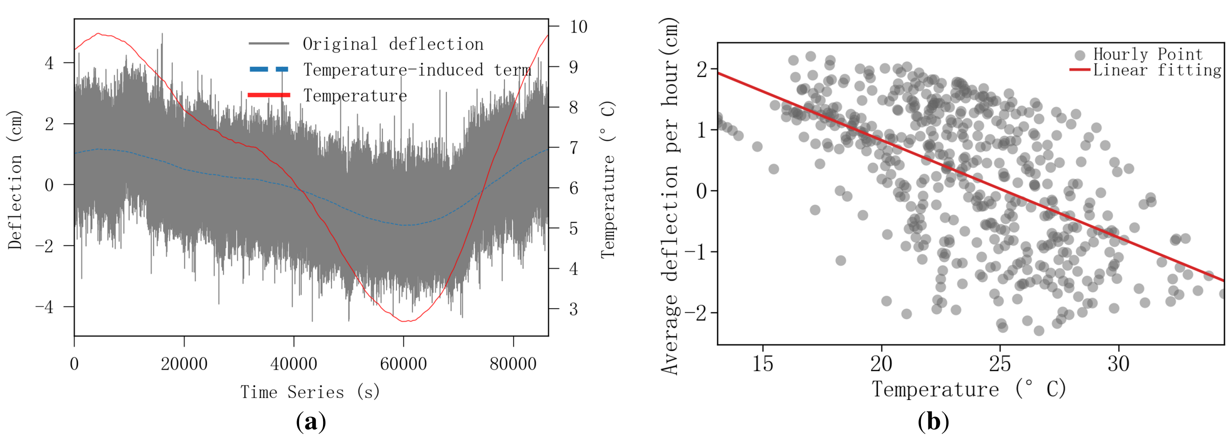
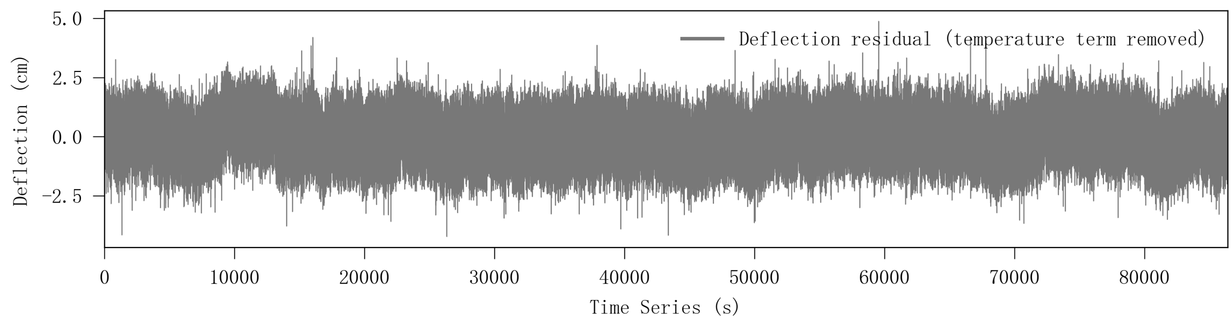


Figure 4: (Continued)



(c)

Figure 4: Deflection-temperature correlation analysis and separation. (**a**) Raw deflection data for the left 1/4 span per hour; (**b**) Correlation between hourly mean deflection and temperature; (**c**) Deflection high-frequency terms after temperature effects are removed.

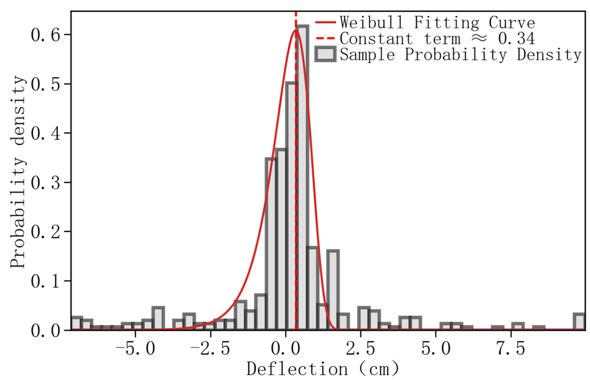


Figure 5: Probability density plot of high-frequency terms for deflection in the left quarter span.

Fig. 6 further compares Weibull with GEV and Lognormal on the left 1/2 span. Weibull provides the best overall fit, and the metric differences from statistical results of all measurements are minor, supporting the robustness of the dead-load extraction procedure.

