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DYNAMIC IDENTIFICATION AND THERMO-MODAL RESPONSE OF A STEEL-GLASS HALL UNDER LONG-TERM MONITORING

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Abstract. *Long-term vibration-based monitoring of heritage structures is often hindered by environmental variability, with temperature-induced frequency shifts masking damage-sensitive changes. This study presents a digital twin-oriented framework for the thermo-modal analysis and dynamic identification of a heritage steel–glass hall under continuous monitoring. The proposed approach integrates probabilistic inference, physics-informed learning, and decision-oriented analysis within a unified pipeline.*

In the first stage, a Bayesian linear regression model is employed to describe the dependence of modal frequencies on the steel–glass temperature differential, providing uncertainty-aware predictive envelopes. In the second stage, a physics-informed neural network is trained on the residuals to capture nonlinear thermo-mechanical interactions while enforcing smoothness constraints consistent with physical behavior. A damage-sensitive indicator is constructed from thermo-normalized residuals using an epistemically weighted statistical distance metric, enabling identification of anomalous deviations from baseline structural behavior.

The framework is applied to the Marcus Aurelius Exedra Hall at the Capitoline Museums in Rome, monitored through a continuous IoT-based sensing system. Results show that the hybrid model improves prediction accuracy and reduces temperature-induced variability. Moreover, the residual-based indicator provides a normalized and uncertainty-aware measure of deviation from the expected structural behaviour, improving the interpretability and robustness of anomaly detection compared to the use of raw residuals alone. The study highlights the potential of integrating Bayesian inference and physics-informed learning within digital twin architectures for robust, uncertainty-aware structural health monitoring of complex heritage structures.

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1 Introduction

The increasing adoption of Structural Health Monitoring (SHM) systems has significantly improved the assessment of in-service structural performance and safety in civil infrastructure. This is particularly relevant for heritage structures, where conservation constraints and limited intervention possibilities require continuous, non-invasive, and reliable monitoring strategies. A key limitation in SHM is the strong influence of environmental and operational variability on measured structural responses [1]. In particular, temperature fluctuations can induce significant variations in dynamic behavior, leading to apparent changes in modal properties that may obscure or mimic structural damage. As a result, separating environmental effects from true structural changes remains a central challenge in long-term monitoring.

Recent studies have demonstrated that environmental effects can significantly bias modal parameter estimation if not properly accounted for. De Iuliis et al. [2] showed that neural networks can effectively capture complex relationships between operational conditions and ambient vibration responses in cable-stayed bridges. To overcome the limitations of purely data-driven approaches, hybrid and physics-informed strategies have been widely investigated. Fusco et al. [3] proposed an efficient physics-based framework for generating synthetic datasets for bridge monitoring, enabling realistic simulation of nonlinear structural behavior and training of data-driven damage detection models. Cianci et al. [4] introduced a physics-informed framework combining thermo-mechanical modelling with Gaussian Process regression, enabling accurate prediction of temperature-induced displacements and improved anomaly detection under non-stationary conditions. Further developments in hybrid SHM include the work of Svendsen et al. [5], who integrated finite-element models, experimental modal data, and statistical learning to enhance damage detection in steel bridges under environmental variability. Huang et al. [6] embedded thermo-mechanical models into deep learning architectures to improve prediction of temperature-induced responses in arch bridges, while Zhang et al. [7] proposed a multi-scale graph learning framework with temperature-adaptive fusion to disentangle environmental effects from structural degradation. In addition, Jian et al. [8] developed a fully self-supervised representation learning method that separates damage-sensitive features from operational variability without requiring labeled data.

Within this context, this paper investigates the dynamic identification and thermo-modal response of a heritage steel-glass hall subjected to long-term monitoring. The main objective is to characterize the evolution of modal properties under changing environmental conditions and to quantify the influence of temperature on the measured frequencies through an uncertainty-aware hybrid modelling strategy. The novelty of the work lies in the integration of automated operational modal analysis with a Bayesian-PINN framework, where global thermo-modal trends are described probabilistically and nonlinear effects are captured through physics-informed residual learning. This approach enables temperature normalization, interpretable uncertainty quantification, and the definition of a robust damage index for the consistent interpretation of long-term dynamic variability in complex heritage structures.

2 Hybrid Bayesian regression and ensemble-based neural residual modeling framework

In this work, a hybrid probabilistic framework is proposed to model the relationship between temperature variations and structural vibration frequencies while explicitly accounting for epistemic uncertainty. The approach combines Bayesian inference, used to capture global stochastic dependencies, with Physics-Informed Neural Networks (PINNs), which are introduced to learn nonlinear residual dynamics not explained by the baseline model.

