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Review

Effectiveness of Vibration-Based Techniques for Damage Localization and Lifetime Prediction in Structural Health Monitoring of Bridges: A Comprehensive Review

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Abstract: Bridges are essential to infrastructure and transportation networks, but face challenges from heavier traffic, higher speeds, and modifications like busway integration, leading to potential overloading and costly maintenance. Structural Health Monitoring (SHM) plays a crucial role in assessing bridge conditions and predicting failures to maintain structural integrity. Vibration-based condition monitoring employs non-destructive, in situ sensing and analysis of system dynamics across time, frequency, or modal domains. This method detects changes indicative of damage or deterioration, offering a proactive approach to maintenance in civil engineering. Such monitoring systems hold promise for optimizing the management and upkeep of modern infrastructure, potentially reducing operational costs. This paper aims to assist newcomers, practitioners, and researchers in navigating various methodologies for damage identification using sensor data from real structures. It offers a comprehensive review of prevalent anomaly detection approaches, spanning from traditional techniques to cutting-edge methods. Additionally, it addresses challenges inherent in Vibration-Based Damage (VBD) SHM applications, including establishing damage thresholds, corrosion detection, and sensor drift.

Keywords: vibration-based SHM; sensors; challenges; damage thresholds

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1. Introduction

In recent years, there has been a remarkable advancement in sensor technology, numerical simulation methods, and damage diagnosis techniques. What was until recently limited to conventional inspection methods carried out by experts has evolved towards smart sensors and decisions guided by artificial intelligence. These advancements have led to the widespread adoption of Structural Health Monitoring (SHM) in bridge infrastructures [1]. SHM has proven to be an invaluable tool, providing continuous and reliable information about the state and response of bridge structures.

SHM technology plays a critical role in providing essential information for making informed decisions regarding the operation and maintenance of bridge structures. This includes issuing warnings about potential overloads and damage, thus facilitating timely countermeasures and maintenance actions. On the other hand, Structural Health Monitoring (SHM) systems have seen a growing adoption in tall structures, aimed at ensuring their safety and functionality. For instance, Brownjohn et al. [2] undertook an extensive monitoring study focusing on the evolution of dynamic responses and structural properties of a 280-meter-high, 65-story office tower. Meanwhile, Zhang et al. [3] conducted comprehensive measurements on several super-tall buildings to discern their responses to wind-induced stresses during severe weather conditions. The Burj Khalifa, for instance, features an integrated real-time SHM and structural identification system, serving to continuously monitor and evaluate its structural integrity and performance.

Thanks to its effectiveness and practicality, SHM technology has emerged as an efficient means of evaluating the health of a bridge structure. Over the past few decades, there has been a notable increase in confidence in vibration-based SHM systems, particularly when used on highway or railway bridges. This technology holds great potential for enhancing the safety, performance, and longevity of bridges, ensuring their reliability under varying conditions and loads, ultimately contributing to the improvement of overall transportation infrastructures.

This has been furthered by the rapid development and integration of sensor technology, numerical simulation methods, and damage diagnosis techniques, which have driven the widespread use of SHM in bridge infrastructures. Also, advancements in electrical infrastructures made the implementation of SHM systems more feasible and cost effective, easily applicable in real-world scenarios without requiring excessive labor.

Vibrations on bridge structures can originate from a variety of dynamic loads, such as human and traffic activities, wind action, and more. Vibration analysis of a bridge structure can help assess its health state, facilitating efficient maintenance activities, and ensuring its reliability, durability, and operational functionality. This requires the utilization of cutting-edge diagnostic tools and techniques capable of performing damage detection and characterization, that is, identifying, quantifying, and locating any potential damage [4]. One essential aspect of SHM for civil infrastructure lies in its emphasis on long-term evaluation, where the system identifies a 'normal' structural performance or an 'initial health state condition' of the bridge and then follows its evolution in time towards different states [5].

In that respect, within SHM techniques, vibration-based approaches have emerged as the most widely adopted [6–13]. Their primary objectives include detecting structural damage, assessing its severity, and precisely locating it along the bridge. Additional tasks encompass evaluating the overall safety of the structure, predicting the remaining service life, establishing reliable thresholds, and facilitating maintenance decision making, whenever possible (Figure 1).

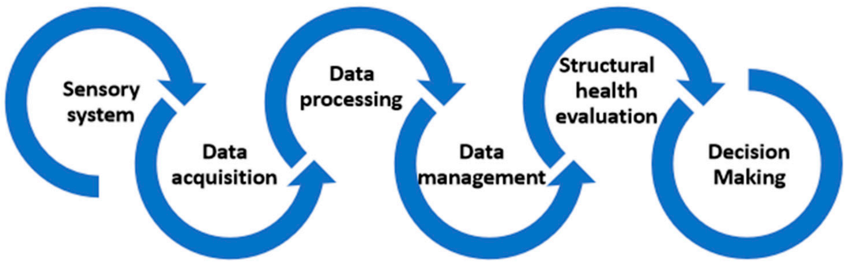

Figure 1. Vibration-based structural health monitoring systems.

More specifically, Rytter [14] proposed a damage identification-based scale on four levels. Recently [15,16], the scientific community extended the classification to five levels, as follows: level 1, damage detection; level 2, damage localization; level 3, damage quantification; level 4, damage typification; level 5, evaluation of structural integrity and residual lifetime.