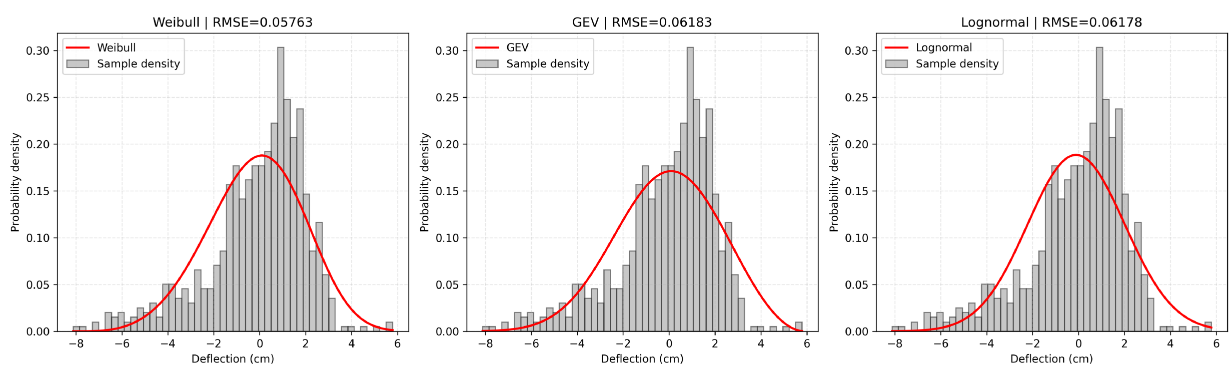


Figure 6: Probability density plots fitted by GEV, lognormal, and Weibull distributions.

The dead-load components at each deflection monitoring point under the as-built bridge condition were obtained, serving as the baseline sequence for deflection measurements. Subsequently, the deflection monitoring data from the second month after opening to traffic were analyzed to derive their dead-load components. Using Eq. (1), the evaluation scores for each deflection monitoring point were calculated, with the results shown in Fig. 7.

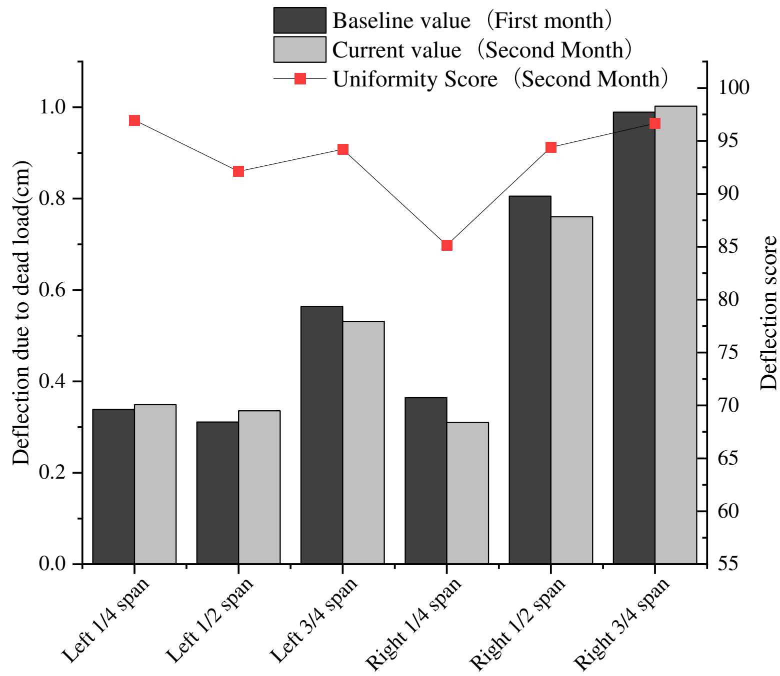


Figure 7: Deflection under dead load component and rating in the second month of operation.

According to Eqs. (2) and (3), the uniformity score for deflection was calculated as 93.59. Using Eq. (4), the non-uniformity coefficient was determined to be 0.9894. After adjusting the uniformity score, the final deflection assessment result for the second month of traffic operation was 92.60.

Similarly, processing the cable force monitoring data yielded an assessment result of 97.61. Weighted summation of the deflection and cable force scores produced a static performance assessment result of 95.11 for the bridge structure in the second month of operation. Using this method, the static performance of the bridge structure was sequentially calculated for the subsequent four months, with the respective assessment results shown in Fig. 8.

