International Journal of Innovation and Modern Applied Science

Vol. 12 Issue 02 , July 2026

Doi : https://doi.org/10.57109/8301

ISSN No.: 665-8984

Identifiability and Observability of Structural Damage from Vibration Signals: A Theoretical Framework for Predictive Structural Health Monitoring

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ABSTRACT: Vibration-based structural health monitoring is increasingly used to support predictive maintenance of civil engineering structures. However, before any statistical, data-driven, or physics-informed method can claim to identify structural damage, one must first determine whether the damage variable is mathematically inferable from the available measurements. This paper develops a theoretical framework for analyzing observability and identifiability of structural damage from vibration signals. Civil structures are modeled as parameter-dependent dynamical systems under partial and noisy observation, and damage diagnosis is formulated as an inverse problem. Within this setting, five non-equivalent notions are distinguished: state observability, damage-parameter identifiability, damage detectability, scenario distinguishability, and estimability under uncertainty. Three main results are established. First, observability of the structural state does not imply identifiability of damage parameters. Second, sparse or poorly designed sensing may destroy local identifiability even when the full structural response is informative. Third, environmental and operational variability can transform theoretical identifiability into practical non-identifiability. The paper further discusses the implications of these results for artificial intelligence, physics-informed structural health monitoring, and maintenance-oriented decision support. The proposed framework provides a rigorous basis for interpretable, robust, and decision-relevant structural diagnosis in civil infrastructure.

Keywords: Structural Health Monitoring; Identifiability; Observability; Inverse Problems; Vibration-Based Damage Detection; Predictive Maintenance; Civil Engineering Structures; Physics-Informed Learning.

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1. INTRODUCTION

Since it fulfills a fundamental need of infrastructure management, i.e. identifying structural deterioration before it develops into a high-risk and high-cost situation, Structural Health Monitoring (SHM) of civil engineering structures has grown to be a significant research and engineering field. Similarly, the possibility to measure dynamic responses non-destructively, in addition to their ability to contain information about stiffness changes, damping modifications, or boundary-condition perturbations, vibration-based monitoring is particularly appealing in bridges, buildings, and other various instrumented systems (Avci et al., 2021; Sivasuriyan et al., 2021). Machine learning, deep learning, as well as physics-informed paradigms have recently replaced traditional modal and signal-based techniques in the discipline (Mammeri et al., 2025; Plevris & Papazafeiropoulos, 2024; Riyahi et al., 2026).

Despite these advances, a fundamental mathematical issue remains insufficiently addressed. Before claiming that an artificial intelligence model, a statistical decision rule, or a physics-informed method can identify structural damage, one must first ask whether the damage variable is actually observable and identifiable from the available measurements. Damage cannot be measured immediately. This problem is key. There is an only depiction seen. That is the limited, noisy, and sensor-dependent depiction of the structural dynamics under erratic excitation and shifting ambient conditions. As a result, the issue is not one of prediction only. It is also one of information content. That is, under what assumptions does the monitoring system have sufficient structurally relevant data to differentiate between damaged and undamaged states?

In civil structures, sensing is restricted, excitation is rarely controlled, operational and environmental variability is significant, and damage may be minor or geographically dispersed. This is where this difficulty is especially important. Because of this, a monitoring system may seem to be successful in forecasting (Hafsi et al., 2023). Yet, it may do poorly mathematically in parameter recovery. In certain cases, a physically relevant diagnosis is not always implied by empirical precision. The Z24 bridge context is an example of physics-informed SHM investigations which are directly affected by this problem (Riyahi et al., 2026). This is demonstrated by recent data-driven physics-informed SHM investigations. Strong prediction results encourage more in-depth consideration of what is actually being inferred from monitored reactions (Riyahi et al., 2025).

The objective of this paper is to develop a rigorous theoretical framework for analyzing observability and identifiability of structural damage from vibration signals (Li et al., 2025). The core thesis is that trustworthy predictive structural health monitoring must begin with a formal study of whether damage is, in principle, observable, identifiable, distinguishable, and stably inferable from the measurements actually collected. To this end, the paper models civil structures as parameter-dependent dynamical systems under partial observation, formulates damage diagnosis as an inverse problem, and clarifies the difference between state observability, parameter identifiability, damage detectability, scenario distinguishability, and estimability under uncertainty.