The starting point is a stochastic linear model that describes the dependence of the measured frequency f on the temperature T:

$$f(T) = a_0 + a_1 T + \varepsilon, \qquad \varepsilon \sim \mathcal{N}(0, \sigma^2) \tag{1}$$

where a_0 and a_1 represent the intercept and slope of the temperature-frequency relationship, while σ models measurement noise and unmodeled variability. In a Bayesian framework, these parameters are treated as random variables rather than fixed quantities, allowing uncertainty to be propagated through the model. Gaussian priors are assigned as:

$$a_0 \sim \mathcal{N}(\mu_{a_0}, \sigma_{a_0}^2), \qquad a_1 \sim \mathcal{N}(\mu_{a_1}, \sigma_{a_1}^2) \tag{2}$$

Given the dataset $\mathcal{D} = \{(T_i, f_i)\}_{i=1}^N$, the posterior distribution is obtained via Bayes' theorem:

$$p(\theta \mid \mathcal{D}) \propto p(\mathcal{D} \mid \theta)\, p(\theta), \tag{3}$$

where $\theta = (a_0, a_1, \sigma)$. Since this posterior is not analytically tractable, it is approximated using a Metropolis-Hastings Markov Chain Monte Carlo (MCMC) procedure. This sampling strategy allows exploration of the full parameter space and provides a distribution over plausible model configurations rather than a single deterministic estimate.

The Bayesian model provides a global linear trend:

$$f_{\text{Bayes}}(T) = \mathbb{E}[a_0] + \mathbb{E}[a_1] T \tag{4}$$

However, real structural systems often exhibit nonlinearities and localized effects that cannot be captured by a simple linear formulation. To address this limitation, the residual between observations and the Bayesian prediction is defined as:

$$r(T) = f(T) - f_{\text{Bayes}}(T) \tag{5}$$

This residual is assumed to contain the unmodeled physics of the system, including nonlinear dependencies and possible hidden mechanisms. A PINN is then introduced to approximate this term:

$$r_\theta(T) \approx \mathcal{N}_\theta(T), \tag{6}$$

where $\mathcal{N}_\theta$ is a feedforward neural network trained to minimize a loss function composed of a data-fitting term and a regularization term:

$$\mathcal{L}(\theta) = \frac{1}{N} \sum_{i=1}^{N} \left(r_\theta(T_i) - r(T_i)\right)^2 + \lambda \Omega(\theta). \tag{7}$$

The inclusion of the regularization term $\Omega(\theta)$ is essential to enforce smoothness and avoid overfitting, ensuring that the learned residual remains physically consistent rather than purely data-driven noise fitting.

To further improve robustness and quantify epistemic uncertainty, an ensemble of K independently trained PINNs is employed. Each network is initialized with different random weights and trained separately, leading to a collection of residual estimators $\{r_{\theta_k}(T)\}_{k=1}^K$. The ensemble mean and variance are defined as:

$$\mu_r(T) = \frac{1}{K}\sum_{k=1}^{K} r_{\theta_k}(T), \tag{8}$$

$$\sigma_r^2(T) = \frac{1}{K}\sum_{k=1}^{K}\left(r_{\theta_k}(T) - \mu_r(T)\right)^2. \tag{9}$$

The final hybrid predictive model is then expressed as:

$$f_{\text{hybrid}}(T) = f_{\text{Bayes}}(T) + \mu_r(T). \tag{10}$$

This formulation is particularly important because it separates global epistemic uncertainty (captured by the Bayesian posterior) from local model uncertainty (captured by the variability of the PINN ensemble).

A posterior predictive distribution is also constructed by sampling from the Bayesian posterior and propagating uncertainty through both the linear and nonlinear components:

$$f^{(s)}(T) = a_0^{(s)} + a_1^{(s)}T + \mu_r(T) + \epsilon^{(s)}, \tag{11}$$

where $\epsilon^{(s)} \sim \mathcal{N}(0, \sigma^{(s)2})$. Prediction intervals are then obtained from empirical percentiles of the sampled trajectories.

A key element of the proposed methodology is the definition of a Damage Index (DI), which provides a normalized measure of deviation between observed and predicted behavior:

$$DI(T) = \frac{|f(T) - f_{\text{hybrid}}(T)|}{\sigma_r(T)}. \tag{12}$$

The rationale behind this definition is that raw residuals alone are not sufficient to assess anomalies, since their magnitude depends on the intrinsic uncertainty of the model. By normalizing the residual with respect to the epistemic standard deviation $\sigma_r(T)$, the Damage Index becomes a statistically meaningful quantity: deviations are interpreted relative to the model confidence. In regions where the model is highly uncertain, larger deviations are expected and therefore penalized less, whereas in regions of high confidence even small deviations become significant indicators of abnormal behavior.

