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Feature Extraction and Intelligent Model Updating of Cable-Stayed Bridges Based on Multi-Point Dynamic Strain Measurements under Complex Operational Conditions

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ABSTRACT: To address the challenge that the baseline state of FE models for operational highly statically indeterminate bridges is difficult to evaluate accurately, this paper proposes an intelligent multi-parameter inversion and updating framework driven by measured dynamic strains and a LSTM neural network. First, to tackle the complex environmental interferences coupled within short-term monitoring strain signals, a moving-window baseline detrending and refined thermal effect decoupling algorithm is employed. This successfully strips away long-term dead loads and temperature drift, extracting pure mechanical strain sequences with a high signal-to-noise ratio. Second, to overcome the mode omission issue caused by strain nodes at single measurement points, the multi-channel FDD method, combined with the stabilization diagram validation of the covariance-driven SSI-COV method, is utilized to robustly identify the first three baseline natural frequencies of the bridge under authentic operational conditions. Building upon this, an LSTM based nonlinear inverse surrogate model network is constructed, with macroscopic structural frequencies as inputs and local stiffness parameters as outputs. By feeding the measured frequencies into this network, the updated equivalent elastic moduli are obtained to update the FE model. The results demonstrate that the relative errors of the first three modal frequencies converged substantially from the initial 72.25%, 56.57%, and 46.56% down to 16.87%, 24.45%, and 11.18%, respectively. This framework effectively bridges the deviation in mechanical information between the theoretical model and the actual structure, significantly enhancing the fidelity of the digital twin baseline, and providing a reliable physical model foundation for subsequent seismic performance assessments and lifecycle health management of the bridge.

KEYWORDS: Cable-stayed bridge; structural health monitoring; dynamic strain; frequency domain decomposition; model updating; long short-term memory

1 Introduction

At present, China's bridge engineering industry is experiencing a strategic transition from a phase dominated by massive construction to an integrated framework emphasizing construction, management, and maintenance. By the end of 2024, the national bridge inventory surpassed 1.1 million, characterized by a steadily increasing proportion of super long-span bridges. As critical transportation nodes spanning expansive rivers and maritime gulfs, cable-stayed bridges have been widely implemented due to their exceptional structural efficiency [1]. Nevertheless, under prolonged exposure to complex service environments, the structural stiffness and safety reserves of these bridges are bound to degrade, driven by the

coupled evolution of operational traffic dynamic loads, environmental corrosion, and material aging. To address this, integrating Structural Health Monitoring (SHM) systems to achieve real-time performance tracking and condition-based early warning has emerged as a fundamental guarantee for the safety of urban infrastructure. A high-fidelity condition assessment depends not merely on multi-source sensory data, but more imperatively, on the construction of a baseline finite element (FE) model that precisely mirrors the true mechanical responses of the physical structure [2]. Such a model provides the essential foundation for online damage inversion and structural evaluation, serving as the absolute prerequisite to comprehensively unlock the potential of digital twin technologies in bridge engineering.

The calibration of high-fidelity finite element (FE) models heavily relies on the rational selection of objective functions. In current research on bridge model updating, static test data are frequently adopted as the primary target responses [3]. For instance, Martini et al. [4] utilized computer vision techniques to identify the quasi-static deflection responses of bridges subjected to moving vehicles, extracting influence line information for model updating. Meanwhile, Lin et al. [5] proposed an influence line-based updating method incorporating adaptive global optimization; their experimental results on a long-span suspension bridge demonstrated excellent agreement between the updated theoretical influence lines and the measured data. Evidently, model updating based on static data has matured considerably. However, static characteristics inherently lack information regarding the global mass distribution of the structure, which easily leads the updated FE model into the pitfall of stiffness-mass cross-compensation [6]. Consequently, model updating strategies utilizing dynamic response data are deemed more scientifically rigorous. Against this backdrop, acquiring high-quality measured dynamic characteristics is of paramount importance. Traditional operational modal analysis (OMA) for bridges typically relies on dense arrays of acceleration sensors, which are, however, susceptible to the interference of local high-frequency vibration modes [7]. Conversely, in routine bridge health monitoring, strain sensors exhibit higher engineering practicality and deployment density, as they can directly reflect the internal force states of structural components. In recent years, extracting dynamic characteristics utilizing multi-source indirect responses has emerged as a mainstream research trend. Ni et al. [8] successfully identified bridge vibration frequencies by combining a tire pressure model of test vehicles with measured relative axle displacements. Furthermore, Xu et al. [9] demonstrated the feasibility of extracting the modal frequencies of curved bridges from vertical wheel accelerations using a 3D vehicle-bridge interaction model. Although indirect identification methods have broadened the scope of frequency-domain analysis, a critical challenge remains unresolved: how to rapidly and robustly extract bridge frequencies from massive strain monitoring data under authentic operational conditions characterized by unknown vehicle weights, speeds, and complex environmental excitations. To address this, Singular Value Decomposition (SVD) is introduced herein to construct a Power Spectral Density (PSD) matrix by synergizing multi-point strain responses [10]. Theoretically, this approach can effectively filter out low-frequency temperature trend components and high-frequency local vehicular impact noise, thereby precisely extracting the natural frequencies that reflect the macroscopic global stiffness of the structure [11].

Once high-precision measured frequencies are extracted, model updating essentially becomes an inverse optimization problem, aiming to minimize the discrepancy between theoretical and measured responses [12]. Traditional updating frameworks widely adopt heuristic iterative algorithms like the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). Nevertheless, due to the enormous degrees of freedom in cable-stayed bridge FE models, traditional algorithms require massive, repetitive executions of the FE solver for forward analysis during the iteration cycles [13]. Such a process imposes an overwhelming computational burden, falling short of the requirements for real-time or near-real-time online calibration. As deep learning technologies evolve, data-driven intelligent surrogate models offer a new paradigm for computationally efficient model updating [14]. Specifically, the Long Short-Term Memory (LSTM) network

distinguished by its powerful nonlinear mapping capacity and superiority in extracting sequential temporal features is highly capable of accurately capturing the intricate, nonlinear coupled mappings between multi-order frequency features and the foundational structural stiffness parameters.

To address the aforementioned limitations, this paper proposes an efficient FE model updating framework for cable-stayed bridges based on operational dynamic strain monitoring data and an LSTM-based inverse surrogate model. Unlike conventional bridge model updating studies that mainly rely on static load tests, influence lines, or dedicated modal testing, the proposed framework is developed for the real operational condition of in-service bridges. First, rigorous data cleansing is performed on a 30-min strain dataset collected under daily random traffic, where unknown vehicle information and temperature variations are coupled in the measured responses. Then, the strain-based Frequency Domain Decomposition (FDD) method is employed to identify the first three baseline natural frequencies of the bridge, which are subsequently used as the dynamic objective function for FE model updating. On this basis, the global equivalent elastic moduli of the main girder and stay cables are selected as updating parameters, and an LSTM-based inverse surrogate model is constructed to establish the nonlinear mapping from ordered modal-frequency features to global equivalent stiffness parameters. It should be noted that the LSTM is not introduced for long-sequence prediction, but rather as a gated nonlinear regressor to capture the coupling among modal-frequency features and to enable rapid parameter inversion. The results show that the updated FE model achieves much better agreement with the measured frequencies, reducing the relative errors of the first three modal frequencies from 72.25%, 56.57%, and 46.56% to 16.87%, 24.45%, and 11.18%, respectively. This study broadens the application of strain monitoring data in dynamic-characteristic-based model updating and provides an efficient engineering pathway for digital twin baseline calibration and subsequent bridge performance assessment.

2 Methods and Principles

2.1 Data Cleaning Principles

In practical bridge SHM systems, the raw data acquired by strain sensors typically constitute a superposition of multiple physical effects and are inevitably corrupted by interferences such as environmental noise, equipment zero-drift, and asynchronous sampling. To accurately extract the mechanical strains that reflect the transient dynamic characteristics of the structure, this study designs a multi-stage data cleansing and decoupling algorithm. This procedure primarily encompasses four steps: patio-temporal alignment, baseline detrending, refined thermal effect correction, and the extraction of significant excitation events.

2.1.1 Spatiotemporal Alignment and Resampling of Multi-Source Monitoring Data

Constrained by the transmission mechanisms of on-site data acquisition equipment, inherent discrepancies often exist in the raw sampling frequencies across various strain channels and temperature sensors [15]. For instance, the actual sampling rate of certain channels may be merely 1 Hz accompanied by packet loss, whereas the target analysis frequency is 10 Hz. To guarantee dimensional consistency for subsequent multi-point joint matrix operations, the discrete data are initially resampled onto a unified time axis. Let the uniform time sequence be defined as $t = [t_1, t_2, \dots, t_N]^T$, with a time step of $\Delta t = 1/f_s$ (where f_s is set to 10 Hz in this study). For the original non-uniform time sequence τ_i and its corresponding observation values $y(\tau_i)$, a first-order linear interpolation is employed for data reconstruction.

$$y(t_k) = y(\tau_i) + \frac{y(\tau_{i+1}) - y(\tau_i)}{\tau_{i+1} - \tau_i} (t_k - \tau_i) \quad (1)$$

where $t_k \in [\tau_i, \tau_{i+1}]$. This method not only compensates for the missing data but also effectively aligns the spatial phases across all sensors.