The rest of the paper is divided into four sections. Section 2 introduces the mathematical framework. In addition to the inverse-problem formulation and the structural dynamic model, it includes the measurement operator, observability, and identifiability. Section 3 presents the key theoretical findings, along with the implications for predictive maintenance, artificial intelligence, and SHM. The paper is concluded with Section 4. In this section, the conclusion is provided. Also, future views are outlined.

2. MATERIALS AND METHODS

2.1. Epistemic Positioning and Scope of the Study

In addition to its system-theoretic nature, this study is also theoretical. Neither a novel training method, nor a benchmark experiment, nor a numerical comparison are suggested. On the contrary, it clarifies the suitable mathematical circumstances to use vibration measurements in civil constructions. This has an aim of meaningfully inferring structural deterioration. Therefore, the current "Materials and Methods" section should be interpreted as a theoretical methodology. It is not considered as an actual protocol.

The epistemic position adopted here is that damage diagnosis is fundamentally a parameter-dependent inverse problem posed on a dynamical system under partial observation. This viewpoint is consistent with recent SHM reviews. They serve to emphasize that machine learning and physics-informed monitoring require stronger interpretability and physical consistency (Avci et al., 2021; Mammeri et al., 2025; Sivasuriyan et al., 2021). Additionally, it is consistent with observability-oriented structural system identification. In this process, recoverability depends not only on the structural model, but also on the sensing operator (Sun et al., 2021; Zhang & Sun, 2020).

As a result, the study's scope is limited to the problem's mathematical architecture. In other words, analytical criteria for damage detectability, inverse formulation, identifiability, distinguishability, structural dynamics, sensing, and observability. As a result, the study advances the area both theoretically and mathematically. It is also important to note that it is maintenance-oriented.

2.2. Parameter-Dependent Structural Dynamics Model

Let $q(t) \in \mathbb{R}^n$ denote the generalized displacement vector and $u(t) \in \mathbb{R}^m$ the excitation vector. A parameter-dependent structural model is written as

$$M(\theta, d)\ddot{q}(t) + C(\theta, d)\dot{q}(t) + K(\theta, d)q(t) = Bu(t),$$

where M, C, and $K$are the mass, damping, and stiffness matrices, θdenotes nominal structural parameters, and $d \in \mathcal{D} \subset \mathbb{R}^s$denotes damage parameters.

A common representation is a stiffness-loss model:

$$K(\theta, d) = K_0(\theta) - \sum_{j=1}^{s} d_j K_j, d_j \geq 0.$$

This formulation makes explicit the mapping from deterioration variables to measurable dynamic response.

Introducing the state vector

$$x(t) = \begin{bmatrix} q(t) \\ \dot{q}(t) \end{bmatrix},$$

the second-order model becomes

$$\dot{x}(t) = A(\theta, d)x(t) + G(\theta, d)u(t).$$

For sufficiently small vibrations around an operating equilibrium, this linearized form is often appropriate. More generally, one may consider a nonlinear model

$$\dot{x}(t) = f(x(t), u(t), \theta, d),$$

to account for nonlinear supports, contact, or damage mechanisms. In all cases, the key idea is unchanged: damage is represented as a perturbation of the structural operators.

2.3. Measurement Model and Partial Observation

Let $y(t) \in \mathbb{R}^r$ denote the measured output. A general observation model is

$$y(t) = \mathcal{H}(q(t), \dot{q}(t), \ddot{q}(t), u(t); \theta, d) + \eta(t),$$

where $\mathcal{H}$ is the sensing operator and $\eta(t)$ denotes measurement noise.

In a linearized setting,

$$y(t) = H_0 q(t) + H_1 \dot{q}(t) + H_2 \ddot{q}(t) + Du(t) + \eta(t),$$

or equivalently

$$y(t) = C_y(\theta, d)x(t) + D_y(\theta, d)u(t) + \eta(t).$$

Civil SHM is inherently a partial observation problem. In most real monitoring settings, the number of measured channels is far smaller than the number of structural degrees of freedom. Symbolically,

$$y(t) = Pz(t) + \eta(t),$$

where $z(t)$ denotes an ideal full structural response and P is the projection induced by the sensor network. Consequently, diagnosability depends not only on the structure itself, but also on sensor placement, sensing modality, and the extent to which damage-sensitive directions remain visible after measurement reduction.

