Data-informed finite element modeling of thermal effects in bridges exploiting frequency and temperature monitoring data

Data-Informed Finite Element Modeling of Thermal Effects in Bridges Exploiting Frequency and Temperature Monitoring Data

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Abstract Temperature changes can strongly affect the dynamic behavior of bridges, making it difficult to distinguish between environmental effects and actual structural damage. To develop reliable damage detection methods, it is essential to generate realistic data that include both thermal variability and damage scenarios. However, real data from damaged structures are rare, so numerical simulations are often used. This study proposes a data-informed finite element (FE) modeling approach that reproduces temperature effects directly from measurements. Instead of relying on traditional thermo-mechanical models, the method learns how temperature influences the effective mechanical properties of the structure using long-term monitoring data (modal frequencies and temperature). A set of temperature-sensitive parameters is first generated within realistic ranges, and the FE model is used to compute the corresponding modal frequencies. These data are used to train a surrogate model linking dynamic response to material properties. The surrogate is then applied to field monitoring data to infer how these parameters vary in practice. A regression model is finally built to relate temperature to the identified parameters. Once trained, the model enables realistic simulation of thermal effects for any temperature history. Importantly, it also provides a consistent framework to introduce and simulate damage scenarios, allowing the generation of synthetic datasets that capture both environmental variability and structural degradation. This is particularly valuable for testing and validating damage detection algorithms under realistic operating conditions. The approach is demonstrated on the KW51 railway bridge, accurately reproducing observed thermal trends and enabling the generation of realistic data for both healthy and damaged states.

Keywords: Structural health monitoring; Finite element modeling; Temperature compensation; Deep neural networks; Unsupervised anomaly detection

Introduction

Vibration-based structural health monitoring (SHM) relies on tracking changes in modal properties to detect damage or degradation before catastrophic failure [1]. However, validating damage detection algorithms remains constrained by the scarcity of real damage data. In most monitoring campaigns, structures operate under healthy conditions, and genuine damage events are rare [2, 3]. This hinders the estimation of detection thresholds, probability of detection (POD) and probability of false alarm (PFA) under realistic environmental variability.

A common strategy is to generate synthetic datasets using finite element models (FEMs) [4, 5]. A baseline FEM, updated to match experimental modal data, can simulate various damage scenarios. However, one major challenge remains: the realistic modeling

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of temperature effects. Temperature variations alter the dynamic response by modifying material stiffness, connection rigidity, and boundary conditions [6]. If temperature effects are not properly modeled, synthetic modal responses lack realism, and temperature compensation algorithms cannot be meaningfully evaluated under damaged conditions.

Previous studies have investigated temperature effects through empirical regression models [7], temperature compensation approaches [8], and thermo-mechanical (TM) FEM simulations [9]. Despite their solid physical basis, TM-based approaches face practical limitations: they require accurate temperature inputs at every element, neglect thermal inertia effects, and often struggle to reproduce empirical temperature-frequency relationships observed in real bridges.

This study introduces a data-informed temperature modeling approach that links field measurements with an updated FEM using surrogate modeling. The methodology is demonstrated on the KW51 railway bridge [10, 11]. This conference contribution presents a concise version of a more comprehensive study [12], where additional methodological details and extended validations are provided.

1. Methodology

The proposed framework combines baseline monitoring data with a calibrated FEM to infer temperature-dependent material properties using surrogate modeling. Specifically here we use as monitoring data the frequencies of vibration. As such, let $\mathbf{F} \in \mathbb{R}^{S\times n}$ contain the first n modal frequencies for S samples, $\mathbf{T} \in \mathbb{R}^{S\times m}$ the temperature readings from m sensors, and $\mathbf{E} \in \mathbb{R}^{S\times k}$ the k temperature-sensitive FEM parameters (e.g., Young's moduli).