2.1.2 Baseline Drift Elimination via Moving Median Filtering

Due to the inherent zero-drift of sensors caused by aging and the slow variations in the macroscopic environment, the raw strain signals exhibit pronounced low-frequency baseline drift. Traditional moving average (MA) filtering is susceptible to localized “mean-shifting” artifacts when abrupt peak values are induced by passing vehicles, consequently leading to waveform distortion of the mechanical strains. To mitigate this, a more robust moving median filter (MMF) is adopted in this study to fit the baseline. Let W denote the length of the sliding window (set to 60 s in this study). The slowly varying baseline strain $\varepsilon_{baseline}(t)$ at time t can thus be defined as the median of the data points within the window.

$$\varepsilon_{baseline}(t) = Median \{ \varepsilon_{raw}(\tau) | \tau \in [t - W/2, t + W/2] \} \quad (2)$$

By subtracting this baseline from the raw strain, the low-frequency drift can be preliminarily eliminated, thereby isolating the high-frequency fluctuating mechanical strain increments.

$$\varepsilon'_{mech}(t) = \varepsilon_{raw}(t) - \varepsilon_{baseline}(t) \quad (3)$$

2.1.3 Strain-Temperature Decoupling and Refined Thermal Effect Correction

In a natural service environment, the total strain ε_{raw} of a bridge structure theoretically consists of the mechanical strain ε_{mech} , the temperature-induced strain $\varepsilon_{thermal}$, and the environmental noise v . Although the majority of the low-frequency trend has been eliminated through moving median filtering, to thoroughly eradicate the residual thermal components induced by short-term temperature variations, this study further introduces a temperature decoupling model based on linear regression [16]. Assuming an approximately linear mapping relationship between the structural strain and the ambient temperature $T(t)$ within a short-term observation window (e.g., 30 min), the following regression equation can be constructed.

$$\varepsilon_{raw}(t) = a * T(t) + \beta + \varepsilon_{mech}(t) \quad (4)$$

where a denotes the equivalent thermal sensitivity coefficient of the measurement point (incorporating the effects of material thermal expansion and temperature-induced secondary internal forces caused by structural constraints), and β represents a constant bias term. Once a is determined via the least squares method, a refined temperature correction is performed on the signal, utilizing the mean temperature T of the specified duration as the baseline.

$$\varepsilon_{corr}(t) = \varepsilon_{raw}(t) - a(T(t) - \bar{T}) \quad (5)$$

Subsequently, a secondary baseline detrending procedure is executed to ultimately obtain the purified mechanical strain sequence ε_{mech} under the combined actions of vehicular and environmental excitations.

2.1.4 Adaptive Extraction of Significant Vehicular Load Events

Upon acquiring the purified mechanical strains, to evaluate the local response patterns of the bridge under operational traffic flows, it is imperative to extract significant events induced by the passage of heavy-duty vehicles from the continuous monitoring signals (i.e., Peak Picking). This study establishes an adaptive threshold extraction mechanism based on local statistical characteristics [17].

Taking the measurement point most sensitive to the longitudinal force of the main girder (e.g., Sx10) as a reference, the standard deviation σ of the mechanical strain over the entire duration is calculated. The dynamic threshold T_h is defined as:

$$T_h = k * \sigma \quad (6)$$

where the empirical coefficient k is set to 2.5 in this study. When a strain peak satisfies $\varepsilon_{mech}(t_p) > T_h$ and its time interval from adjacent peaks exceeds a minimum clearance (e.g., 3 s, designed to mask multiple spurious peaks generated by a single passage of a multi-axle vehicle), it is classified as a valid and significant vehicular excitation event. In this context, the empirical coefficient k is set to 2.5, a value primarily derived from engineering trade-offs regarding the balance between false positives and missed detections during the extraction of significant vehicle events. When the threshold is set too low, background noise fluctuations and localized random spikes are prone to being misidentified as vehicle events; conversely, when the threshold is set too high, genuine peaks induced by vehicle loads may be overlooked. Based on the background fluctuation levels, peak distribution characteristics, and manual verification results of the 30-min operational strain records analyzed in this study, a threshold of 2.5σ demonstrates a relatively stable capability for identifying significant vehicle load events. In practical engineering applications, this parameter may be appropriately adjusted to suit specific monitoring noise levels and event detection requirements.

2.2 Principle of Modal Frequency Identification Based on Strain FDD

2.2.1 Construction of the Cross-Spectral Density Matrix

Initially, measurement points with complete sampling rates and high signal-to-noise ratios (e.g., Sz1, Sz3, Sx10) are selected to construct the multi-point response vector $y(t)$. Utilizing Welch's method, the time-domain signals are divided into segments with a specific overlap ratio (e.g., 50%). The Cross-Spectral Density (CSD) matrix $G_{yy}(f_k)$ at discrete frequencies f_k is then estimated via the Fast Fourier Transform (FFT).

$$G_{yy}(f_k) = \frac{1}{N_{seg}} \sum_{i=1}^{N_{seg}} Y_i(f_k) Y_i^*(f_k) \quad (7)$$

where $Y_i(f_k)$ denotes the Fourier transform of the response vector for the i -th segment, $*$ indicates the conjugate transpose, and N_{seg} is the total number of segments.

2.2.2 Singular Value Decomposition and Frequency Extraction

At each discrete frequency point f_k , Singular Value Decomposition (SVD) is performed on the Hermitian matrix $G_{yy}(f_k)$.

$$G_{yy}(f_k) = U(f_k) S(f_k) U^H(f_k) \quad (8)$$

where $S(f_k)$ is a diagonal matrix containing the singular values $s_i(f_k)$ (sorted in descending order), and $U(f_k)$ is the corresponding singular vector matrix.

Under the assumption of ambient white noise excitation, the system's response near a natural frequency is predominantly governed by that specific mode. Therefore, the frequencies corresponding to the local peaks on the first singular value spectrum $s_1(f_k)$ are identified as the natural frequencies of the structure. Meanwhile, the corresponding first singular vector approximates the strain mode shape of that order. By extracting the prominent peaks of the $s_1(f_k)$ curve within the frequency band of interest (0.1~4.0 Hz), the first three baseline natural frequencies of the structure are ultimately identified.

3 Engineering Project Overview

This study takes an operational cable-stayed bridge in China as the case study. The bridge is oriented north-south and spans a railway station yard. To meet strict railway clearance and construction demands while crossing seven railway tracks below, the bridge axis forms a skew angle of approximately 55° with the railway lines. The practical information of the bridge is depicted in Fig. 1. Characterized as a single-tower cable-stayed bridge with double cable planes, it possesses a span combination of $88 + 80$ m (yielding a total length of 168 m) and a deck width of 16.7 m, with the main girder fabricated from C50 prestressed concrete. Because the bridge is situated along a heavily trafficked urban corridor and spans a railway network, it is unavoidably exposed to a multitude of complex environmental excitations such as heavy traffic loads and extreme temperature fluctuations throughout its operational life. Therefore, utilizing this bridge as a benchmark for health condition monitoring and assessment is highly representative.



Figure 1: Actual bridge information.

To acquire real-time insights into the mechanical behavior and safety condition of the bridge during its operational lifespan, a comprehensive SHM system has been deployed. This study primarily relies on the dynamic response data acquired by this system for subsequent analysis. Among the monitored parameters, strain monitoring serves as a core approach for evaluating the cross-sectional stiffness degradation and local stress states of the main girder. As illustrated in Fig. 2, the strain sensors are predominantly installed at critical load-bearing cross-sections of the main girder, encompassing the vicinity of the pylon base as well as the mid-span and quarter-span regions. Aligned with the model updating requirements of this study, data from six representative strain measurement points were selected for in-depth analysis. Specifically: (1) Sz-series sensors (Sz1, Sz3, Sz5, and Sz7): These sensors are concentrated at the root section of the main girder near the centerline of the pylon. This region is subjected to the most pronounced global bending moments and axial forces, making it highly sensitive to variations in the macroscopic bending stiffness of the entire bridge; (2) Sx and Sy-series sensors (Sx10 and Sy14): Positioned on the straight webs of the main girder (e.g., at the mid-span or quarter-span), these sensors are primarily utilized to capture the local strain characteristics and the synergistic load-bearing mechanisms of the transverse connections under eccentric vehicular loads.