In this study, the first month after the bridge's opening was selected as the baseline period, and its score was normalized to 100 for display purposes. Starting from the second month, as traffic volume and axle loads gradually increased and stabilized, fluctuations in live loads and variations in data quality heightened the uncertainty in extracting dead-load components. This contributed to a slight decline in the score during the subsequent months.

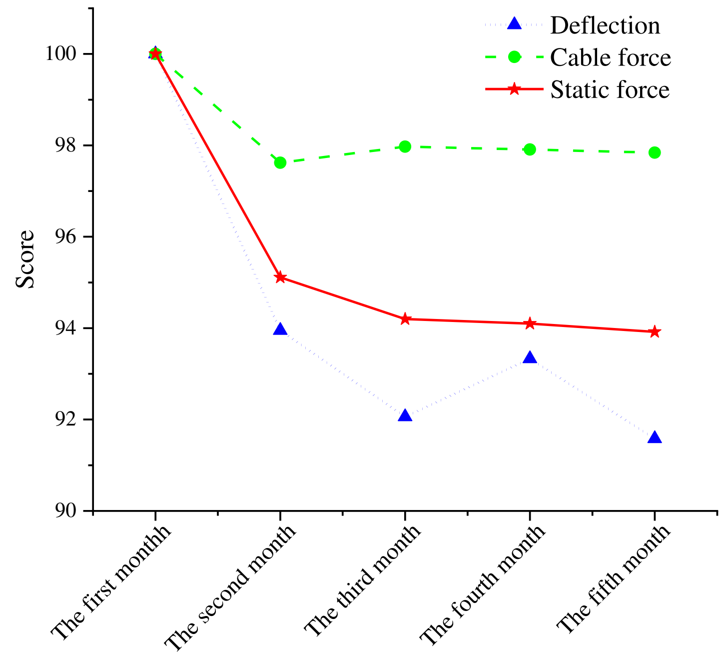


Figure 8: Monthly deflection, cable force, and static performance evaluation results for the bridge.

The lower score in Month-2 is mainly attributed to the early-operation baseline not being fully stabilized, which affects the monthly statistical extraction under random live loads. This short-term deviation should not be directly interpreted as structural deterioration. To reduce the deviation caused by the early-stage instability, we also re-evaluated the data of subsequent months using Month 2 as the baseline, as presented in Section 3.5.

3.3 Dynamic Performance Evaluation

Using acceleration sensor monitoring data from the left 1/4 span of the main girder as the research subject, the dynamic performance of the case-study bridge was evaluated. The acceleration sensor operated at a sampling frequency of 50 Hz, and the collected vertical acceleration data are shown in Fig. 9. Similarly, a fast Fourier transform (FFT) was applied to the acceleration time-domain data from the first month of bridge operation, yielding the bridge structure's spectrum as depicted in Fig. 10. Based on the peak characteristics in the spectrum, the fundamental frequency of the bridge structure was determined to be 1.614 Hz.

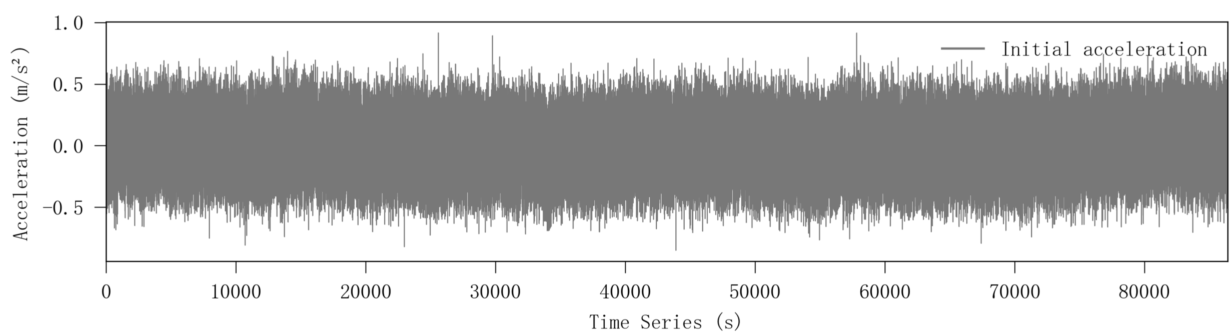


Figure 9: Vertical acceleration data for the left 1/4 span of the main beam.