Vibration characteristics are inherently linked to a structural parameter. Any damage to the structure causes alterations in some of these parameters, making them valuable indicators in predicting the structural health condition. By monitoring the signals captured through sensors installed on the structure, vibrational features can be extracted, and corresponding changes can be detected and interpreted.

Advancements in modern computer technology, sensor technology, and signal processing have significantly enhanced the ability to accurately and rapidly analyze and process test signals. However, there is a lack of comprehensive technical standards and specifications for vibration-based SHM. The absence of explicit guidelines regarding the choice of sensors, their optimal installation locations, and how to effectively evaluate the structural health condition using monitored data, makes it difficult for engineers to implement SHM effectively. This work aims at addressing this issue by providing a comprehensive review of vibration-based techniques and technical codes. The goal is to offer a useful reference for the application of technical methods and standard specifications in vibration-based SHM.

More specifically, the goals of this literature review can be summarized as follows:

1. To comprehensively review the applicability of various vibration-based techniques utilized in the structural health monitoring of bridges.
2. Furthermore, the review seeks to identify and analyze the challenges associated with detecting and characterizing damage using vibration-based techniques, considering factors such as noise interference, environmental conditions, and structural complexities.
3. In addition to evaluating current methodologies, this paper aims to discuss emerging approaches and technologies to enhance the accuracy and efficiency and especially to identify appropriate alarm thresholds.
4. Moreover, the review endeavors to explore strategies for lifetime prediction and prognosis in bridge structures based on vibration-based data analysis, addressing issues such as fatigue, sensor drift, corrosion, and degradation.
5. By synthesizing the existing literature and research findings, this review aims to provide readers with insights into the advancements, limitations, and future directions in the field of vibration-based damage identification for structural health monitoring of bridges.

Section 2 of the paper focuses on reviewing various vibration-based SHM approaches, with special attention to the more recently developed approaches (Table 1). Their advantages and drawbacks are discussed, offering insights into their suitability and effectiveness in practical applications.

Table 1. Vibration-based damage detection methods.

Method	Section
Modal frequencies and shapes	Section 2.1
Damping	Section 2.2
Modal Strain Energy (MSE)	Section 2.3
Residual Force Vector (RFV)	Section 2.4
Artificial Neural Network (ANNs)	Section 2.5
Statistics-based	Section 2.6

Section 3 delves into the challenges currently faced in the SHM field and discusses potential future developments (Table 2). Addressing these challenges and embracing advancements is crucial to further enhancing the effectiveness and practicality of vibration-based techniques.

Table 2. Challenges in SHM.

Challenge	Section
Establishing alarm thresholds	Section 3.1
Stiffness degradation evaluation	Section 3.2
Corrosion detection	Section 3.3
Fatigue crack length	Section 3.4
Sensors and the issue of drift	Section 3.5
Impact of environmental factors and operational conditions	Section 3.6
Emerging technologies and methodologies	Section 3.7

2. Vibration-Based Damage Detection (DD) Techniques

Structural health monitoring (SHM) of bridges involves assessing the condition of the structure over time to detect any potential damage or deterioration. Various vibration-based techniques are employed to accomplish this, each with its own advantages and limitations. The following techniques are worth considering for damage detection in SHM, as analyzed in the following sections:

1. Natural Frequencies and Mode Shapes: Natural frequencies and mode shapes are inherent characteristics of a structure. Changes in these properties can indicate damage or alterations in structural stiffness. Monitoring changes in natural frequencies and mode shapes can help detect damage such as cracks or degradation phenomena.
2. Damping: Damping refers to the energy dissipation capacity of a structure. Changes in damping characteristics can indicate the presence of damage or changes in material properties. Monitoring damping can provide additional insights into structural behavior and aid in damage detection.
3. Modal Strain Energy (MSE): Modal strain energy is a measure of the strain energy associated with each mode of vibration. It represents the distribution of strain energy throughout the structure. Monitoring changes in modal strain energy can help identify regions of high stress or strain, which may indicate the presence of damage.
4. Residual Force Vector (RFV): The residual force vector represents the difference between measured and predicted forces in the structure. Changes in the residual force vector can indicate the presence of external forces or structural damage that was not accounted for in the predictions. Monitoring the residual force vector can help detect anomalies in the structural behavior.
5. Artificial Neural Network (ANNs): Artificial neural networks are computational models inspired by the structure and function of the human brain. They can be trained to recognize patterns in complex data sets, making them suitable for analyzing large numbers of sensor data collected from SHM systems. ANN can learn the relationships between various sensor readings and structural conditions, enabling accurate damage detection and prediction.
6. Statistics-based Methods: Statistics-based methods involve analyzing the statistical properties of sensor data to detect anomalies or changes in the structural behavior. These methods can identify deviations from normal operating conditions, which may indicate the presence of damage or deterioration.

The mentioned techniques have been selected both because they are the most widely adopted and because they offer complementary approaches to monitoring the health of bridges. By integrating multiple methods, SHM systems can provide comprehensive insights into the condition of a structure, enabling timely detection of damage and informed maintenance decisions. Each of the methods listed above is examined in detail in the following section and relevant references are provided.