In prolonged natural service environments, variations in the temperature field induce significant temperature-induced secondary internal forces and baseline drift within the highly statically indeterminate structural system of a cable-stayed bridge. To achieve the effective decoupling of thermal effects, temperature sensors were synchronously deployed across the cross-sections of the main girder. As illustrated in Fig. 3, the temperature measurement points (T1–T8) are symmetrically distributed along the webs, as well as the top

and bottom slabs of the main girder. This configuration enables the real-time recording of the temperature evolution patterns at the structural boundaries and in the ambient atmosphere, thereby providing reliable physical inputs for the temperature detrending and the refined correction of thermal effects in the strain monitoring data.

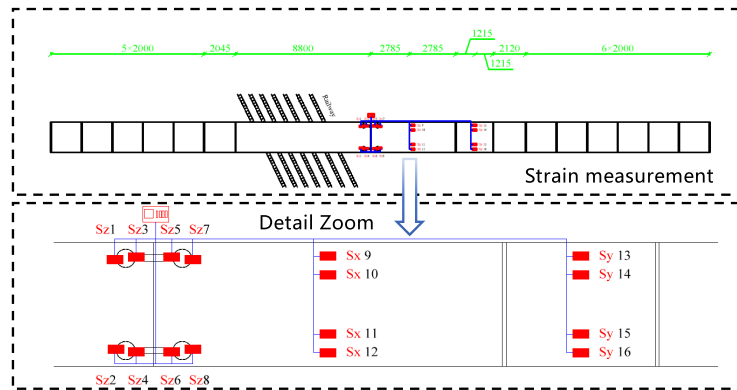


Figure 2: Strain measurement arrangement information.

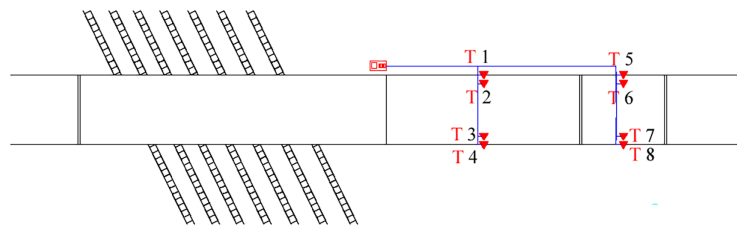


Figure 3: Temperature measurement arrangement information.

It should be noted that strain and temperature sensors are installed on both sides of the bridge in the existing SHM system. For consistency of data quality, sampling continuity, and multi-channel analysis, only one side with representative and complete measurements was selected in this study. Since the present work focuses on low-order global modal frequencies and the overall equivalent stiffness state of the bridge, this choice is considered adequate for the present objective. Nevertheless, it may limit the characterization of torsional effects, transverse asymmetry, and side-to-side local differences, which will be investigated in future work.

To translate the measured monitoring data into a physical condition assessment of the bridge, a three-dimensional baseline FE model of the entire bridge was established using Midas/Civil NX, following a meticulous review of the original as-built drawings. The full bridge is discretized into 861 frame elements. Specifically, the main girder and pylons are simulated using spatial beam elements to accurately capture the flexural and torsional stiffness of the C50 concrete components. The stay cables are modeled with tension-only cable elements, wherein the Ernst formula is applied to correct the reduction in the equivalent elastic modulus induced by the sag effect. Furthermore, a free vibration analysis is conducted utilizing the multiple Ritz vector method to extract the first three mode shapes of the structure. The configuration of the bridge's FE model is illustrated in Fig. 4.

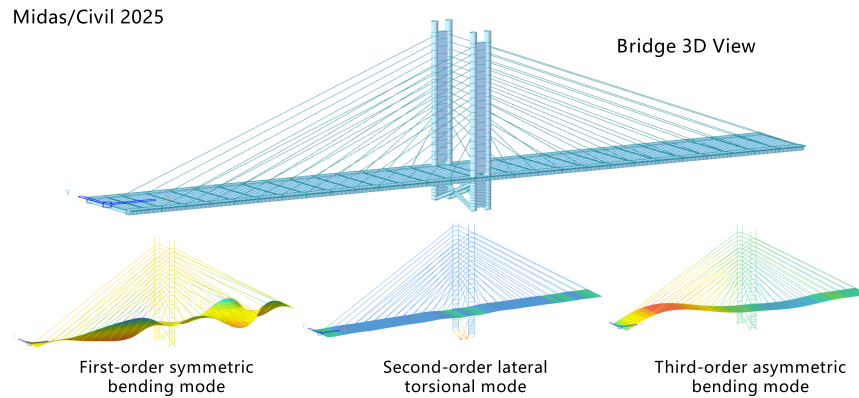


Figure 4: Bridge finite element information.

4 Processing of Operational Monitoring Data and Modal Frequency Identification

Based on the measured static and dynamic response data acquired from the bridge's structural health monitoring system, data cleansing, temperature decoupling, and frequency-domain feature extraction are conducted. By filtering out environmental noise and slow-varying temperature drift, purified mechanical strain sequences with high signal-to-noise ratios are obtained. Subsequently, the FDD method is utilized to robustly identify the baseline natural frequencies of the bridge from the output-only responses under routine traffic excitations. This procedure provides a reliable objective function for the subsequent parameter updating of the FE model.

4.1 Overview and Spatiotemporal Alignment of Monitoring Data

To accurately capture the dynamic mechanical behavior of the bridge under authentic operational environments, this study extracts 30 min of continuous raw strain monitoring data during a typical workday, alongside the 24-h environmental temperature evolution data recorded on the day of testing.

Six representative dynamic strain measurement points, deployed at critical cross-sections of the main girder, are selected. Constrained by the heterogeneity of the on-site data acquisition equipment, the actual sampling rate for certain channels (Sz1, Sz3, Sx10) is 10 Hz, whereas the remaining channels operate at approximately 1 Hz. To satisfy the dimensional consistency requirements for subsequent joint matrix operations, a first-order linear interpolation algorithm is initially employed to resample and align the data from all strain channels onto a unified 10 Hz time axis, ensuring the strict synchronization of the spatial phases across all measurement points. Simultaneously, the slow-varying data from the temperature sensor (T1) at the main girder cross-section over the entire day is extracted. The data reveals a typical diurnal temperature cycle on the day of testing. The extraction of this 24-h dataset is primarily intended to establish a macroscopic mapping baseline between temperature variations and structural strains. The extracted actual monitoring data are illustrated in Fig. 5. It should be specifically noted that, for channels with an original sampling rate of approximately 1 Hz, the linear interpolation processing described herein is utilized solely for the temporal alignment of multi-source monitoring data, temperature-strain correlation analysis, and low-frequency trend identification; it is not intended to recover high-frequency physical information exceeding the original sampling frequency. Consequently, these interpolated 1 Hz channels do not participate in the extraction of modal frequencies falling within ranges above their respective Nyquist frequencies.