Thresholds for anomaly detection are defined in a purely data-driven manner using percentiles of the training distribution:

$$DI_{\text{warning}} = \text{Percentile}_{95}(DI), \qquad DI_{\text{alarm}} = \text{Percentile}_{99}(DI). \tag{13}$$

This approach avoids arbitrary threshold selection and ensures that the detection mechanism is consistent with the statistical properties of the healthy-state system. Overall, the proposed framework integrates Bayesian inference and physics-informed learning into a unified probabilistic structure capable of both accurate prediction and robust uncertainty-aware damage detection.

3 Results and Discussion

The proposed framework was validated on the Marcus Aurelius Exedra Hall, located within the Capitoline Museums in Rome, Italy. The hall is a modern heritage steel-and-glass structure designed by Carlo Aymonino, built to connect the historical spaces of the Palazzo dei Conservatori while preserving the archaeological remains of the Temple of Jupiter Capitolinus. The

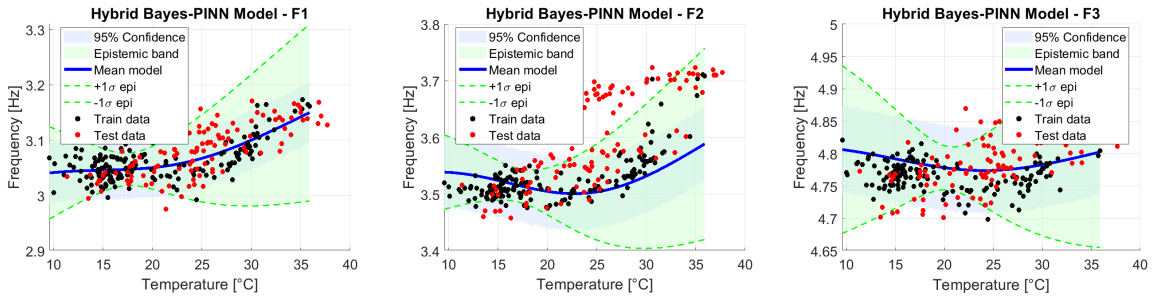


Figure 1: Frequency-temperature relationship reconstructed using the proposed Bayesian-PINN framework representing the predictive mean, the 95% confidence interval and the epistemic uncertainty associated with the PINN ensemble.

structure consists of a semi-elliptical steel framework enclosed by extensive glazed surfaces. The roof and façades are supported by six circular steel columns connected to box-section girders through bolted and welded joints, resulting in a lightweight and flexible structural system particularly sensitive to environmental and thermal actions. These characteristics make the hall an appropriate benchmark for investigating temperature-induced variations in structural dynamic properties. The structure is instrumented with a permanent wired SHM system based on a Power-over-Ethernet (PoE) star-network architecture. The monitoring system comprises distributed sensor nodes connected to a central gateway, which coordinates data acquisition and transmits the measurements to a remote server for storage and analysis. Each sensor node is equipped with a triaxial low-noise MEMS accelerometer (Analog Devices ADXL354) operating at a sampling frequency of 100 Hz. The continuous monitoring infrastructure provides uninterrupted long-term time histories of the structural dynamic response. Furthermore, the thermal loading affecting the structure is characterized using external ambient temperature data as the primary environmental descriptor.

An Automated Operational Modal Analysis (AOMA) procedure is adopted to extract time-varying modal parameters from the recorded structural response under ambient excitation [9]. In particular, the identification framework is based on the Stochastic Subspace Identification (SSI) method, which enables the extraction of stable modal frequencies from output-only vibration measurements without requiring knowledge of the input excitation. To ensure robustness and automation over long-term monitoring datasets, a stabilization diagram is first constructed and used to distinguish physical modes from numerical and spurious solutions. Subsequently, the k-means clustering strategy is employed to automatically group consistent modal estimates and track the evolution of the dominant natural frequencies over time. This procedure allows for continuous identification of the first vibration modes and the generation of reliable frequency time histories suitable for environmental correlation studies.

The resulting dataset supports the analysis of temperature-frequency dependence, highlighting a correlation between environmental conditions and observed dynamic properties. The proposed hybrid Bayesian-PINN framework was evaluated on three frequency components. Figure 1 reports the frequency-temperature relationship for each frequency component, where the Bayesian predictions are augmented by the PINN-based residual correction. In addition to the mean predictions, both aleatoric uncertainty (derived from the Bayesian posterior variance) and epistemic uncertainty (estimated through the ensemble PINN residual spread) are displayed as confidence bands. The reconstructed frequency-temperature relationships show a good agreement with the experimental observations with the exception of frequency F_2, for which a larger number of data points in the test dataset fall outside the confidence interval. As

illustrated in Figure 1, the predictive mean (solid blue line) captures the global trend of the data, while the model is able to correct local deviations through the PINN-based residual component. The shaded region represents the 95% predictive interval, which incorporates both parameter uncertainty from the Bayesian inference and observational noise. The epistemic uncertainty associated with the PINN ensemble is relatively small in regions with dense measurements, where the ensemble members are in strong agreement, and increases towards the edges of the domain, where the lack of training data leads to higher model disagreement. This behavior is consistent with a well-calibrated epistemic uncertainty estimate.