2.1. DD Using Modal Frequencies and Shapes

The use of natural frequency in SHM was one of the first techniques used for damage detection in bridge structures. It involves identifying the natural frequencies and resonant modes of the structure. Even under significantly different loading conditions, such dynamic properties remain relatively constant, solely dependent on the structure itself. A reduction in natural frequencies indicates structural degradation or damage caused by extreme events, leading to a decrease in stiffness [17]. Among dynamic parameters, natural frequencies stand out as effective indicators of structural damage in vibration-based SHM systems. Lower frequencies may experience a slight drop, while higher frequencies may exhibit a more significant reduction [18]. However, implementing algorithms to extract these modal properties is not always straightforward and the intricacies involved in implementing these methods can be challenging. For example, changes in temperature can affect the natural frequency of the structure. The impact of temperature on the detection of damage, particularly based on the relative frequency shift in beam-like structures, was investigated, among others, by Gillich et al. [19].

Since 1979, there have been numerous studies exploring the use of natural frequency parameters for the development and application of vibration-based damage detection techniques in bridge structures.

For instance, Gentile et al. [20] conducted a study on an iron arch bridge, analyzing vertical and horizontal natural frequencies through periodic dynamic tests to assess the condition of the bridge structure. Their research revealed a slight decrease in the resonant frequency of the first bending mode during the second Ambient Vibration Test (AVT), suggesting potential structural deterioration or damage occurrence. However, despite its apparent effectiveness, this technique showed limitations in delivering precise results, being very sensitive to mixed excitation sources and variable environmental conditions.

Garcia-Macias et al. [21] developed an advanced software suite designed for the autonomous management of integrated Structural Health Monitoring (SHM) systems. Their approach encompasses automated operational modal analysis, precise frequency tracking, sophisticated filtering of environmental impacts, and the identification of structural damage using cutting-edge novelty analysis techniques. Furthermore, the potential of their proposed vibration-based SHM procedure was tested on two real bridges. Uwayed et al. [22] introduced a damage detection method for laminated CFRP composite plates, focusing on modal characteristics. This method extends the capabilities of a recently enhanced curvature damage index by utilizing a vibration-based approach. It applies both theoretical and experimental response data to precisely identify and quantify damage within structures.

However, frequencies alone are not generally sufficient to identify the location of local damage since they represent global indicators and lack location information. Therefore, they are commonly used in conjunction with mode shapes, which contain critical location information and are more sensitive to identifying local damage [23–27]. The mode shapes of a structure illustrate the distribution of displacements across its elements during vibration. By analyzing mode shapes, engineers can pinpoint regions of high deformation, indicating potential areas of damage or weakness. Unlike frequencies, which give a global view of the structural response, mode shapes offer valuable insights into the localized behavior, making them essential for accurate damage localization.

To identify and assess damage effectively, a comprehensive approach combining both frequency and mode shape information is generally adopted: frequencies provide an overall understanding of the structural dynamic behavior, while mode shapes complement this knowledge by offering precise localization of potential damage regions. By leveraging these modal parameters together, engineers can make informed decisions about the condition and health of critical structures, enabling timely maintenance and ensuring their long-term performance and safety.

During the monitoring process, the extracted mode shapes of the structure are compared to those relevant to the undamaged state, obtained either from measurement or from project reports or from structural modelling. Potential local damage can be identified by means of two widely used damage indices, named Modal Assurance Criterion (MAC) and COordinate Modal Assurance Criterion (COMAC), respectively:

$$\mathrm{MAC}\left(\phi_i^u, \phi_i^d\right) = \frac{\left[\left(\phi_i^u\right)^T \phi_i^d\right]^2}{\left[\left(\phi_i^u\right)^T \phi^u\right]\left[\left(\phi_i^d\right)^T \phi_i^d\right]} \tag{1}$$

$$\mathrm{COMAC}\left(\phi_i^u(x_j), \phi_i^d(x_j)\right) = \frac{\left(\phi_i^u(x_j)\phi_i^d(x_j)\right)^2}{\left(\phi_i^u(x_j)\right)^2\left(\phi_i^d(x_j)\right)^2} \tag{2}$$

where ϕ_i^u and ϕ_i^d are the i-th undamaged and damaged mode shape, respectively, and x_j is the coordinate of the j-th point.

The MAC value reflects the similarity between mode shapes, with a perfect match resulting in a value of 1, which signifies that the structure is in good condition, as the mode shapes closely resemble the undamaged reference. Conversely, significantly lower MAC values indicate structural damage, as there are differences between extracted and reference mode shapes.

In comparison to MAC, the COordinate Modal Assurance Criterion (COMAC) provides both similarity and location information. A COMAC value close to 1 at a specific location x_j implies that the structure remains intact at that point. On the other hand, a COMAC value less than 1 at x_j suggests the presence of damage at that location.

Extensive research [28–34] has been dedicated to the identification of local damage in structures using a combination of frequencies and mode shapes. These parameters contain both global and local information, making them effective for damage detection. To ensure successful practical application, researchers have proposed various improvements to the above criteria.