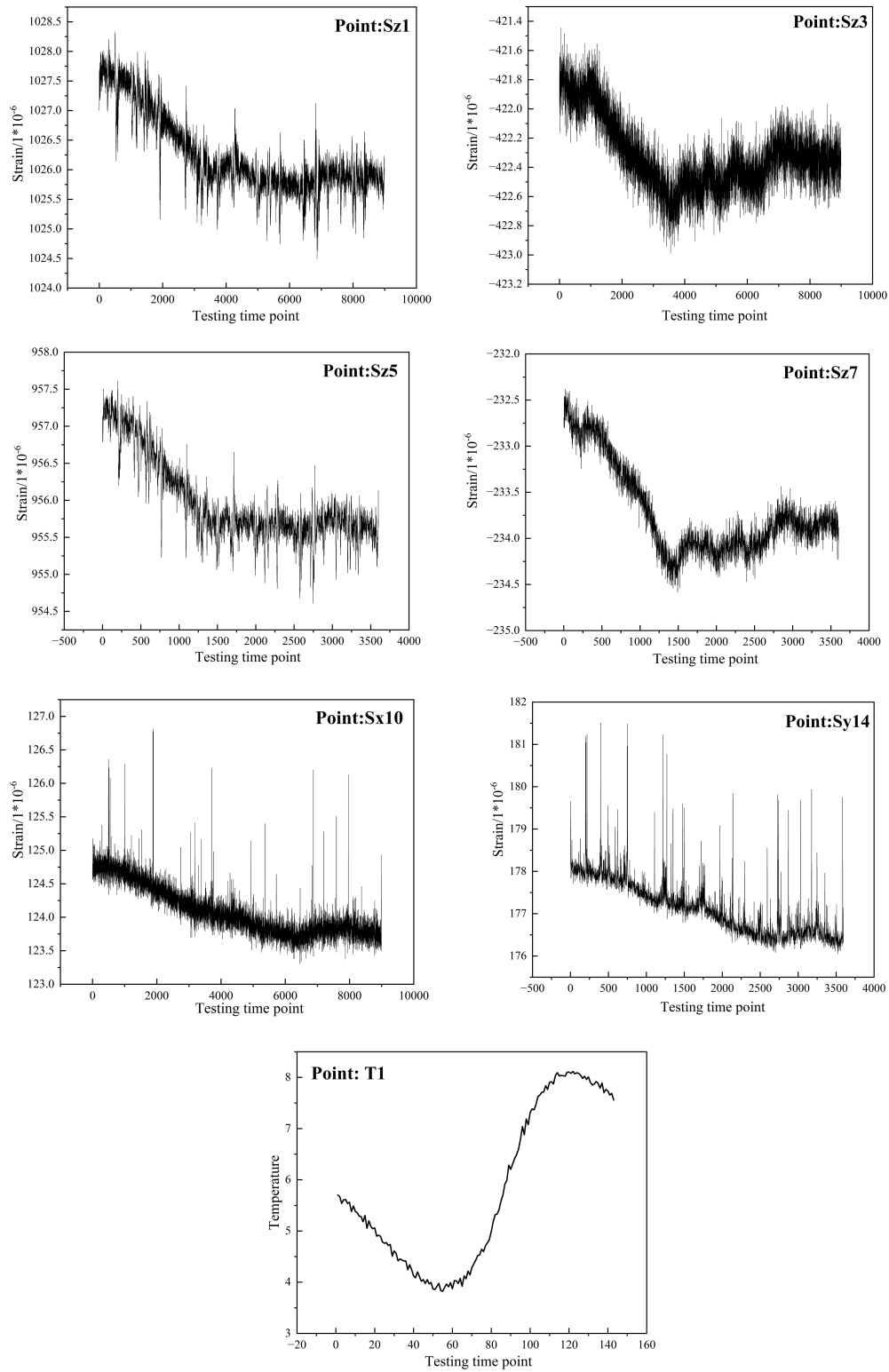


Figure 5: Sensor actual measurement data.

4.2 Raw Strain Data Cleansing and Thermal Decoupling

Raw strain measurements inherently couple multiple signal components, including sensor baseline drift, slow-varying environmental temperature trends, and transient dynamic impacts from vehicles. To address this, a multi-stage data cleansing framework is utilized to conduct in-depth processing of the 30-min time-history data.

4.2.1 Baseline Drift Elimination and Refined Temperature Calibration

Applying the aforementioned data cleansing and decoupling algorithms, the 30-min measured strain responses of the bridge under random operational traffic excitations were processed. Fig. 6 depicts the raw strain time histories for each sensor location, along with the underlying baselines isolated via a 60-s moving median window.

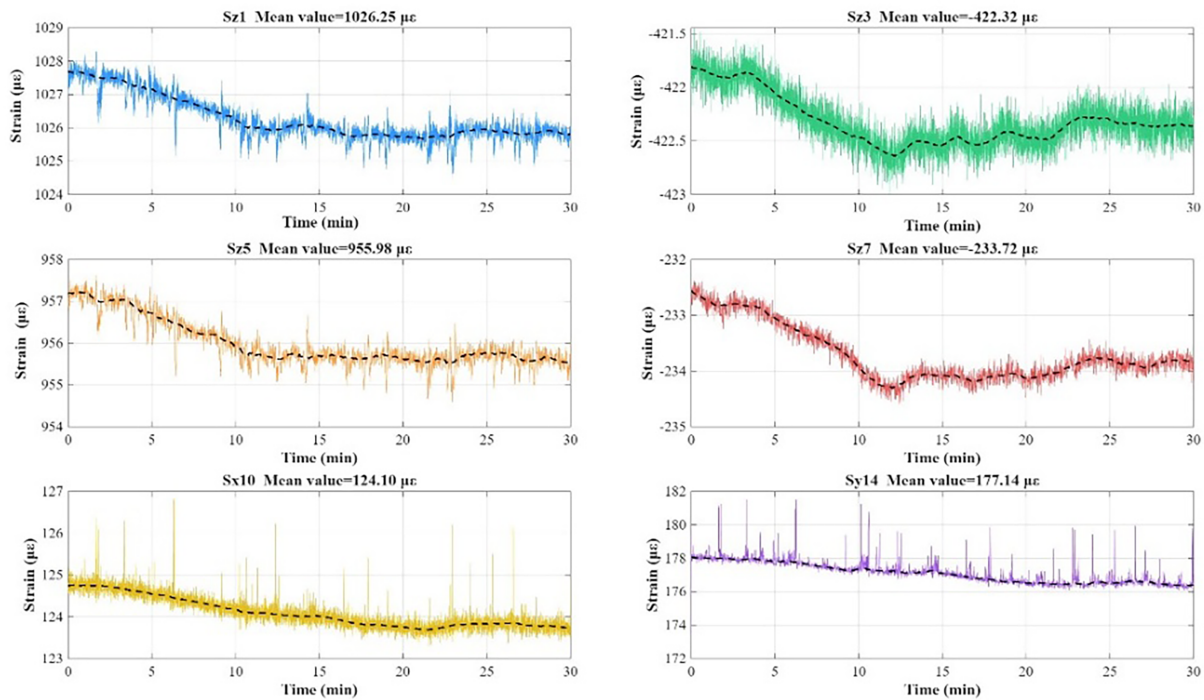


Figure 6: Original strain and baseline.

It is evident that the raw measurements encompass massive initial biases caused by long-term dead loads and sensor zero-drift for instance, the mean strain at point Sz1 at the pylon root reaches a relatively large initial bias of 1026.25 µε. Furthermore, these data demonstrate a distinct low-frequency drift trend within the 30-min observation window. Direct application of such data to frequency-domain analysis would result in the low-frequency trends severely masking the true high-frequency dynamic signatures of the bridge. Through the implementation of baseline detrending and refined thermal calibration, the purified mechanical strain sequences are isolated, as depicted in Fig. 7. The cleansed strain responses consistently fluctuate around a zero-mean baseline across all sensors, successfully stripping away the interference of slow-varying environmental variables. Additionally, the red dashed lines delineate the dynamic threshold limits of $\pm 2.5\sigma$, which clearly differentiate the ambient background white noise from sudden, localized excitation responses.

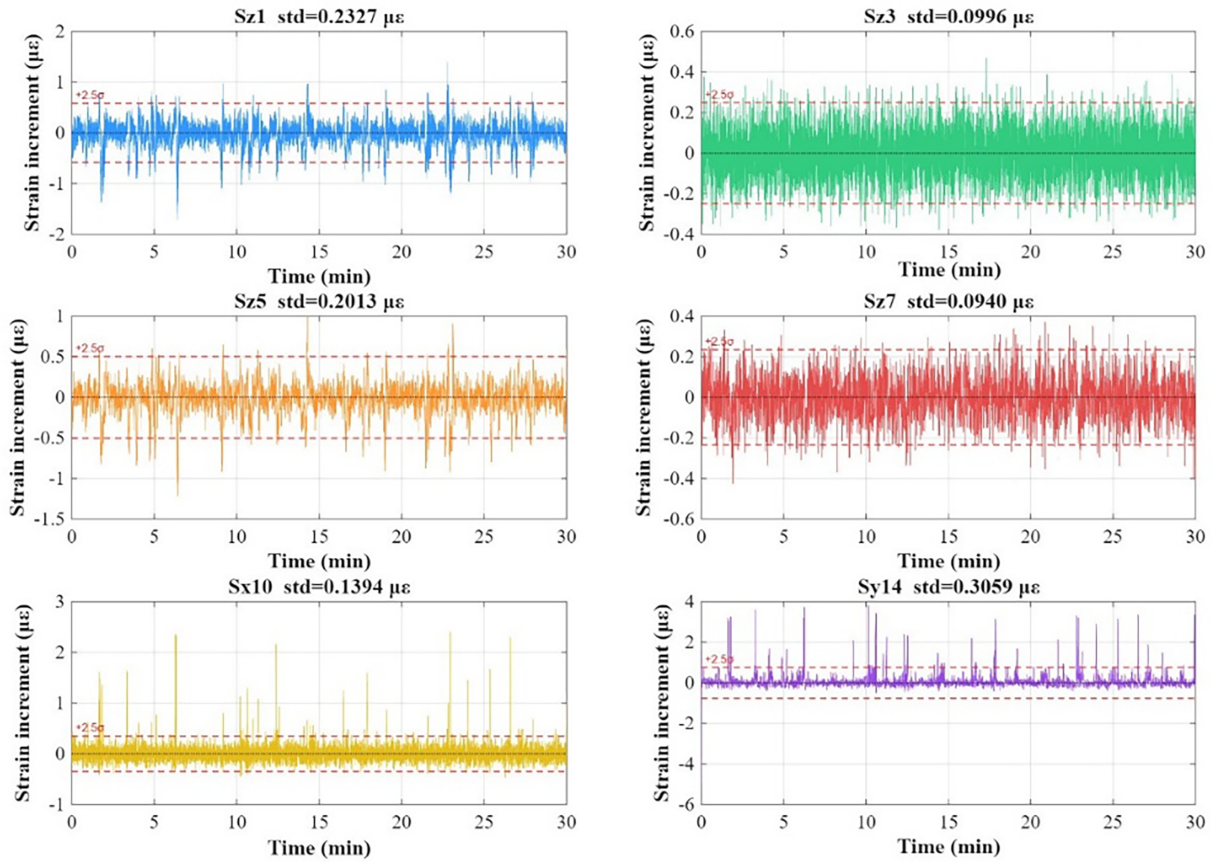


Figure 7: Temperature-corrected mechanical component.