2.4. State Observability

For fixed (θ, d), consider the linear parameter-dependent system

$$\dot{x}(t) = A(\theta, d)x(t) + G(\theta, d)u(t), y(t) = C_y(\theta, d)x(t) + D_y(\theta, d)u(t).$$

The pair $(A, C_y)$is observable if distinct initial states produce distinct output trajectories under the same input. In finite dimensions, observability is characterized by the rank of the observability matrix or, equivalently, by positive definiteness of the observability Gramian (Kailath, 1980). In nonlinear settings, one usually speaks of local observability (Farrar & Worden, 2013; Hermann & Krener, 1977).

Observability in SHM refers to whether there is sufficient information in the monitored vibration signals to reconstruct the internal dynamical state of the structure. Observability, however, is concerned with concealed states rather than secret harm parameters. This distinction is crucial.

2.5. Damage Parameter Identifiability

Let

$$\mathcal{F}: \mathcal{D} \subset \mathbb{R}^s \to \mathcal{Y}$$

denote the forward map that associates a damage vector $d$with the corresponding ideal output trajectory y_d. The damage parameter is globally identifiable if

$$\mathcal{F}(d_1) = \mathcal{F}(d_2) \Rightarrow d_1 = d_2$$

for all admissible d_1, d_2. It is locally identifiable at $d^\star$if this implication holds in a neighborhood of $d^\star$.

If $\mathcal{F}$is differentiable, then around $d^\star$,

$$\mathcal{F}(d^\star + \delta d) \approx \mathcal{F}(d^\star) + D\mathcal{F}(d^\star)\delta d.$$

In finite-dimensional form, this yields the sensitivity matrix

$$S(d^\star) = \frac{\partial \mathcal{F}}{\partial d}(d^\star).$$

A necessary local condition for identifiability is injectivity of $D\mathcal{F}(d^\star)$, and a sufficient differential condition in finite dimensions is that $S(d^\star)$have full column rank.

This notion must be distinguished from state observability. A system may be observable at the state level while remaining non-identifiable at the level of damage parameters.

2.6. Damage as Perturbation, Distinguishability, and Inverse Formulation

Let $d = 0$denote the healthy configuration. A perturbation model can be written as

$$A(\theta, d) = A_0(\theta) + \sum_{j=1}^{s} d_j A_j(\theta) + R(d),$$

with $R(d) = o(\| d \|)$ as $\| d \| \to 0$. This expresses damage as a perturbation of the structural dynamics.

Two scenarios d_1 and d_2 are distinguishable if

$$\mathcal{F}(d_1) \neq \mathcal{F}(d_2),$$

and indistinguishable otherwise. A useful metric is

$$\Delta(d_1, d_2) = \| \mathcal{F}(d_1) - \mathcal{F}(d_2) \|_{\mathcal{Y}}.$$

Detectability compares a damaged state with the healthy reference, while distinguishability compares two admissible scenarios.

Damage diagnosis is then formulated as the inverse problem

$$y^{\mathrm{obs}} = \mathcal{F}(d) + \eta.$$

In Hadamard's sense, this inverse problem may fail to be well posed because of non-uniqueness, instability, or model mismatch (Kaipio & Somersalo, 2005; Tarantola, 2005). A regularized variational formulation is

$$\hat{d} \in \arg\min_{d \in \mathcal{D}} \left[\| y^{\mathrm{obs}} - \mathcal{F}(d) \|_{\Sigma^{-1}}^{2} + \lambda \mathcal{R}(d) \right],$$

where $\mathcal{R}(d)$ encodes structural prior assumptions. Regularization does not create information; it stabilizes inference by restricting the admissible solution set.

2.7. Analytical Criteria for Detectability

The previous concepts become operational only when associated with analytical criteria.

A first criterion is the sensitivity matrix

$$S(d^\star) = \frac{\partial \mathcal{F}}{\partial d}(d^\star).$$

If some columns of $S(d^\star)$ are very small, the corresponding parameters are weakly detectable. If several columns are nearly collinear, the corresponding damage scenarios become difficult to separate.

A second criterion is the Fisher information matrix

$$\mathcal{I}(d^\star) = S(d^\star)^\top \Sigma^{-1} S(d^\star),$$

which quantifies the information content of the measurements with respect to the damage parameters.