One promising direction for improvement is the accurate construction of the baseline mode shapes. Finite Element (FE) model updating has emerged as a widely used technique for this purpose [35–37]. Conventional FE model updating involves regenerating the baseline of frequencies and mode shapes. The frequencies and mode shapes obtained from the FE model are then compared with those measured by the monitoring system to detect potential local damages in the structure with respect to the original as-built condition. By updating the stiffness matrix (sometimes excluding the mass matrix), the FE model is adjusted to match the measured frequencies and mode shapes. Mathematically, the FE model updating process can be cast as a constrained optimization problem, as:

$$f = a\sum_{i=1}^{N}\frac{\left|f_i^{exp} - f_i^{num}\right|}{f_i^{exp}} + b\sum_{i=1}^{N}\left(1 - MAC\left(\phi_i^{exp}, \phi_i^{num}\right)\right) \tag{3}$$

where f_i^{exp} and f_i^{num} are the experimental and numerical natural frequencies of mode i, respectively, ϕ_i^{exp} and ϕ_i^{num} are the experimental and numerical i-th mode shape, respectively, a and b are weight factors and N is the total number of considered modes.

The objective is to find the best set of parameters (e.g., stiffness values) that minimizes the difference between measured and updated modal parameters while satisfying certain constraints related to the structural properties. By utilizing FE model updating as a tool for constructing accurate baseline mode shapes, researchers can enhance the reliability and precision of damage detection methods. This approach allows identification and assessment of local damage in structures more effectively. However, the results given by this approach are strictly affected by uncertain parameters connected to the material and geometric characteristics, structural details, soil–foundation interaction and others of environmental origin, such as temperature. Therefore, especially in old structures, costs can exceed benefits and thus engineers should carefully evaluate the use of this technique in designing SHM systems.

2.2. DD Using Damping

While frequencies and mode shapes are widely used in SHM systems to assess the condition of structures, damping is less frequently considered in practice due to its measurement complexity [26,38–42]. Nonetheless, several researchers have explored the potential of damping as an indicator of structural health. The rationale is that damping increases with damage.

Frizzarin et al. [38] analyzed damping using ambient vibration data to detect damage without relying on a baseline, successfully demonstrating this approach on a large-scale concrete bridge model with seismic damage. Mustafa et al. [39] introduced an energy-based damping evaluation approach for assessing the health condition of a truss bridge through numerical simulations. Cao et al. [40] compared damping-based damage detection methods on reinforced concrete structures and fiber-reinforced composites, shedding light on the factors influencing damping capability for damage detection. More recently, Liu et al. [26] proposed a novel complex eigen-parameter identification method to simultaneously evaluate stiffness reduction and damping defects on a non-classically damped shear building.

While local damage could ideally lead to observable changes in damping, the measurement is susceptible to noise, especially in structures experiencing ambient environmental vibrations, making it challenging to detect subtle changes in damping due to local damage. Moreover, selecting or constructing an appropriate damping model is a non-trivial task. The classical Rayleigh damping model is commonly used due to its simplicity. However, it may not be applicable to all structures, leading to the proposal of more advanced damping models. It is essential to consider different damping models for different types of structures.

Another limitation of using damping alone for damage identification is that it represents a global property of the structure, akin to frequency. As a result, damping alone may not accurately identify the specific location of local damage. A comprehensive approach combining multiple SHM indicators, such as damping, frequencies, and mode shapes, is often necessary to achieve a more accurate and reliable assessment of structural health.

2.3. DD Using Modal Strain Energy (MSE)

Stubbs et al. [43] introduced the concept of Modal Strain Energy (MSE) for damage localization. MSE has proven to be valuable in accurately identifying and quantifying structural damage, even without prior baseline data. The general definition of MSE for a structure in the r-th mode can be expressed as:

$$MSE_r = \frac{1}{2}\Phi_r^T K \Phi_r \tag{4}$$

where K is the stiffness matrix of the structure and Φ_r is the r-th mass-normalized mode shape.

Since then, MSE has been widely studied and utilized as an effective parameter for identifying and localizing damage in structures, contributing significantly to the development of SHM.

Zhang et al. [28] improved the damage localization method by utilizing MSE and estimating the damage size without relying on baseline modal properties. They defined the contribution of element j to the r-th mode MSE as:

$$C_{rj} = \frac{\Phi_r^T k_j \Phi_r}{\Phi_r^T K \Phi_r} = \frac{\Phi_r^T k_j \Phi_r}{\omega_r^2} \tag{5}$$

where k_j is the stiffness of element j and ω_r is the r-th mode frequency.

Carrasco et al. [44] presented a method based on changes in MSE to effectively locate and quantify damage in a space truss model. They observed that the magnitude of these changes served as a reliable indicator of the overall damage extent. The test results demonstrated that the method succeeds in accurately localizing the damaged elements within the truss structure. However, minor damages have little effects on modal properties of the structures; hence, in these cases, the MSE technique may prove inefficient. To extend the use of MSE technique to such cases, Cha et al. [45] have proposed a hybrid approach in which damage detection based on the MSE is integrated with multi-objective optimization algorithms. Since model robustness and measurement uncertainties are a fundamental issue in model-updating-based damage detection [46–48], the authors also introduced white noise of 5% in the selected modal shapes, obtaining an error in damage detection lower than 5%. In the end, the research of Cha et al. demonstrates that the proposed hybrid method is substantially insensitive to sensor drift and has good damage detection capability both in severity and localization, although with incomplete mode shapes.