4.2.2 Extraction and Verification of Prominent Vehicular Load Events

Building upon the isolation of the purified mechanical strain components, the extraction of prominent vehicular load events was subsequently conducted. As depicted in Fig. 8, the environmental temperature T1 experienced merely negligible fluctuations (a maximum variance of 0.1590°C) throughout the testing interval, signifying that routine social vehicles were the dominant excitation source triggering the sudden local strain mutations. Utilizing the longitudinally sensitive measurement point Sx10 on the main girder as a baseline, the intelligent algorithm framework successfully recognized and marked 76 substantial peaks surpassing the dynamic threshold (2.5σ) within its mechanical strain time history, as indicated by the red inverted triangles. These discrete transient strain impact crests not only verify the data cleansing algorithm's superior proficiency in retaining high-frequency transient physical signatures, but also supply high-quality impact samples for assessing the structure's true stress state under unknown operational traffic streams in subsequent analyses.

4.3 Bridge Frequency Identification Based on Operational Strain Responses

Following the baseline detrending and thermal decoupling of the raw strain data within the aforementioned framework, the acquired purified mechanical strain components, characterized by a high signal-to-noise ratio (SNR), are utilized for the OMA of the structure. Compared to static deflections or local strain amplitudes, the macroscopic natural frequencies of a structure are significantly more sensitive to variations in global stiffness and are less susceptible to the interference of localized eccentric vehicular loads.

Consequently, the FDD method, in conjunction with the Stochastic Subspace Identification (SSI) method, is adopted to extract the measured baseline natural frequencies of the bridge.

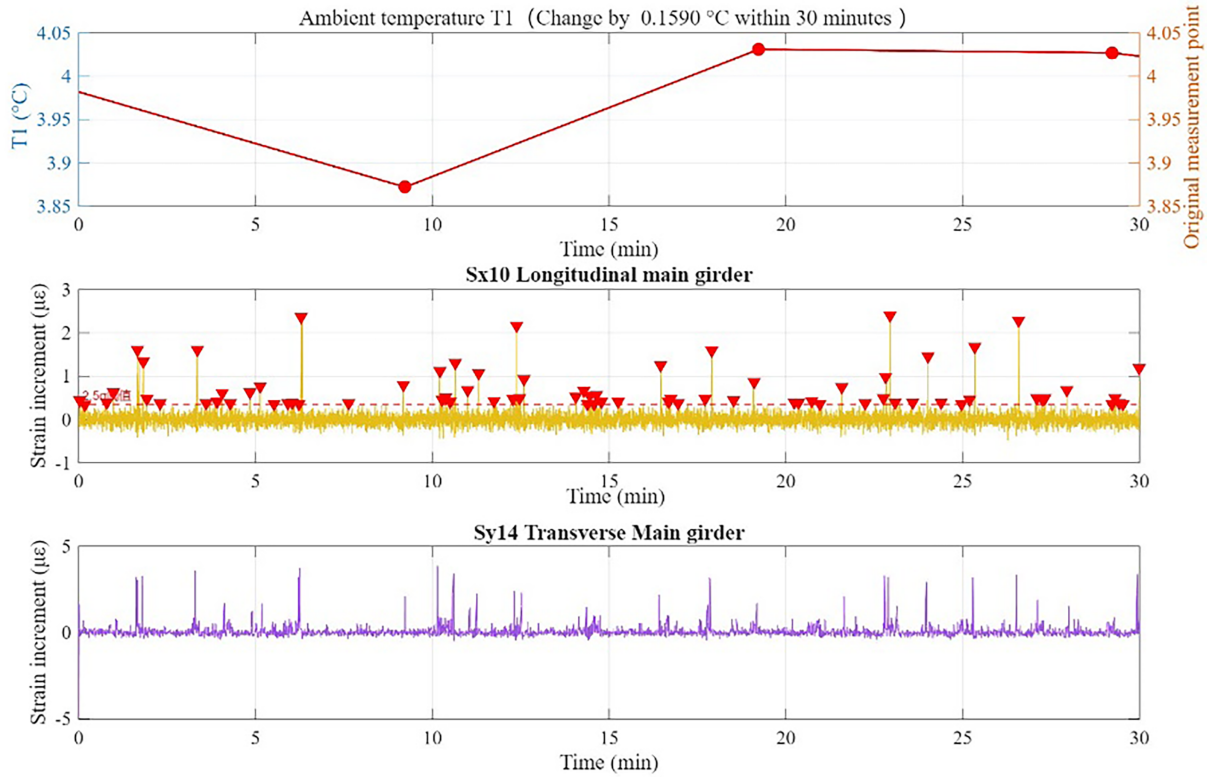


Figure 8: Vehicle event extraction.

4.3.1 Single-Sensor Power Spectral Density (PSD) Analysis

Welch's method is employed to estimate the auto-power spectral density (PSD) of the purified mechanical strains at each measurement point to preliminarily explore the resonance frequency bands of the structure. The segment length is set to 60 s to strike an optimal balance between frequency resolution and statistical stability.

As illustrated in Fig. 9, all measurement points exhibit significant energy concentration within the frequency band of interest (0–4.5 Hz), accompanied by the emergence of multiple resonance peaks (e.g., 0.883 and 2.883 Hz). However, constrained by the spatial distribution characteristics of strain modal nodes, a single measurement point often fails to comprehensively reflect all the modal frequencies of the structure. For instance, there is a distinct difference in the sensitivity to various modal orders between the Sz-series sensors (located at the pylon root) and the Sx10 sensor (located at the mid-span of the main girder). Therefore, a joint frequency domain decomposition analysis utilizing multiple measurement points is conducted to preclude the omission of structural modes.

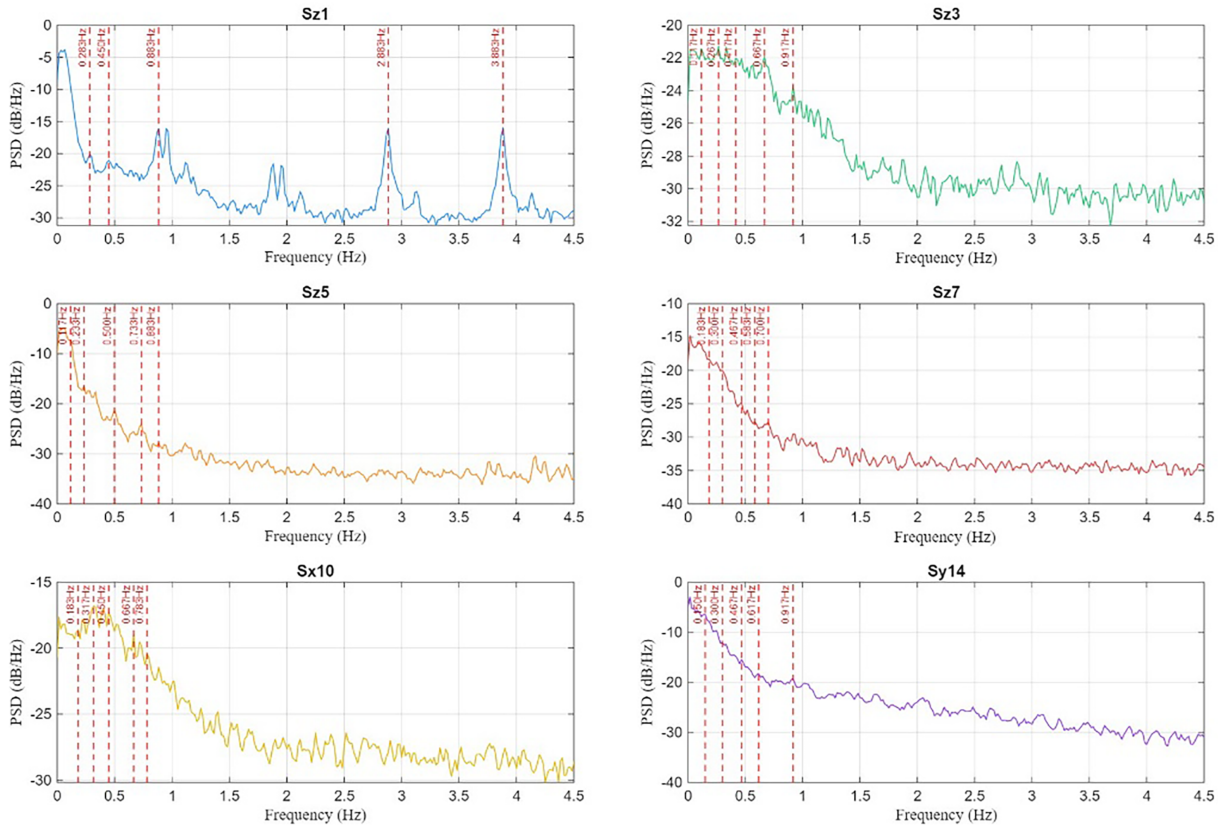


Figure 9: PSD curves of typical strain measurement points.