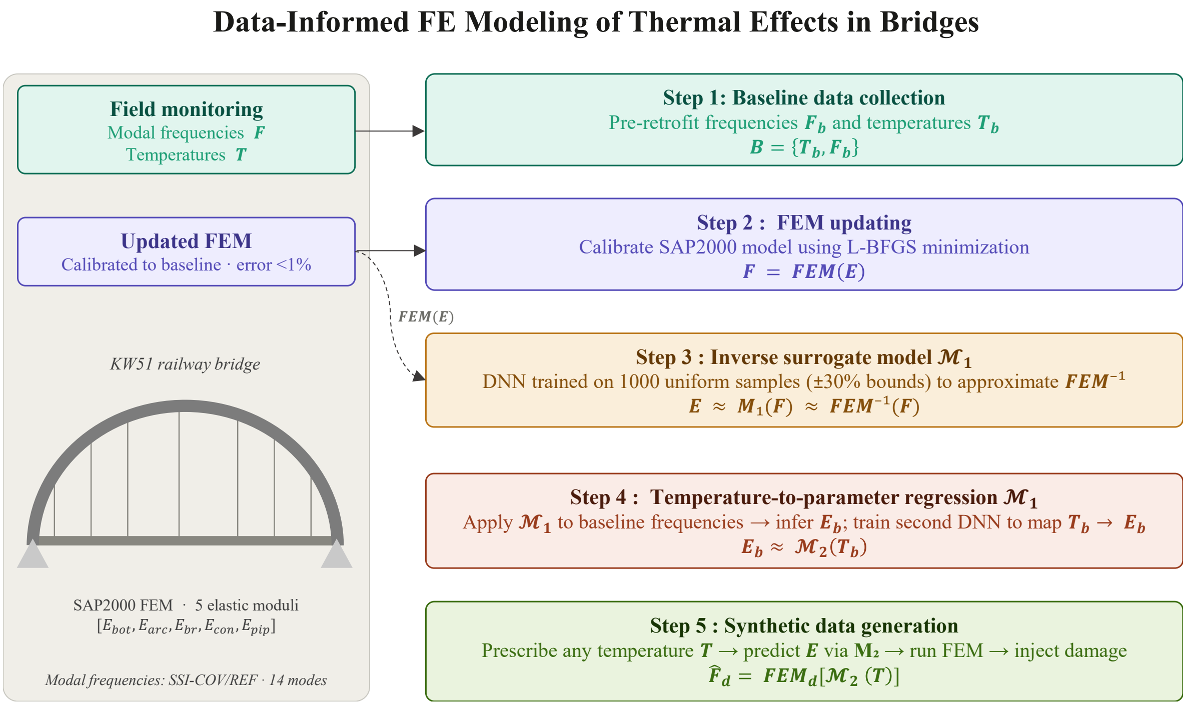

Fig. 1. *Flowchart of the proposed methodology.*

The workflow, summarized in Fig. 1, proceeds in five steps.

Step 1: Baseline data collection. Baseline frequency and temperature data $\{\mathbf{T}_b, \mathbf{F}_b\}$ are collected under healthy conditions.

Step 2: FEM updating. An initial FEM is calibrated using $\mathbf{F}_b$ to minimize the