A third criterion is the condition number

$$\kappa(S(d^\star)) = \frac{\sigma_{\max}(S(d^\star))}{\sigma_{\min}(S(d^\star))},$$

which measures the local stability of inversion.

Together, these criteria indicate whether a given monitoring configuration is adequate for damage detection, localization, and maintenance-oriented inference.

3. RESULTS AND DISCUSSION

3.1. Conceptual Separation of the Main Inferential Notions

The primary concepts utilized in vibration-based SHM are comparable. Yet, they are not equivalent. This is true according to the first outcome of the suggested framework. The major concern of observability, though, is concealed states. As, identifiability is related to hidden parameters, the ability to distinguish damage from a healthy state is known as detectability. Similarly, distinguishability is the ability to distinguish between two permissible circumstances. Adding to that, estimability is the question of whether inference is stable and significant in the face of limited noise and uncertainty.

This distinction is central because many SHM pipelines, especially data-driven ones, tend to collapse several inferential layers into a single prediction stage. A model may detect class differences without uniquely identifying physical damage parameters. A system may be damage-detectable but not damage-localizable. A parameter may be theoretically identifiable but practically unstable.

Figure 1 summarizes the information chain proposed in this paper.

Fig1. Conceptual chain in predictive structural health monitoring

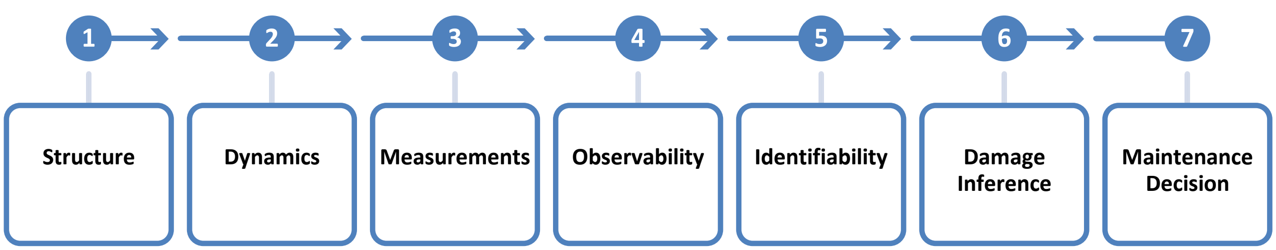


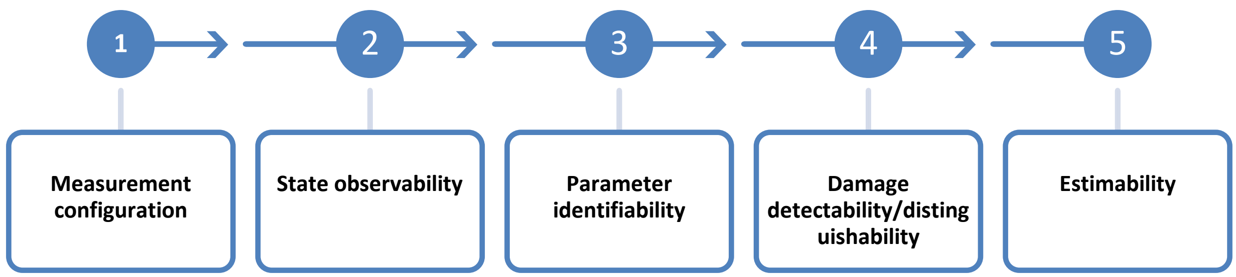
Table 1. Main inferential notions in vibration-based SHM

Concept	Main question	Object of inference	Main SHM role
Observability	Can the internal state be reconstructed?	Dynamic state	State reconstruction
Identifiability	Can the damage parameter be uniquely recovered?	Structural parameters	Damage diagnosis

Detectability	Can damage be separated from the healthy state?	Structural change	Alarm or anomaly warning
Distinguishability	Can two scenarios be told apart?	Competing states	Localization and attribution
Estimability	Can inference be made stably under uncertainty?	Estimated parameters	Decision reliability

The hierarchy may be written as

Fig2. Main inferential notions in vibration-based SHM



These arrows are not equivalences. In particular, observability does not guarantee identifiability.