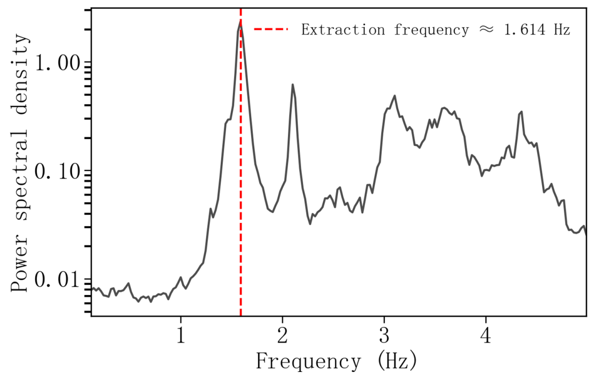


Figure 10: Spectrum diagram.

Temperature induces changes in the elastic modulus of materials and boundary conditions within bridge structures, thereby affecting the fundamental frequency of the bridge structure. The calculated fundamental frequency of the case-study bridge structure is mapped onto the temperature coordinate axis, as shown in Fig. 11. A linear relationship exists between the fundamental frequency of the bridge structure and temperature. Using linear fitting analysis, the linear fitting equation is obtained as $f(T) = -0.003107 \times T + 1.569941$ (Hz).

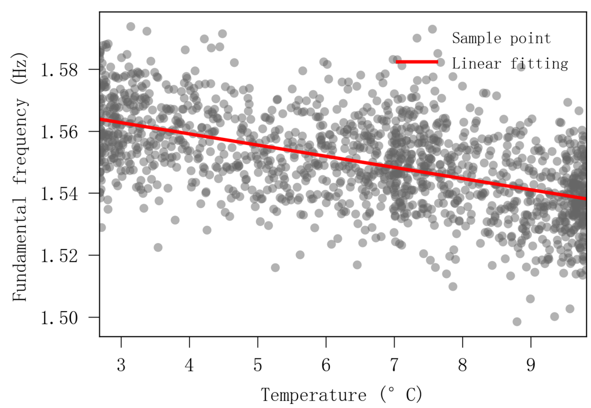


Figure 11: Mapping relationship between bridge structure fundamental frequency and temperature.

The fundamental frequency of the bridge structure in the completed state is 1.614 Hz, corresponding to a temperature of −13.7°C. After eliminating temperature effects, this fundamental frequency was used as the baseline for dynamic performance evaluation. Comparing it with the fundamental frequency obtained from the corrected data in the second month of operation, the dynamic performance score of 96.21 for the bridge structure in the second month was calculated based on Eq. (1). Following this method, the dynamic performance for subsequent months was calculated sequentially, with the results shown in Fig. 12.

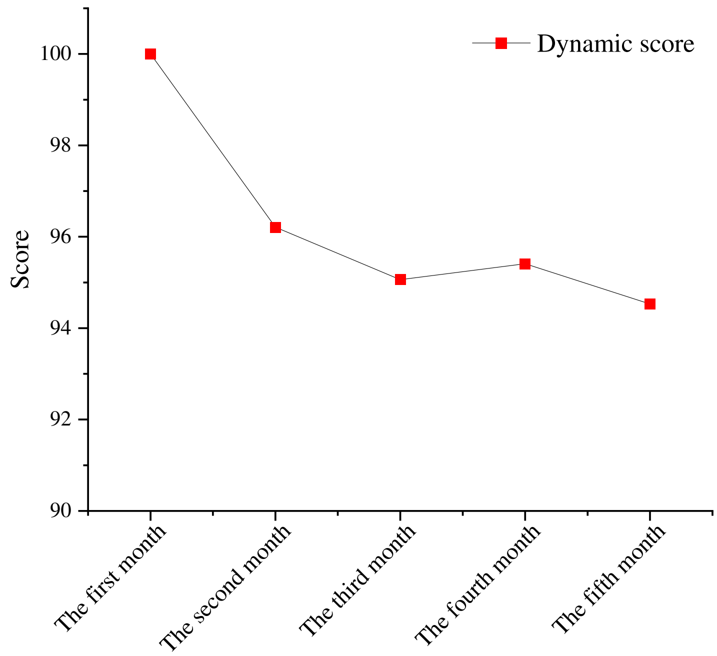


Figure 12: Monthly dynamic performance evaluation results for the bridge.