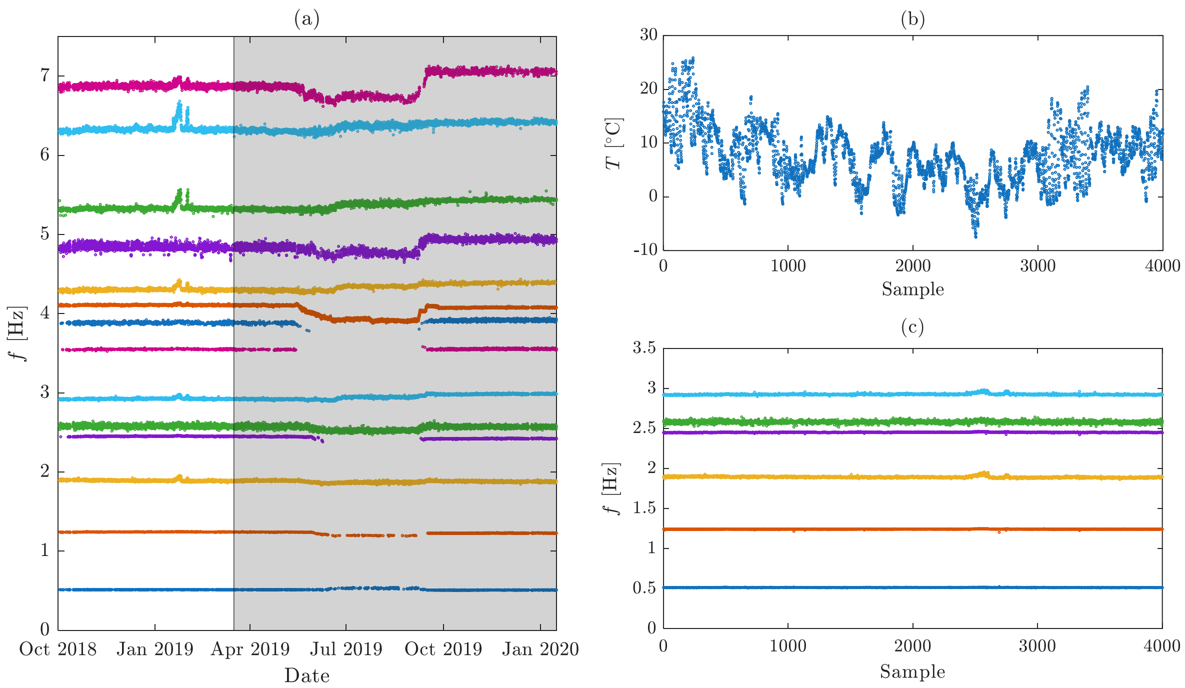

Fig. 2. *(a) Time histories of 14 identified modal frequencies. (b) Processed temperature measurements. (c) Processed first 6 modal frequencies.*

discrepancy between measured and simulated frequencies, yielding $\mathbf{F} = \mathrm{FEM}(\mathbf{E})$.

Step 3: Inverse surrogate modeling. A large ensemble of simulations is generated by randomly varying temperature-sensitive parameters within realistic bounds. For each sampled $\mathbf{E}$, the modal frequencies $\mathbf{F}$ are computed using the updated FEM. A deep neural network (DNN) regression model $\mathcal{M}_1$ is trained to approximate the inverse mapping [13]:

$$\mathbf{E} \approx \mathcal{M}_1(\mathbf{F}) \approx \mathrm{FEM}^{-1}(\mathbf{F}) \tag{1}$$

Step 4: Temperature-to-parameter mapping. The baseline frequencies $\mathbf{F}_b$ are passed through $\mathcal{M}_1$ to estimate corresponding parameters $\mathbf{E}_b = \mathcal{M}_1(\mathbf{F}_b)$. A second DNN regression model $\mathcal{M}_2$ maps the baseline temperatures to these parameters:

$$\mathbf{E}_b \approx \mathcal{M}_2(\mathbf{T}_b) \tag{2}$$

Step 5: Synthetic data generation. For any temperature $\mathbf{T}$, the temperature-dependent parameters $\mathbf{E} = \mathcal{M}_2(\mathbf{T})$ are predicted and assigned to the FEM. Structural damage can then be introduced to obtain $\widehat{\mathbf{F}}_d = \mathrm{FEM}_d(\mathbf{E})$, enabling realistic synthetic data generation for SHM algorithm validation.

2. Experimental Study: KW51 Railway Bridge

2.1 Bridge Description and Monitoring Data

The KW51 bridge is a steel single-span tied-arch railway bridge (115 m long, 12.4 m wide) [10, 11]. Between May and September 2019, it underwent a retrofitting operation to correct a construction error [14]. The monitoring dataset covers 7.5 months before retrofit, the retrofit period, and 3.5 months after retrofit. Modal identification was performed hourly using the SSI-COV/REF method [15].

Fig. 2(a) shows the 14 identified modal frequencies, Fig. 2(b) the temperature, and

Fig. 2(c) the first 6 frequencies used in this study. A single thermocouple beneath the deck recorded structural temperature. The frequency-temperature relationship is generally linear, with a bilinear behavior near 0 °C for some modes due to frost-induced ballast stiffening [14]. Missing data imputation techniques are applied to the dataset.