2.4. DD Using a Residual Force Vector (RFV)

With access to measured mode shapes, natural frequencies, and an initial baseline model, it is possible to calculate a Residual Force Vector (RFV). This vector is obtained by solving an eigenvalue equation using the natural frequencies and mode shapes of the damaged structure for the i-th mode:

$$\left(K_d - \omega_{d_i}^2 M_d\right)\phi_{d_i} = 0 \quad (6)$$

where ω_d and ϕ_d are the natural frequency and the mode shape of the damaged structure, while K_d and M_d are the stiffness and mass matrices, defined as:

$$K_d = K_a + \Delta_K \quad (7)$$

$$M_d = M_a + \Delta_M \quad (8)$$

where K_a and M_a are the stiffness and mass matrix of the undamaged structure and Δ_K and Δ_M are the changes in stiffness and mass matrices.

Substituting Equations (7) and (8) into Equation (6) and rearranging, the definition of the residual force vector R_i for the i-th mode is obtained:

$$R_i = \left(K_a - \lambda_{d_i} M_a\right)\Phi_{d_i} \quad (9)$$

Each mode corresponds to a unique RFV, which can be interpreted as the harmonic force excitation required to apply to the undamaged structure, represented by K_a and M_a, at the frequency $\sqrt{\lambda_{d_i}}$, to elicit the same mode shape Φ_{di} as measured in the damaged structure. Each row of the RFV corresponds to a specific degree of freedom in the numerical model of the structure. In the event of damage to an element connected to a particular degree of freedom, the corresponding entry in the RFV becomes significantly larger compared to other entries with no damage. This distinctive pattern allows for the identification of the damaged location. However, additional algorithms are needed to quantify the extent of the damage precisely.

Shen et al. [49] proposed a residual force vector-based method where the vector is derived through the integration of static displacement data and the stiffness matrix pertinent to the finite element model of the structure. The method intelligently identifies damaged elements within the structure by pinpointing the non-zero elements within the permutation of the force residual vector. Following this identification, the extent of damage to these elements is calculated using an equilibrium equation. This equation is uniquely formulated from the global stiffness matrix, focusing solely on the elements identified as damaged, thereby providing a precise measure of the damage degree within the unit.

Sheinman [50] demonstrated a closed-form algorithm for damage identification through several numerically simulated examples. Kosmatka and Ricles [51] successfully identified single damage events (stiffness loss, connection loosening, and lump mass addition) in a laboratory space truss using the RFV method. Complete mode shapes obtained from measurements at each degree of freedom aided in pinpointing the damage location. An additional weighted sensitivity algorithm estimated the magnitude of stiffness/mass change, with better correlation between the analytical model and baseline modal properties resulting in improved estimates of damage severity.

Farhat and Hemez [52] proposed a sensitivity-based algorithm that minimized the norm of the RFV by updating stiffness and mass elemental parameters. They efficiently expanded incomplete mode shapes by minimizing the RFV, saving computational effort by updating only elements with large RFV entries. The method was successfully demonstrated on simulated cantilever and plane truss structures, with an emphasis on including modes storing sufficient strain energy in damaged elements. Brown et al. [53] further extended the method to lightly damped structures, updating the mass and stiffness matrices before handling the remaining RFV with the damping matrix. The method showed satisfactory results in simulated studies with damping below 3%.

Yang and Liu [54] dealt with the issue of incomplete and/or noisy measured modal parameters, evaluating the damage location with node residual force vector and then quantifying damage extents relying to three different techniques: (a) the algebraic solution, (b) the Minimum-Rank Elemental Update (MREU) and (c) the natural frequency sensitivity. The study shows that the RFV method enables locating of damage in measured and unmeasured locations, but the location accuracy is clearly dependent on noise. The first two methods are in general disreputable. In particular, the algebraic solution of RFV has the advantage of being the simplest technique in damage quantification, but often gives false damage in the presence of noise. The MREU method requires a stringent mathematical condition on the rank of the perturbed matrix, only satisfied in a small number of real cases. Even if this precondition is fulfilled, the method gives a large error with measurement noise. The natural frequency sensitivity method has proven to be the most effective technique, providing accurate damage extents, according to the damage deployment of the tested structures, and excluding the false damaged elements. The robustness of this method in estimating damage extents is in the easy and precise measurement of the lower natural frequencies.

From studying the aforementioned works, it is clear that the accuracy of the RFV method in locating damage relies on the measurement of mode shapes. When mode shapes are sparsely measured, it is necessary either to reduce the system matrices or expand the mode shapes. Matrix reduction sacrifices the structure of the matrices, rendering the direct use of the RFV method for damage location less effective. Conversely, expanding mode shapes from few measurements raises concerns about the accuracy of damage localization. However, when the measurements are sufficient, the RFV method proves to be a robust method for locating damage, and its potential for accurately sizing damage is promising, whereas when the measurements are limited, the effectiveness of the RFV method can be enhanced with the natural frequency sensitivity technique.

2.5. DD Using Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) method is one of the artificial intelligence computational models inspired by biological neurons; they are based on machine learning for algorithm training and predicting damage based on dynamic data acquisition, with processing units representing neurons, having multiple inputs and a single output.