3.2. Proposition 1: Observability Does Not Imply Damage Identifiability

Proposition 1. Consider the linear parameter-dependent system

$$\dot{x}(t) = A(d)x(t) + Gu(t), y(t) = Cx(t),$$

with $d \in \mathcal{D} \subset \mathbb{R}^s$. Assume that for every admissible d, the pair $(A(d), C)$is observable. Then observability of $(A(d), C)$for all $d$does not imply identifiability of d.

If there exist two distinct damage states $d_1 \neq d_2$such that

$$C(sI - A(d_1))^{-1}G = C(sI - A(d_2))^{-1}G$$

for all admissible complex frequencies s, then $d$is not identifiable from the input-output behavior.

Discussion. The difference between state reconstruction and parameter reconstruction is formalized in this proposition. Observability ensures that the measured output may be used to recreate the internal state if the model is known. A distinct concern is posed by identifiability: can the output be used to uniquely recover the unknown parameter itself? Therefore, even when the system is dynamically well observed, several damage scenarios in civil SHM may result in the same measured dynamic behaviour. The practical implication is clear: a monitoring system may justify anomaly warning or intensified surveillance while still being unable to support unique damage attribution.

3.3. Proposition 2: Sparse Sensing Can Destroy Local Identifiability

Proposition 2. Let

$$\mathcal{F}_{\text{full}}: \mathcal{D} \subset \mathbb{R}^s \to \mathcal{Y}_{\text{full}}$$

be a differentiable full-field forward map, and let the measured output be

$$\mathcal{F}_{\text{meas}}(d) = P\,\mathcal{F}_{\text{full}}(d),$$

where P is the projection induced by the sensor network. Assume that $\mathcal{F}_{\text{full}}$ is locally identifiable at $d^\star$, that is, $D\mathcal{F}_{\text{full}}(d^\star)$ is injective. Then local identifiability may fail for $\mathcal{F}_{\text{meas}}$ if

$$\ker(P\,D\mathcal{F}_{\text{full}}(d^\star)) \neq \{0\}.$$

Discussion. This proposition shows that identifiability is a property of the structure-measurement pair, not of the structure alone. While sparse sensing may eliminate informative directions through projection, the full structural response may contain sufficient information to differentiate neighbouring damage states. In SHM terms, poor sensor location or insufficient sensor density may collapse damage-sensitive variations and destroy local identifiability.

This is especially relevant for large civil structures, where practical monitoring is often restricted to a small number of sensors. An SHM system might still be helpful in these circumstances for anomaly screening, but not for component-level maintenance planning or high-confidence localization.

3.4. Proposition 3: Noise and Environmental Variability Can Turn Theoretical Identifiability into Practical Non-Identifiability

Proposition 3. Let

$$y^{\text{obs}} = \mathcal{F}(d,\xi) + \eta,$$

where d is the damage parameter, ξ is a nuisance variable representing environmental or operational effects, and η is measurement noise. Assume that, in the idealized noise-free and nuisance-fixed case, the reduced map $d \mapsto \mathcal{F}(d,\xi^\star)$ is locally identifiable at $d^\star$. Then practical identifiability may fail if either:

the smallest singular value of $D_d\mathcal{F}(d^\star,\xi^\star)$ is too small relative to the noise level, or

the nuisance sensitivity $D_\xi\mathcal{F}(d^\star,\xi^\star)$ overlaps with the damage-sensitive directions.

Discussion. This proposition formalizes the gap between structural identifiability and practical identifiability. In real civil structures, temperature, traffic, wind, humidity, and boundary-condition changes may perturb monitored responses in ways comparable to incipient damage. Under such conditions, the inverse problem may remain theoretically informative but practically unstable or ambiguous.

For maintenance, this means that uncertainty quantification and nuisance-aware interpretation are not optional. They are part of what makes SHM output decision-relevant.

3.5. Implications for AI-Based and Physics-Informed SHM

The aforementioned assertions significantly impact AI-based SHM. It also affects physics-informed SHM. The main lesson is evident as a result. That is the difference between empirical prediction performance and physical identifiability. A model's performance may be enhanced by stable discriminative patterns found in the dataset. These patterns, however, are not required to align with damage parameters. We define parameters as those that can be uniquely recognized. Alternatively, detectability, dataset-specific separability, or nuisance regularities could be represented (Bolandi et al., 2022).