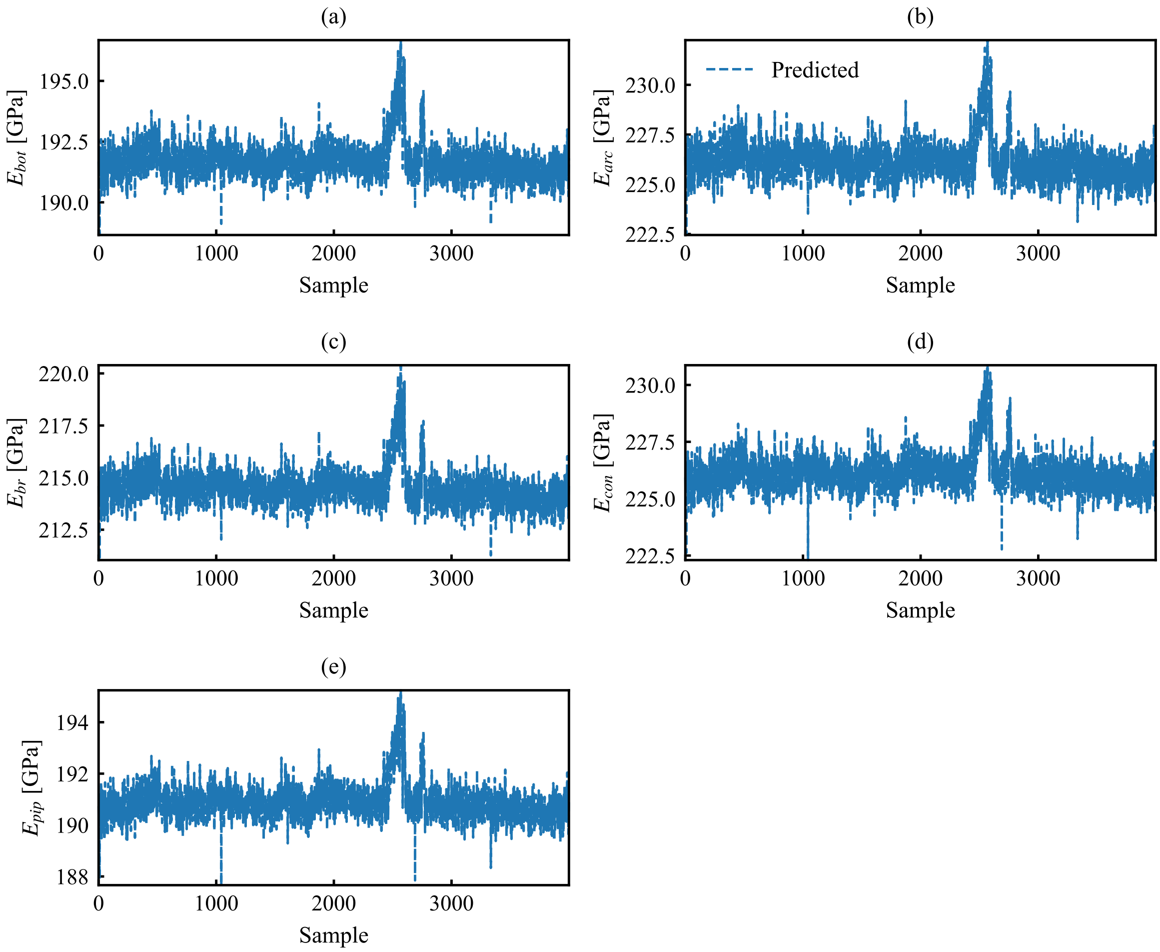

Fig. 3. *Predicted effective Young's moduli from experimental frequencies using $\mathcal{M}_1$: (a) E_{bot}, (b) E_{arc}, (c) E_{br}, (d) E_{con}, (e) E_{pip}.*

2.2 Data-Informed Model Construction

Step 1. Only pre-retrofit data are used as baseline. The first 6 modal frequencies and a 24-dimensional lagged temperature vector $\mathbf{T}_b = [T_b(t), T_b(t-1), \ldots, T_b(t-23)]$ form the baseline dataset (4000 samples after k-NN imputation). The lag of 24 hours captures one daily cycle and accounts for thermal inertia [8].