Data sets, weights, bias, training, the activation function and prediction are the basic components of ANNs-based algorithms: "data sets" are the input data acquired by the sensors system, generally abundant; "weights" are the quantities, which need to be calibrated, that multiply input data to obtain the output; "bias" is an assigned systematic distortion function of a given data set; "training" means finding weights and bias in a continued adjustment of both parameters toward the target result; the "activation function" is a function that makes the ANN capable of resolving non-linearities; "prediction" is the result obtained by filtering input data with weights and bias. When the ANN has only one hidden level, it is called Shallow Artificial Neural Network (SANN); conversely, for a higher number of hidden layers, it is called Deep Artificial Neural Network (DANN). Figure 2 shows a simple predictive model that takes an input, performs a calculation, and gives an output; to minimize the error, the Back Propagation (BP) technique is usually adopted. In this technique, the estimation of error ε is carried out by using the loss function, i.e., a function that compares expected and predicted results, thus allowing adjustment of weights and bias during ANN training.

ANNs have been successfully utilized in various applications, including vibration-based damage identification [55–58]. ANNs are particularly suitable for problems which have abundant data yet are challenging to solve using explicit algorithms. BP has been effectively used by Ramu and Johnson [59] and Pandey and Barai [60] for damage identification, with network topology playing a crucial role in performance. In particular, BP based on the gradient descent method is a widely used training algorithm, proven to be effective in predicting damage when: (1) initial weights are not too far from a good solution; (2) the computational system is sufficiently fast; (3) an extensive database is available. However, Hochreiter et al. [61] demonstrated that it is difficult to optimize the weights when the ANNs is organized in multiple hidden layers. To overcome this limit, Hinton and

Salakhutdinov [62] introduced the Deep Learning (DL) concept to reduce data dimensionality and overcome the previous three limitations. Kuo and Lee [63] developed a structural damage identification method leveraging the capabilities of one-dimensional convolutional neural networks (1D-CNN). Their approach refines the placement of sensors, concentrating efforts on regions exhibiting significant displacements, which markedly diminishes damage detection time. This approach has led to a notable reduction in sensor deployment by 16.67% and has streamlined the process, requiring merely four CNN models to assess a structure comprising thirty connections. The efficacy of their technique is underscored by an impressive damage detection accuracy rate of 96.62%. Nick et al. [64] introduced a novel two-stage damage detection approach tailored for steel frameworks, employing ANNs. This method accentuates the utilization of adjusted damage indices, derived from modal flexibility and strain energy to first pinpoint the locations of damage. Subsequently, it employs ANNs to quantify the extent of the damage accurately. Simulations demonstrated the method's effectiveness in identifying both single and multiple instances of damage in a non-destructive manner. Shi et al. [65] developed an SHM procedure for identifying and quantifying structural damage, using Convolutional Neural Networks (CNN) in tandem with Short-Time Fourier Transform (STFT). This method excels in recognizing damage patterns and assessing the severity of diverse, previously unknown damage. Utilizing the IASC–ASCE benchmark, which offers vibration signals from a variety of damage scenarios, the data are converted into STFT spectrograms that serve as training material for the CNN. Their research notably introduces a novel condition-based damage function, capable of estimating damage severity across various modes, marking a significant advancement in the field.

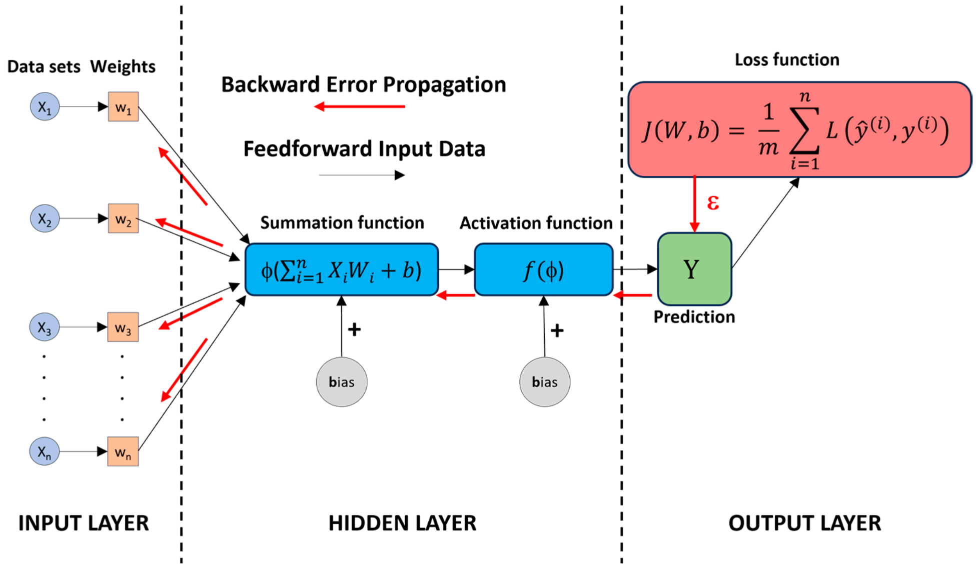

Figure 2. Simple predictive model of SANN.

Barai and Pandey [66] compared the performance of a Time-Delay Neural Network (TDNN) to a backpropagation network on a 21-bar truss, finding TDNN to generally perform better despite longer training times. An intriguing aspect of Marwala and Hunt's work [67] was the proposal of a committee of neural networks. Marwala [68] demonstrated this approach on a damaged experimental cylinder, training three networks with different data (frequency response functions, modal data, and wavelet transform data) and combining their outputs for improved predictions with respect to individual networks. The enhanced performance was assessed on different structural alterations having varied apparent effects in the frequency, modal, and time domains.