4.3.2 FDD-Based Joint Frequency-Domain Feature Extraction

To successfully decouple closely spaced modes and mitigate localized noise, representative sensors (Sz1, Sz3, and Sx10) with intact sampling rates and superior signal-to-noise ratios (SNRs) were chosen to form the multi-point response vector. The system's singular value spectrum curves were subsequently derived by constructing the cross-channel cross-power spectral density (CPSD) matrix and applying SVD at individual discrete frequency points.

As illustrated in Fig. 10, the first singular value curve (blue solid line) demonstrates clear resonance peaks that stand out conspicuously against the background noise, while the second and third singular value curves remain at significantly lower energy magnitudes. An automated peak-picking algorithm successfully isolated the three most dominant peaks on the primary singular value spectrum, corresponding to candidate natural frequencies of 0.883, 2.883, and 3.883 Hz.

4.3.3 Cross-Validation via SSI-COV Stabilization Diagram

Because the operational traffic excitations acting on the bridge are not perfectly ideal white noise, the power spectral peaks might be intertwined with periodic harmonics stemming from vehicle-bridge interaction. To address this, the covariance-driven Stochastic Subspace Identification (SSI-COV) technique is additionally incorporated. Through the generation of a system stabilization diagram, a robust cross-validation framework is employed to corroborate the modal frequencies identified by the FDD approach.

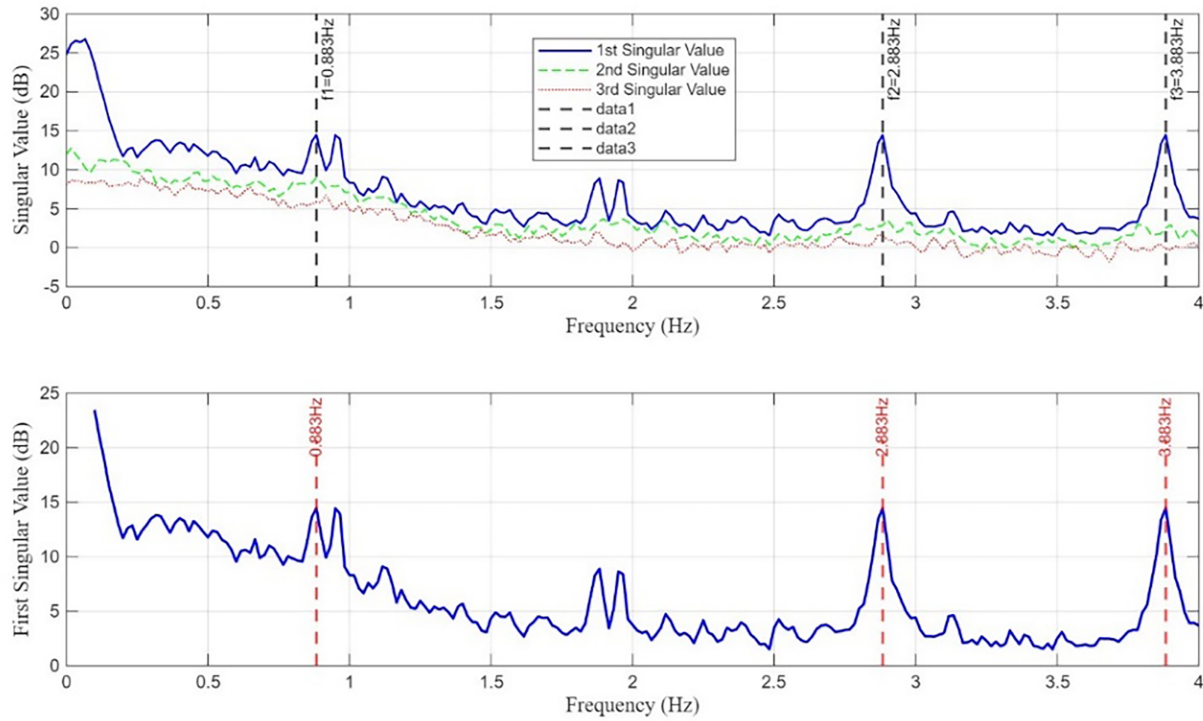


Figure 10: First singular value spectrum curve of FDD multi-point joint frequency domain decomposition.

In the stabilization diagram analysis, the maximum physical order of the system is set to 30. As illustrated in Fig. 11, with the increment of the system order, highly dense vertical alignments of stable poles emerge at 0.883, 2.883, and 3.883 Hz. The stable appearance of these poles across different orders (under the criteria of frequency variation $<1\%$ and damping ratio variation $<5\%$) compellingly suggests that the three peaks extracted by FDD are genuine physical modes of the structure, rather than spurious mathematical models or traffic noise harmonics. In the SSI-COV stabilization diagram, the maximum model order is set to 30. Stable poles are identified using standard OMA thresholds: a frequency variation of $<1\%$ and a damping ratio variation of $<5\%$. The maximum order of 30 was determined based on the target frequency band, the number of low-order modes of interest, and pole convergence in preliminary trials, thereby preventing mode omission at lower orders and the introduction of excessive spurious mathematical models at higher orders.

4.3.4 Evaluation of the Initial FE Model and Frequency Comparison

Synthesizing the feature extraction from FDD and the cross-validation via the SSI stabilization diagram [18], the first three baseline natural frequencies of the bridge under actual operational conditions were finalized. Concurrently, a free vibration analysis was performed on the initial baseline FE model to extract its theoretical frequencies for comparison, with the detailed results presented in Table 1.

The comparison demonstrates that, primarily due to the idealized assumptions regarding material properties (e.g., the initial elastic moduli of the main girder and cables) and boundary conditions, highly significant discrepancies exist between the theoretical frequencies of the initial model and the measured dynamic characteristics. Given that this initial model is incapable of accurately reflecting the current authentic physical state of the structure, performing an FE model parameter updating procedure driven by measured data becomes necessary.

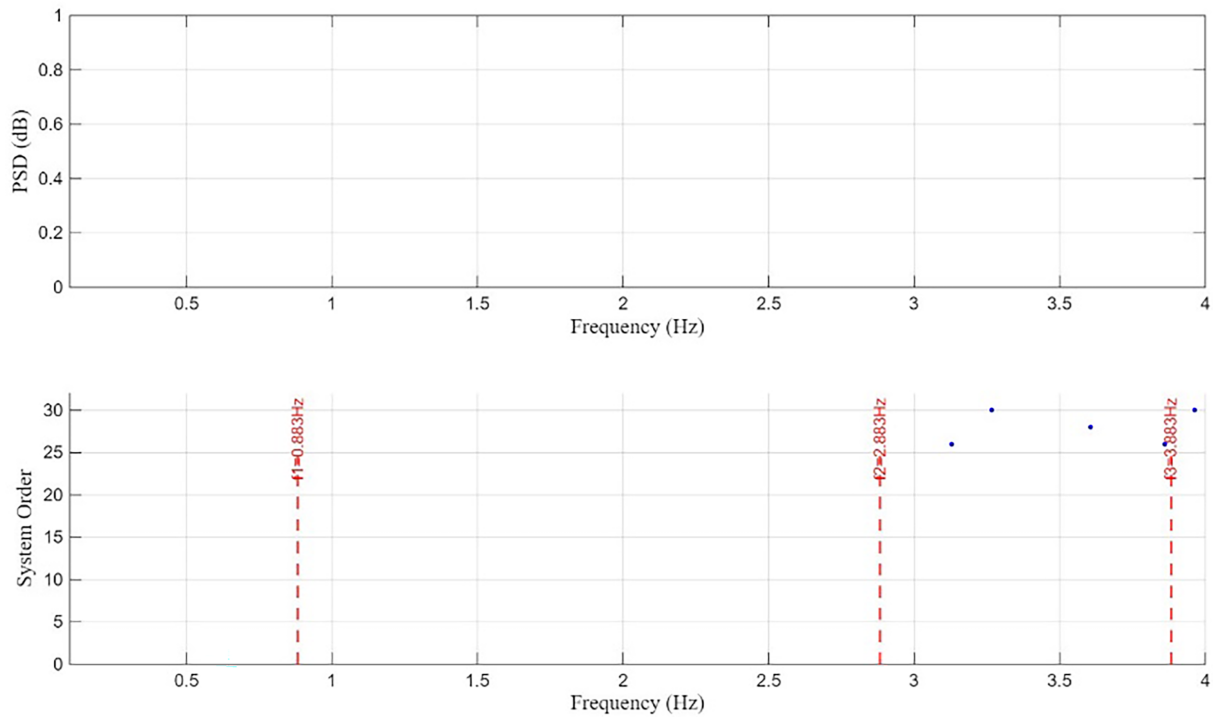


Figure 11: SSI-COV stabilization diagram.