Step 2. A detailed FEM was developed in SAP2000 [5]. A sensitivity analysis identified 11 influential parameters, and the model was updated using the L-BFGS algorithm [16, 17], reducing the average frequency error from 6.9% to below 1% [18].

Step 3. Five temperature-sensitive elastic moduli $\mathbf{E} = [E_{\text{bot}}, E_{\text{arc}}, E_{\text{br}}, E_{\text{con}}, E_{\text{pip}}]$ are selected. A total of 1000 uniformly distributed samples (±30% bounds [19]) are generated via the SAP2000 OAPI, each solved for the first 6 modal frequencies. The DNN surrogate $\mathcal{M}_1$ (hidden layers [256, 128, 64, 32, 16], ReLU, Adam optimizer, MSE loss, 80/20 split) achieves MAPE below 0.03% on the test set for all five parameters.

Step 4. Applying $\mathcal{M}_1$ to the baseline frequencies yields the stiffness parameters $\mathbf{E}_b = \mathcal{M}_1(\mathbf{F}_b)$. Fig. 3 shows the predicted evolution of the five elastic moduli over the 4000 baseline samples. The regression model $\mathcal{M}_2$ (hidden layers [256, 128, 64, 32] with dropout rate 0.2) maps the lagged temperature to these parameters, with MAPE below 0.3%.

2.3 Verification

The predicted stiffness parameters from $\mathcal{M}_2$ are injected into the updated FEM to reconstruct modal frequencies for the 800 unseen test samples. Fig. 4 compares predicted and experimental frequencies. All MAPE values remain below 0.43% (Table 1), confirming accurate reproduction of temperature-dependent modal variations.