2.6. DD Using Statistics-Based Methods

Farrar and Doebling [69] proposed that vibration-based damage detection is essentially a statistical pattern recognition problem and that non-model-based pattern recognition methods are needed alongside existing model-based techniques. The use of novelty detection for condition monitoring has gained traction, where deviations in measured data from normal operating conditions are identified. The control of statistical processes allows both monitoring of the distributions of features and detecting of outliers in the data indicative of damage. This approach effectively detects damage, without necessarily pinpointing its location and extent. Various studies, including those by Worden et al. [70], Fugate et al. [71], and Fanning and Carden [72], have considered statistical process control methods for damage detection, demonstrating their effectiveness compared to other algorithms. In two companion papers, Samman and Biswas [73] investigated four waveform recognition techniques to distinguish between Frequency Response Function (FRF) waveforms of intact and damaged bridges. The first technique used was the Waveform Chain Code (WCC), which characterizes waveforms based on relative slope and curvature, extracting differences in these features as indicators. The second technique, Adaptive Template Matching (ATM), performed a point-by-point magnitude check to detect differences between two FRFs, deriving a tolerance feature representing signal deviation. The third technique was the Frequency Response Assurance Criterion (FRAC), assessed similarity to the MAC, with a value of 1 indicating identical signals and 0 for completely different signals. The fourth technique, known as the Equivalent Level of Degradation System (ELODS), employed a transformer that returned an undistorted signal for an undamaged structure but a distorted version for a damaged signal, yielding a distortion identification function as a feature.

In simulated data without noise, the effectiveness ranking of the techniques was ELODS, WCC and ATM, with SAC being the least effective. However, when applied to data from a highway bridge, only the WCC method successfully detected a crack. It is important to note that all these techniques can only determine the presence of damage but cannot provide information about the location or severity of the damage. Despite this limitation, these methods offer valuable tools for initial damage detection in bridge structures. To overcome this restriction, Pakzad et al. [74] and Dorvash et al. [75] developed and tested the Influenced Coefficient-Based Damage Detection Algorithm (IDDA), where the damage features are studied through the changes in linear regression coefficients produced by the proposed algorithm. Nigro et al. [76] have tested the effectiveness of the IDDA by expanding it to a more complex structural system and investigating the accuracy in structural damage localization by using change point analysis. The statistical treatment of the database took place by using the Univariate Cumulative Sum (UCS), Exponentially Weighted Moving Average (EWMA), Mean Square Error (MSE), Modified MSE (ModMSE), and Multivariate Mahalanobis Distance (MMD) and Fisher Criterion (FC). These statistics were used to build control charts able to detect and localize damage through the correlation between sensors placement and damage features. The experiment carried out by the research group proved that when the IDDA is supported by the control charts, it can detect and locate damage with accuracy. Among the used statistics, the ModMSE has proven to be the best algorithm in locating damage, thanks to its capability of recognizing changes in structural response due to variation in environmental and operational conditions, thus distinguishing between internal (structure) and external (action) changes.

3. Challenges in Structural Health Monitoring

Though scientific research has produced a wealth of theories and applications, it is still far from reaching a consensus on some relevant issues. The most important, in the authors' opinion, is that regarding the definition of alarm thresholds, dealt with in Section 3.1. While several codes propose limits for certain response quantities, it is becoming evident that it is virtually impossible to foresee appropriate thresholds for all possible quantities, especially for damage. Another issue, closely linked to the previous one, regards the evaluation of stiffness degradation, which is often considered as a proxy for damage, as explained in

Section 3.2. In Sections 3.3 and 3.4, detection of corrosion and of crack length are dealt with, which are always of concern when assessing the safety of existing bridges. The last topic treated in Section 3.5 refers to the issue of drift in sensors and its correction, while in Section 3.6 the impact of environmental factors and operational conditions are addressed. Finally, in Section 3.7, an overview of emerging technologies and methodologies is presented.

3.1. Establishing Alarm Thresholds

In structural safety monitoring, a fundamental aspect is the timely implementation of safety-enhancing contingency measures, which involves developing an alarm system. This system assists decision makers in promptly intervening based on monitoring outcomes, while allowing them to allocate attention to other tasks. Violations of preset alarm thresholds trigger commensurate alert levels, prompting the decision maker to take corrective action, thereby preventing failure in the monitored structure. Thus, thresholds are defined at chosen values of one or a combination of several monitored parameters. Therefore, one of the primary challenges in vibration-based SHM is determining what constitutes "alarm" and establishing thresholds for countermeasures. Alarm thresholds can vary significantly depending on the type of structure, its material properties, operating conditions, and the nature of detected damage. While several codes propose limits for certain response quantities, it is becoming evident that it is virtually impossible to foresee appropriate thresholds for all possible quantities, especially for damage. Addressing this challenge often involves a combination of experimental testing, numerical modeling, and data-driven approaches. Experimental testing helps in understanding how damage affects vibration characteristics, such as natural frequencies, mode shapes, damping ratios, and other modal parameters. Numerical modeling techniques, such as Finite Element Analysis (FEA) or analytical models, can simulate various damage scenarios and their effects on structural dynamics. These simulations can provide valuable insights into the expected changes in vibration responses due to different types and severities of damage. Data-driven approaches involve analyzing large data sets of vibration signals obtained from healthy and damaged structures to identify patterns or signatures associated with damage. Machine learning algorithms, such as classification or anomaly detection algorithms, can be trained using these data sets to automatically detect and classify damage based on vibration data. Alternatively, probability-based algorithms can be used. Ideally, a deterministic and precise correlation exists between the observed indicator and the damage measure (degree of damage), as shown in Figure 3.