3.4 Comprehensive Assessment of Static and Dynamic Performance

Static performance primarily reflects the stress state and spatial distribution characteristics of a bridge structure under dead load, while dynamic performance characterizes the overall stiffness of the structure and its variations. Both aspects reveal the service condition of the bridge structure from different perspectives, exhibiting strong complementarity.

Based on the assessment results of both static and dynamic performance, it is necessary to conduct a comprehensive static-dynamic evaluation of the bridge structure. To avoid linear masking effects on the comprehensive assessment results caused by variations in individual performance indicators, a variable-weight integration method is employed to fuse static and dynamic performance. Using static performance scores and dynamic performance scores as evaluation metrics, initial equal weighting is applied. Through Eq. (8), the variable weights for the static indicator (0.5023) and dynamic indicator (0.4977) in the second month after opening to traffic are calculated. Based on this, the composite static-dynamic performance score for the bridge structure in the second month of operation was calculated as 95.66.

By computing the composite performance scores for the bridge structure across different assessment months, the final composite score results for the bridge within several months of completion and operation were obtained, as shown in Fig. 13.

Results indicate that, during the monitoring period, the bridge structure maintained a high composite score of approximately 94, indicating that its overall technical condition remained excellent. The composite score curve shows a slight overall decline over time, reflecting the trend in the bridge structure's comprehensive performance as it ages. The minor rebound observed in the fourth month may be attributed to residual effects from random fluctuations in environmental factors such as temperature, humidity, and wind loads on the extraction of high-frequency components in the monitoring data. Considering the inherent systematic errors within the monitoring system and potential processing inaccuracies, such small-scale numerical fluctuations represent normal data dispersion.

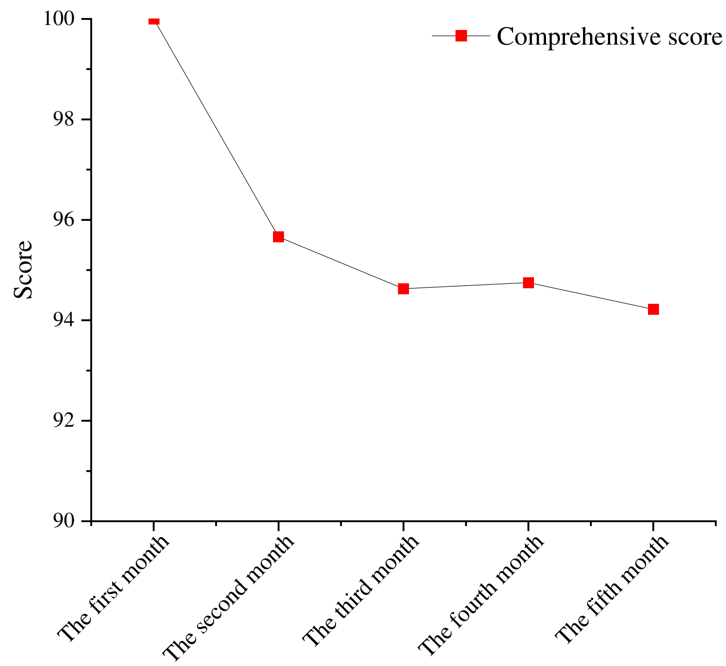


Figure 13: Comprehensive evaluation results of bridge static and dynamic performance.

Regarding the interpretation of small score differences (e.g., 94 vs. 96), it should be emphasized that, over a short monitoring window and in the absence of damage or abrupt traffic-regime changes, such minor variations are mainly attributed to stochastic live-load fluctuations and residual uncertainty from measurement and environmental correction. Hence, a difference of only a few points typically implies a high similarity of structural state between the two months rather than a meaningful performance change.

The proposed static, dynamic, and comprehensive scores are intended not only for performance quantification but also for supporting maintenance decision-making. In routine operation, the monthly scores can be used for trend tracking and early warning: small short-term fluctuations are expected due to traffic randomness and data-processing uncertainty, whereas a persistent decrease over consecutive periods or an abrupt drop may indicate a potential performance change and should trigger further actions. In practice, a staged decision workflow can be adopted: (1) routine monitoring when the score is stable; (2) enhanced monitoring and targeted inspection when the score shows a sustained downward trend or a sudden decrease; (3) detailed diagnosis and intervention when the abnormality is confirmed. The suspected locations can be prioritized by examining the lowest single-point scores and the indicators contributing most to the score reduction. This workflow provides a quantitative basis for maintenance prioritization and timely intervention without requiring bridge closure.