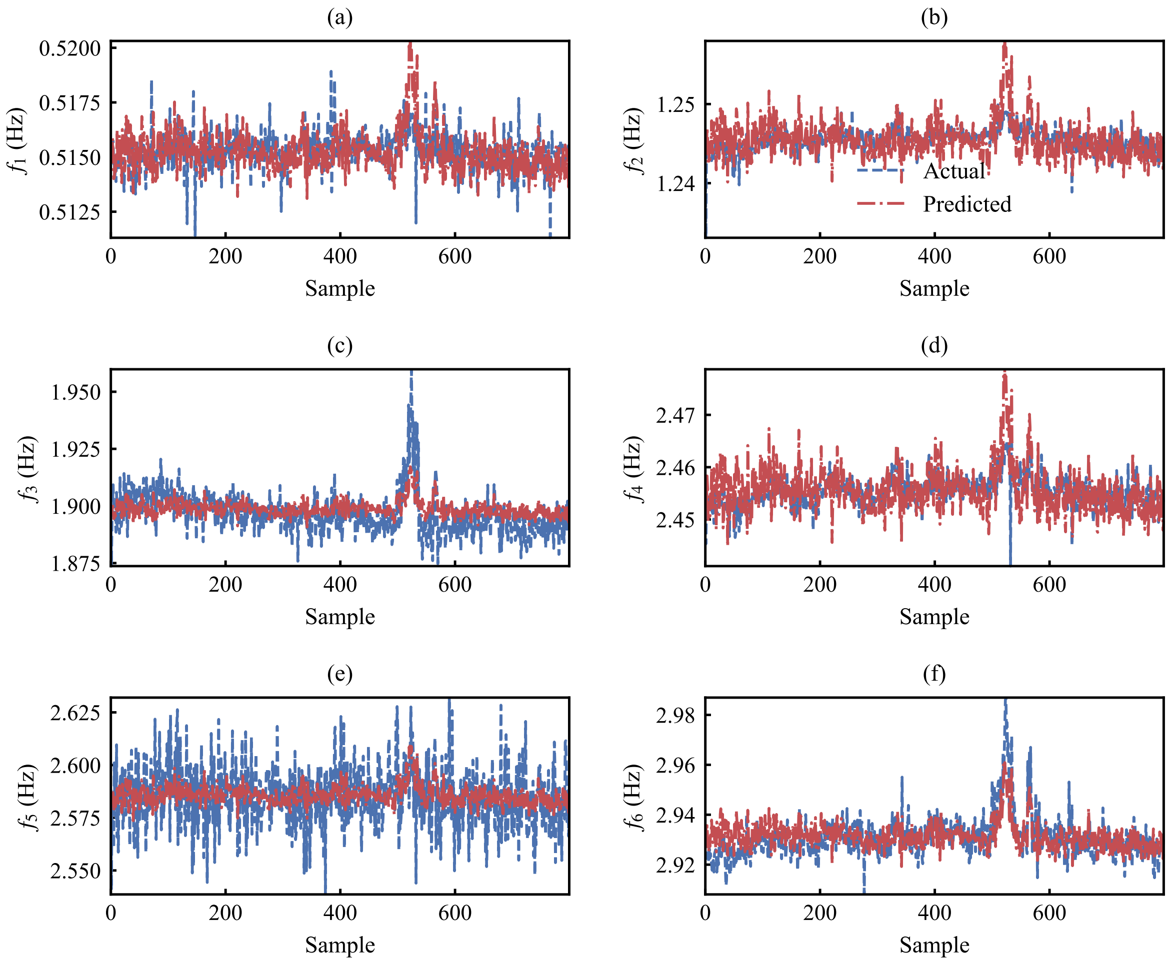

Fig. 4. *Experimental (blue) vs. predicted (red) modal frequencies: (a) f_1, (b) f_2, (c) f_3, (d) f_4, (e) f_5, (f) f_6.*

Table 1. MAPE [%] between experimental and predicted modal frequencies (800 test samples).

	f_1	f_2	f_3	f_4	f_5	f_6
MAPE	0.151	0.135	0.335	0.128	0.422	0.183

2.4 Anomaly Detection on Post-Retrofit Data

To further validate the framework, we test whether the model can reproduce the post-retrofit state. The retrofit is introduced as a 15% increase in the cross-sectional area of brace-to-deck and brace-to-arch connections [5]. Post-retrofit temperatures are passed through $\mathcal{M}_2$, and the predicted parameters together with the retrofit modification are applied to the FEM. Fig. 5 compares the data-informed predictions with the experimental post-retrofit frequencies for modes 2 and 4, achieving MAPE values of 0.096% and 0.125%, respectively.

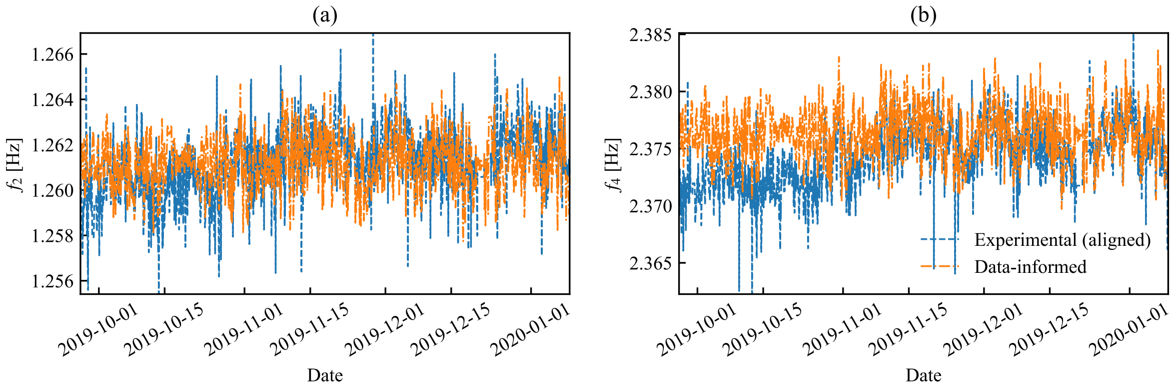

Fig. 5. *Experimental (blue) and data-informed (orange) post-retrofit frequencies: (a) Mode 2, (b) Mode 4.*