Table 1: Comparison of results.

	Actual Measured Value/Hz	Theoretical Value/Hz
First-order frequency	0.883	0.245
Second-order frequency	2.883	1.252
Third-order frequency	3.883	2.075

5 Intelligent FE Model Parameter Inversion Based on an LSTM Surrogate Network

5.1 Definition of Surrogate Model Variables and Cross-Correlation Analysis

Owing to the degradation of material properties and the idealization of boundary conditions, significant discrepancies exist between the theoretical frequencies of the initial FE model and the measured dynamic characteristics. To accurately and efficiently update complex, highly statically indeterminate FE models such as those of cable-stayed bridges, an intelligent parameter inversion framework based on a Long Short-Term Memory (LSTM) neural network is proposed. By establishing a multi-dimensional nonlinear inverse mapping from the macroscopic structural frequencies to the local stiffness parameters, the rapid calibration of the bridge's authentic stiffness state is achieved. Through forward FE computations coupled with Latin Hypercube Sampling (LHS), 30 samples were generated by scaling within physically reasonable boundaries. To construct the inversion network and overcome the limitations of traditional forward surrogate models, this study defines the system responses as the input feature vector, and the structural parameters to be updated (i.e., the equivalent elastic moduli of the main girder and the stay cables) as the output label vector. Restricting the updating parameters to the global equivalent elastic moduli of the main girder and the stay cables is primarily driven by the following considerations: First, these two parameter types exert a direct

and significant influence on the low-order global modal frequencies of the bridge, acting as the dominant parameters governing the macroscopic stiffness of the entire structure. Second, given that the currently available observation data comprises only the first three modal frequencies, introducing additional local parameters would inevitably lead to excessively high parameter dimensionality, ill-posed identification problems, and unstable inversion results. Therefore, this study adopts a low-dimensional, global parameterization strategy designed to prioritize the rapid calibration of the baseline model's overall stiffness state, rather than attempting a simultaneous, fine-grained identification of all local physical parameters. Prior to feeding the sample set into the neural network, a Pearson correlation analysis between the input features and the output parameters was conducted to elucidate the physical mechanisms underlying the nonlinear mapping [19].

As shown in Fig. 12, the sensitivities of the various modal frequencies to the stiffness of different structural components exhibit a high degree of heterogeneity and coupling. Such intricate nonlinear cross-coupling characteristics demonstrate that conventional linear regression or sensitivity matrix methods are inadequate for this inversion task, thereby providing the rationale for introducing a gated nonlinear surrogate model to capture the coupled relationship among ordered modal-frequency features and updating parameters.

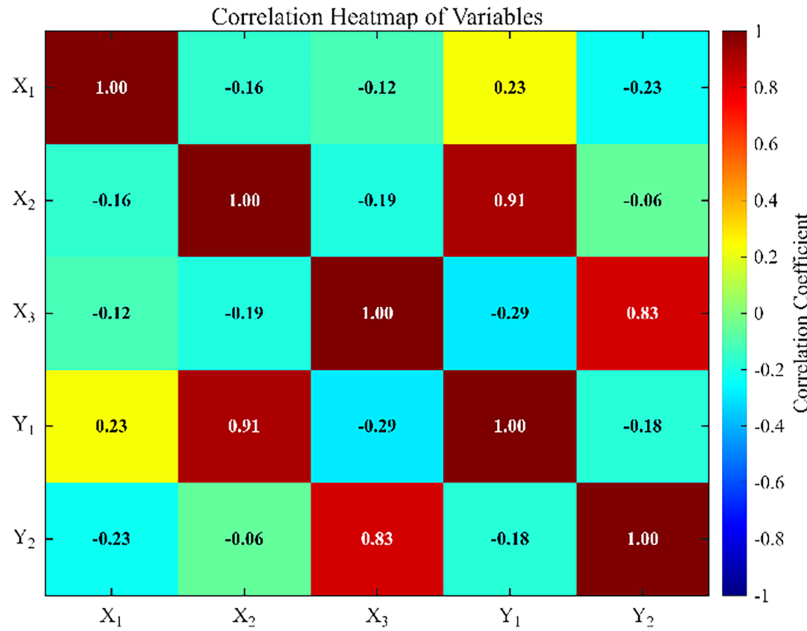


Figure 12: Cross-correlation heat map of model inversion variables.

5.2 Training Process and Convergence Evaluation of the Inverse Mapping Network

The parameter configurations of the 30 generated samples are detailed in Table 2. The dataset is partitioned into a training set (75%) and a validation set (25%) for network fitting. The Mean Squared Error (MSE) is adopted as the loss function for parameter optimization, while the evolutionary trajectory of the Root Mean Square Error (RMSE) is simultaneously tracked. It should be noted that the training dataset in this paper consists of 30 samples size generally considered insufficient for typical high-dimensional deep learning tasks. However, the parameters currently subject to updating in this study are limited to just two global equivalent elastic moduli hose of the main girder and the stay cables while the input features consist solely of the first three modal frequencies. Consequently, this research essentially constitutes an inverse surrogate modeling problem situated within a low-dimensional parameter space. In such scenarios, the sufficiency of

the sample size depends primarily on the dimensionality of the parameters, the extent to which the samples cover the parameter space, and the complexity of the underlying mapping relationship. Based on this premise, Latin Hypercube Sampling was employed in this study to generate samples within a pre-defined range of physically plausible values, thereby facilitating the preliminary learning of the mapping relationship between the modal frequencies and the global equivalent stiffness parameters.

Table 2: Sample dataset.

Sample	Main Girder E	Cable Stay E	Sample	Main Girder E	Cable Stay E
1	0.7	1.22	16	0.7	1.04
2	0.74	1.01	17	0.83	1.17
3	0.72	1.14	18	0.72	1.07
4	0.76	1.28	19	0.74	0.98
5	1.18	0.9	20	0.94	1.01
6	0.72	1.25	21	1.1	1.18
7	0.75	1.12	22	0.78	1.23
8	0.82	1.15	23	0.76	1.11
9	0.94	1.25	24	0.8	1.21
10	1.23	0.79	25	0.92	1.06
11	1.04	1	26	0.75	1.13
12	0.73	1.22	27	0.76	1.12
13	0.8	1.06	28	0.84	1.29
14	0.99	1.15	29	0.82	1.21
15	0.78	0.93	30	1.2	0.82

Fig. 13 records the learning dynamics of the LSTM surrogate model over 2000 iterations. It can be observed that during the initial training phase, the model learns the implicit inverse mapping rules highly efficiently, with both the training and validation loss values (on a logarithmic scale) and RMSE exhibiting a steep decline. After approximately 500 iterations, the error curves for the validation set tend to plateau without any conspicuous rebound in generalization error, indicating the absence of overfitting. Ultimately, the loss stabilizes at an exceptionally low magnitude. This demonstrates that the network has successfully bypassed local optima, achieved an excellent convergence depth within the global parameter space, and thus established a robust computational foundation for high-precision parameter inversion.

5.3 Generalization Validation of the Surrogate Model and Actual Response Prediction

To quantitatively evaluate the precision of the trained LSTM network in inverse deduction, test set samples excluded from the training phase were extracted. Their frequency vectors were inputted into the model, and the predicted elastic moduli were rigorously compared against the actual finite element parameter settings.

The regression scatter plots presented in **Fig. 14** further visually corroborate the goodness-of-fit of the model. The predicted values for the elastic moduli of the main girder and the stay cables, derived from the inversion, tightly converge around the ideal diagonal line, with their coefficients of determination (R^2) reaching exceptionally high values of 0.9960 and 0.9824, respectively.