The current dataset does not include damage scenarios or independent evidence of structural deterioration, so the damage sensitivity of the comprehensive score cannot be quantitatively validated in this study. In future work, this issue will be addressed by incorporating representative damage cases or numerical simulations to test the sensitivity of the score and the robustness of the thresholds.

3.5 Baseline Sensitivity Check Using Month-2 as Reference

Ideally, the baseline for performance evaluation should be monitoring data obtained at completion acceptance, as it provides a reliable reference to separate live-load effects from actual structural changes.

However, such as-built or stabilized baseline data are often unavailable in practice. For most engineering applications, an early-service period with stable traffic can serve as a reasonable baseline.

Note that traffic patterns and volumes may change over time, altering the statistical features of monitoring data even without structural degradation. To account for this, it is recommended to review data characteristics (especially distribution types) every 6–12 months and update the baseline if a systematic shift is detected. This helps minimize bias and ensure reliable long-term trend analysis.

In this study, after observing the unstable Month-1 baseline, we re-evaluated the subsequent months using the traffic-stabilized Month 2 as the baseline, following the same static–dynamic fusion framework. Fig. 14 shows the revised static, dynamic, and comprehensive scores.

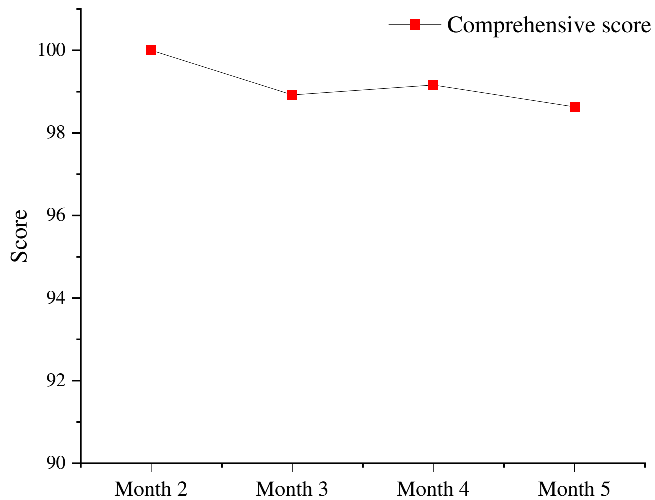


Figure 14: Comprehensive evaluation results of static and dynamic performance using Month-2 as baseline.

Compared with the original results, the re-evaluated curves exhibit mild short-term variations with no artificial early decline, consistent with the healthy condition of the bridge. The remaining monthly differences are mainly caused by live-load variability and statistical uncertainty. If long-term degradation exists, it would present as a persistent downward trend over a longer observation period.

4 Conclusion

(1) A method for assessing the static performance of bridge structures based on dead-load components is proposed. By mining massive monitoring data using the Weibull extreme value distribution model, temperature and live load effects are effectively separated, extracting the dead-load component that characterizes the intrinsic state of the structure. Building upon this, an integrated static performance evaluation index system is established, incorporating single-point deviation, spatial uniformity, and trend consistency considerations, thereby overcoming the limitations of traditional single-index assessments.

(2) A comprehensive assessment method for bridge static and dynamic performance based on variable weight theory is proposed. Recognizing the complementary nature of static and dynamic indicators in characterizing structural condition, variable weight synthesis theory is introduced to construct a weight adjustment mechanism that dynamically responds to indicator degradation levels. If localized stiffness degradation occurs in a girder segment, or if a local prestress loss develops in a cable-related component, the corresponding static indicators would be expected to show a larger deviation from

the baseline together with a more distorted spatial response pattern, leading to a reduction in the static score. If such damage also affects the global stiffness of the structure, the fundamental frequency would further decrease, and the dynamic score would decline accordingly. Through the application of variable weights, this deterioration would be reflected more prominently in the comprehensive score rather than being masked by relatively stable indicators, thereby providing a more accurate reflection of structural trends. In the future, introducing data quality, working condition information, or digital twin parameters into the comprehensive evaluation will help further improve the engineering applicability and robustness of the method.

(3) Engineering case studies validate the method's effectiveness and applicability. When applied to health monitoring data analysis of an arch bridge, results demonstrate that this approach not only quantifies subtle temporal evolution trends in structural performance but also maintains robust assessment outcomes amidst data fluctuation interference. This confirms the method's practical value for bridge operation and maintenance decision-making.

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