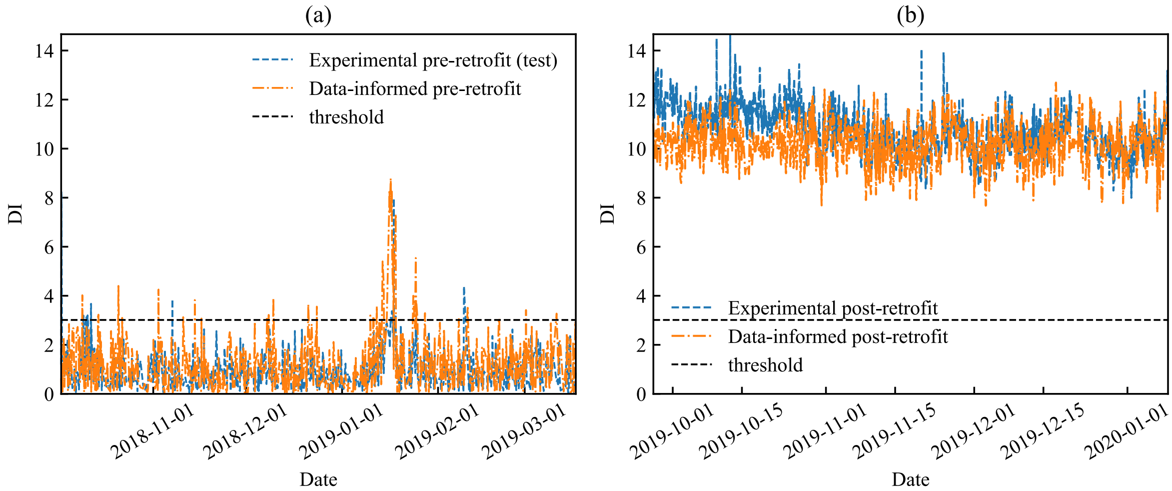

Fig. 6. *DIs for (a) pre-retrofit testing and (b) post-retrofit data, using modes 2 and 4. Blue: experimental; orange: data-informed; dashed: threshold τ.*

A Mahalanobis distance-based DI is computed using pre-retrofit baseline statistics:

$$\mathrm{DI}(s) = \sqrt{(\mathbf{f}(s) - \boldsymbol{\mu}_b)\, \boldsymbol{\Sigma}_b^{-1}\, (\mathbf{f}(s) - \boldsymbol{\mu}_b)^T} \tag{3}$$

where $\boldsymbol{\mu}_b$ and $\boldsymbol{\Sigma}_b$ are the mean and covariance of the pre-retrofit baseline. Fig. 6 shows the DI time histories for pre-retrofit testing data (subplot a) and post-retrofit data (subplot b). Table 2 summarizes the results: the PFA is 1.88% (experimental) and 5.88% (data-informed), while both achieve 100% POD for the post-retrofit state, with the mean DI increasing from approximately 1 to above 10.

Table 2. Anomaly detection results for the KW51 bridge.

Quantity	Experimental	Data-informed
PFA, pre-retrofit test [%]	1.88	5.88
POD, post-retrofit [%]	100.00	100.00
Mean DI, pre-retrofit test	0.945	1.211
Mean DI, post-retrofit	10.743	10.181

Conclusions

This paper presented a data-informed framework for simulating temperature effects in finite element models for SHM. The approach combines monitoring data with an updated FEM through two successive surrogate models: an inverse surrogate that estimates temperature-sensitive parameters from modal frequencies, and a regression model that maps temperature to these parameters.

The experimental KW51 bridge application confirmed the practical potential, reproducing pre-retrofit modal-frequency evolution with errors below 0.43% using a single thermocouple and lagged temperature inputs. The post-retrofit analysis showed that the framework transfers to a modified structural state, achieving 100% POD and closely matching the experimental anomaly detection behavior. Future work will extend the framework to other dynamic indicators such as damping ratios and mode shapes.

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