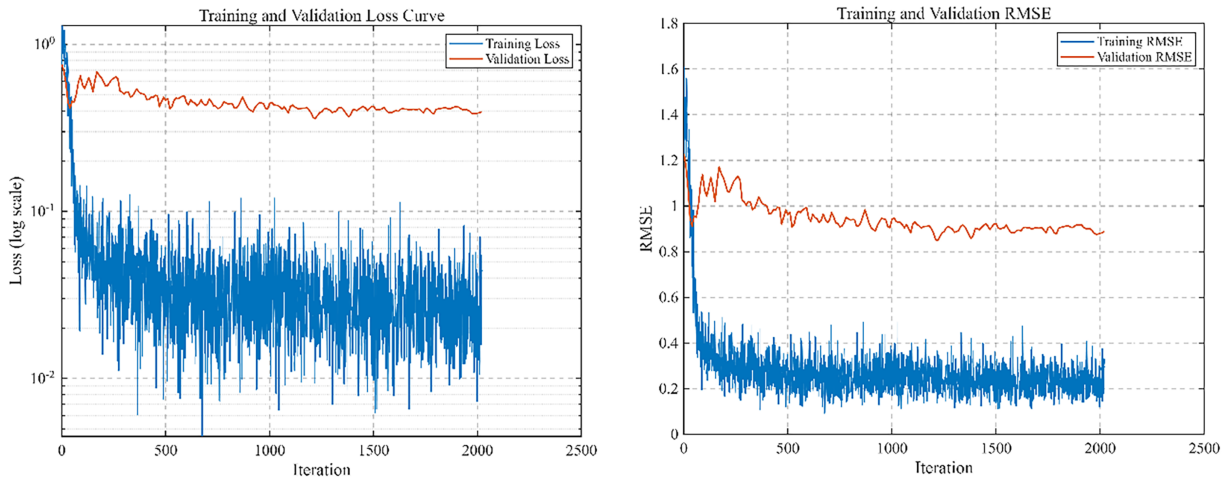


Figure 13: Convergence curves of loss and RMSE for the LSTM inversion during training and validation.

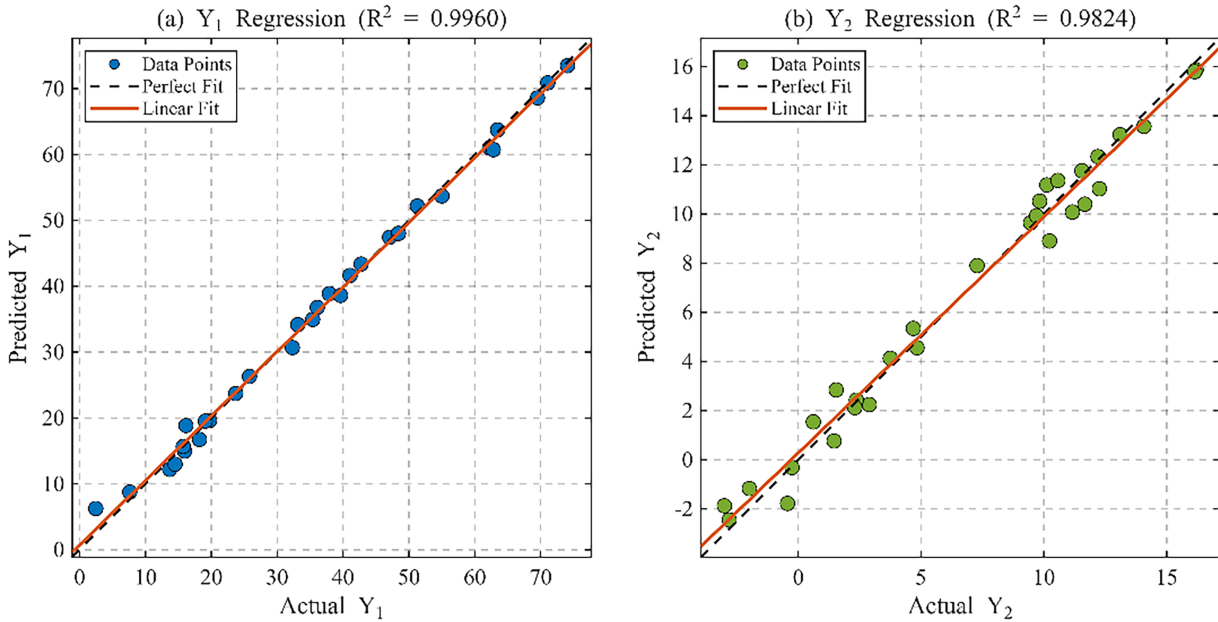


Figure 14: Linear regression analysis of the LSTM parameter inversion results.

5.4 FE Model Updating and Verification Driven by Measured Responses

Building upon the confirmed high fidelity of the LSTM inversion network, the measured first three natural frequencies of the bridge were input into the trained model to instantly reverse-engineer the updated equivalent elastic moduli of the main girder and stay cables.

These intelligently inverted stiffness parameters were then fed back into the original FE model to perform a forward modal analysis, yielding the updated theoretical frequencies. The comparative details of the modal frequencies and corresponding errors before and after the updating procedure are summarized in [Table 3](#).

Table 3: Frequency comparison: before and after update.

	Before Updating	After Updating	Actual Measured Value	Relative Error before Updating	Relative Error after Updating
First-order frequency	0.245 Hz	0.734 Hz	0.883 Hz	72.25%	16.87%
Second-order frequency	2.883 Hz	2.178 Hz	1.252 Hz	56.57%	24.45%
Third-order frequency	3.883 Hz	3.449 Hz	2.075 Hz	46.56%	11.18%

The error evolution detailed in Table 3 provides straightforward evidence of the updating procedure's effectiveness. Notably, the relative error for the first-mode frequency dropped drastically from 72.25% to 16.87%. Similarly, the errors for the second and third modes experienced substantial reductions, decreasing from 56.57% to 24.45% and from 46.56% to 11.18%, respectively. This universal and significant reduction in discrepancy across all targeted modes confirms the surrogate network's effective performance to execute highly efficient and reliable parameter back-calculations in complex structural systems.

It should be noted that a relative error of approximately 10%–25% remains in some modal frequencies after updating. This residual discrepancy can be primarily attributed to the following factors: (1) The idealization of boundary conditions, connection details, and local structural configurations in the FE model; (2) Inherent measurement noise and uncertainties in environmental excitations during output-only modal parameter identification under operational conditions; (3) The exclusive use of global equivalent elastic moduli for the main girder and stay cables as updating parameters, without explicitly accounting for localized component stiffness variations; and (4) The relatively limited constraint information provided by the current inversion objective function, which relies solely on the first three frequencies. Nevertheless, compared to the initial state, the updated model significantly reduces deviations from the measured dynamic characteristics. It serves as an effective starting point for the rapid baseline calibration of in-service bridges and establishes a solid foundation for more refined, multi-parameter updating in the future.

6 Conclusion

To address the bottleneck that the baseline state of FE models for highly statically indeterminate bridges during the operational phase is difficult to evaluate accurately, this paper proposes an intelligent multi-parameter inversion and updating framework for FE models driven by measured dynamic strains and a LSTM neural network. Relying on an actual operational cable-stayed bridge, a complete closed-loop process ranging from monitoring data cleansing and frequency-domain feature extraction to digital baseline calibration is discussed in detail. The main conclusions are drawn as follows:

- (1) Aiming at the complex environmental interferences coupled within the short-term monitored strain signals of the bridge, a moving-window baseline detrending and refined thermal effect correction algorithm was employed. This successfully decoupled the massive initial biases induced by long-term dead loads and temperature drift. The results demonstrate that the processed mechanical strain sequences can capture the authentic transient impacts of operational vehicles with an extremely high signal-to-noise ratio (SNR), thereby providing a high-quality data source for the subsequent modal analysis.

- (2) Overcoming the mode omission issue caused by strain nodes at single measurement points, the multi-channel Frequency Domain Decomposition (FDD) method, combined with the stabilization diagram validation of the covariance-driven Stochastic Subspace Identification (SSI-cov) method, was utilized to robustly identify the first three baseline natural frequencies of the bridge under actual operational conditions. These measured results accurately map the genuine macroscopic stiffness state of the structure, highlighting the unique advantages of strain data in low-frequency macroscopic dynamic evaluations.
- (3) Addressing the limitations of traditional forward surrogate models combined with optimization algorithms, which are time-consuming and prone to falling into local optima—an LSTM inverse mapping network was constructed with macroscopic frequencies as inputs and local stiffness parameters as outputs. By feeding the measured frequencies into the LSTM surrogate model, the updated stiffness parameters were obtained and substituted back into the baseline FE model. The results reveal that the relative errors of the first three structural frequencies converged substantially from the initial 72.25%, 56.57%, and 46.56% down to 16.87%, 24.45%, and 11.18%, respectively. This indicates that the intelligent updating framework can effectively narrow the dynamic discrepancy between the theoretical model and the actual structure, enabling the updated FE model to better reflect the true mechanical information of the structure and substantially enhancing the fidelity of the digital twin baseline. Moving forward, based on the updated high-fidelity FE model, substantive analyses such as virtual evaluations and seismic performance assessments can be conducted to achieve dynamic, lifecycle health management of the bridge.
- (4) It should be noted that the inversion objective function employed in this paper is primarily based on the first three modal frequencies; consequently, the updated results tend to emphasize the characterization of the structure's overall equivalent stiffness state. For highly statically indeterminate systems such as cable-stayed bridges, relying solely on a limited number of frequency-based metrics may still give rise to issues regarding parameter coupling and local non-uniqueness. In future work, multi-source constraint information such as modal shapes, modal strain characteristics, or local static responses will be further incorporated to formulate a joint objective function, thereby enhancing both the uniqueness and accuracy of parameter identification.

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