Because it limits solutions to stay mechanically reasonable, narrows the admissible hypothesis space, and may enhance robustness under data shortage, physics-informed learning is extremely beneficial. It cannot, however, produce missing data. No learning architecture can completely compensate for a weakly informative or highly muddled damage-to-response map.

This concept directly relates to studies that are focused on benchmarks, like the Z24 bridge. Strong prediction performance on these kinds of datasets is useful from a scientific standpoint, but how it is interpreted depends on whether the task relates to scenario-level distinguishability, actual damage diagnosis, or just detectability under a specific sensing and environmental regime (Riyahi et al., 2026).

3.6. Implications for Predictive Maintenance of Civil Structures

The proposed framework shows that predictive maintenance should be understood as a graded inferential process. Not every SHM system supports the same level of maintenance action. If only detectability is achieved, then the rational consequence is anomaly warning or intensified surveillance. If distinguishability and local identifiability are available, then the system can support targeted inspection. If practical estimability is strong under uncertainty, then the output may support intervention planning, severity tracking, and deterioration forecasting.

Accordingly, maintenance decisions should be aligned with the strongest inferential property actually justified by the structure-measurement-model configuration. This leads to the practical hierarchy

$$\text{anomaly warning} \subset \text{inspection support} \subset \text{damage attribution} \subset \text{maintenance planning}.$$

Each level requires additional mathematical support from observability, identifiability, distinguishability, and uncertainty control.

3.7. Limitations and Bridge-to-Practice Discussion

The framework developed in this paper has a clear strength: it makes explicit the informational conditions under which vibration-based damage inference is meaningful. Its first limitation is that it is model-dependent. Observability and identifiability are defined relative to a chosen structural model, damage parameterization, sensing operator, and nuisance representation. If these are poorly chosen, the analysis may characterize the wrong inverse problem.

A second limitation is the gap between idealized identifiability and field identifiability. Real civil structures operate under uncontrolled environmental and operational variability, sensor drift, missing data, and uncertain boundary conditions. Theoretical identifiability should therefore be interpreted as an upper bound on what may be achieved in deployment.

A third limitation is that the paper is intentionally non-experimental. It does not provide a benchmark validation or case study. This is a strength in terms of theoretical clarity, but it also means that the framework does not by itself quantify the gap between mathematical identifiability and field practice for one specific structure.

This limitation also points to the paper’s most useful extension. The present framework can later be instantiated for representative structural classes such as long-span bridges or multi-storey buildings, without changing its theoretical nature. In that sense, the natural continuation of this work is a companion application paper in which observability, identifiability, nuisance robustness, and practical estimability are studied on a concrete monitored asset.

4. CONCLUSION

This paper has developed a theoretical and system-theoretic framework for the analysis of observability and identifiability of structural damage from vibration signals. The main contribution is not a new algorithm or benchmark, but a clarification of the mathematical conditions under which damage can be meaningfully inferred from monitored responses in civil engineering structures.

A first key conclusion is that damage diagnosis is fundamentally an inverse problem and is therefore subject to non-uniqueness, instability, and sensitivity to noise and nuisance variability. A second conclusion is that the inferential structure of SHM is hierarchical: a system may achieve anomaly detection without enabling unique damage localization, and may enable localization without supporting stable parameter estimation. A third conclusion is that sensor design and environmental variability are decisive because they determine the effective information content of the monitoring system.

The paper also shows that artificial intelligence and physics-informed methods must be interpreted relative to the information structure of the underlying inverse problem. Strong predictive performance does not automatically imply physical identifiability. Finally, the study argues that predictive maintenance requires inferential calibration: the level of maintenance action justified by SHM should match the strongest inferential property actually satisfied by the structure-measurement-model configuration.

Future work should apply the proposed framework to representative civil structures, design sensor networks that preserve identifiability under realistic constraints, and integrate uncertainty-aware inverse methods with AI and physics-informed learning. More broadly, the results suggest that progress in SHM and predictive maintenance will depend not only on more powerful algorithms, but also on a deeper understanding of what can and cannot be inferred from monitored structural response.

ACKNOWLEDGEMENTS

The authors acknowledge the support of the 2IACS Laboratory, ENSET Mohammedia, Hassan II University of Casablanca, Morocco. The authors also acknowledge the scientific context of recent work on structural health monitoring of the Z24 bridge, which helped motivate the present theoretical study.

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