The corresponding Damage Index (DI) evolution is shown in Figure 2. The DI is defined as the normalized residual between the observed and reconstructed frequencies, scaled by the epistemic uncertainty estimated from the PINN ensemble. Consequently, the index reflects not only the magnitude of the prediction error but also the confidence of the hybrid model. Residuals occurring in regions characterized by higher model uncertainty produce moderate DI values, whereas comparable residuals in regions where the model is highly confident lead to significantly larger indices. This normalization prevents false alarms caused by poorly sampled regions of the temperature domain and provides a statistically meaningful indicator of anomalous structural behavior. For frequency components F_1 and F_3, the DI remains predominantly below the warning threshold, indicating that the proposed framework successfully captures the environmental variability governing their dynamic evolution. Only isolated threshold exceedances are observed, which can reasonably be attributed to measurement noise, operational variability, or localized modeling inaccuracies rather than to persistent structural anomalies. The overall stability of the DI confirms that the combined Bayesian-PINN approach provides an accurate representation of the healthy structural state. A different behavior is observed for frequency component F_2, which exhibits larger DI fluctuations and a higher number of warning and alarm threshold exceedances. This result is consistent with the wider predictive intervals observed in Figure 1 and suggests that the temperature-frequency relationship associated with this mode is more difficult to model accurately. Such behavior may originate from increased sensitivity of the second mode to operational conditions not explicitly included in the model, from stronger nonlinear effects, or from the reduced density of representative observations within specific temperature ranges. Nevertheless, the uncertainty-aware formulation prevents these deviations from being interpreted as immediate evidence of structural damage, emphasizing instead the importance of distinguishing between modeling uncertainty and genuinely abnormal structural behavior. Overall, the obtained results demonstrate that the proposed hybrid framework not only improves the reconstruction of the temperature-frequency relationship but also provides a damage indicator that explicitly accounts for model confidence. Unlike conventional residual-based indicators, whose thresholds are typically defined using raw prediction errors alone, the proposed DI incorporates epistemic uncertainty into the anomaly assessment process, yielding a more robust and reliable interpretation of long-term monitoring data under varying environmental conditions.

4 Conclusions

The proposed strategy provides an effective framework for interpreting long-term modal variability in heritage structures under environmental influence. Continuous tracking of the identified frequencies allows reliable characterization of temperature-dependent trends and supports subsequent normalization and anomaly detection tasks. The results show that the hybrid Bayesian-PINN model improves the reconstruction of the frequency-temperature relationship, while offering an interpretable separation between aleatoric uncertainty and epistemic uncertainty. This feature is particularly valuable for decision-making in monitoring applica-

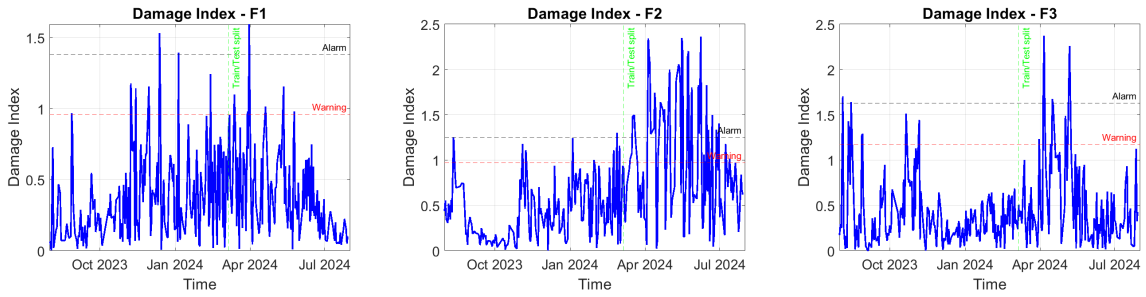


Figure 2: Damage Index (DI) evolution for the three identified frequency components.

tions, where confidence in predictions is as important as accuracy.The Damage Index based on uncertainty-normalized residuals proved effective in highlighting anomalous conditions, with the second frequency component showing higher variability and more frequent threshold exceedances, coherently with its lower predictive capability. Overall, the proposed methodology represents a promising step toward uncertainty-aware digital twins for heritage structures, integrating continuous monitoring data, probabilistic modelling, and physics-informed learning in a unified operational framework.

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