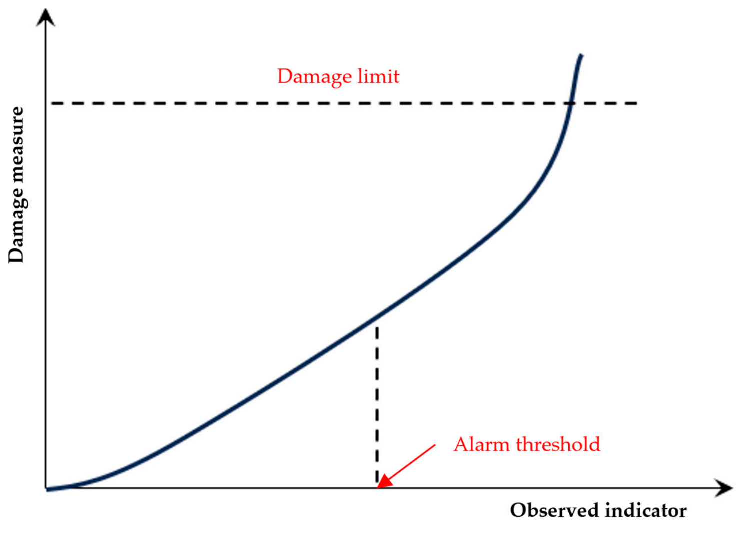

Figure 3. Ideal relationship between the observed indicator and the damage measure.

While alarm thresholds play an essential role in ensuring both structural safety and satisfactory serviceability, there is a notable lack of guidance available to engineers regarding their establishment. For instance, neither Eurocode 7 nor the existing application guidelines offer detailed advice on this matter. This deficiency in guidance becomes particularly problematic when employing the observational method, where the alarm threshold dictates when design adjustments are necessary.

Some of the notable works concerning damage detection through reliability-based alarm thresholds are as follows:

Johan Spross et al. [77] introduced a comprehensive computational algorithm for determining reliability-based alarm thresholds in civil engineering structures. The algorithm utilizes subset simulation with independent-component Markov Chain Monte Carlo (MCMC) and is applicable to both analytical models and finite element models for assessing the limit state function. The threshold is set to ensure the fulfillment of the target failure probability, if observations remain within the defined threshold. This concept is particularly suited for sequentially loaded structures, where observations contribute to predicting the ultimate behavior.

Sattele et al. [78] introduced a methodology for assessing threshold-based Early Warning Systems (EWSs) designed for natural hazards. Their proposed reliability method involves the Probability of Detection (POD) and Probability of False Alarms (PFA). The authors illustrated the formulation of EWSs effectiveness, a metric indicative of risk reduction, as a function of POD and PFA. To model the EWS and quantify its reliability, the authors devised a framework grounded in Bayesian networks. This framework was subsequently expanded to encompass a decision graph, offering a platform for optimizing the warning system. This integrated approach provides a systematic means of evaluating and enhancing the performance of threshold-based EWSs for natural hazards. The proposed framework of Sattele et al. [78] is summarized in Figure 4.

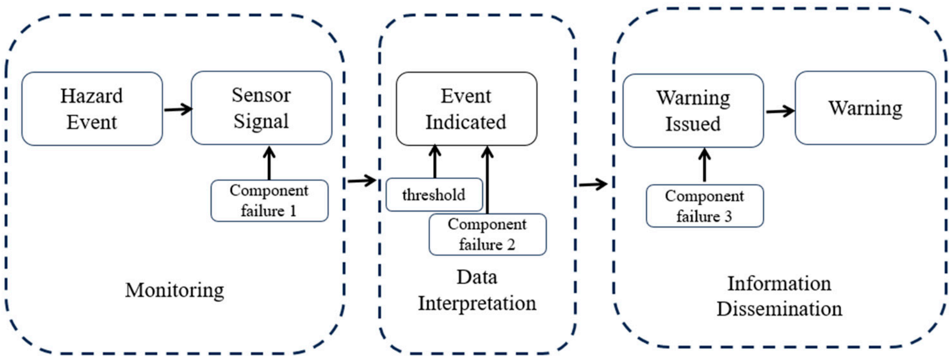

Figure 4. Schematic framework of a Bayesian network representing reliability in terms of Probability of Detection (POD) and Probability of False Alarms (PFA) for alarm systems.

3.2. Stiffness Degradation Evaluation

Stiffness degradation refers to the reduction in the structural stiffness of bridge components over time due to various factors such as material degradation, loading, and environmental effects. Monitoring stiffness degradation can help detect changes in structural behavior, such as increased deflections or shifts in natural frequencies, which may indicate the presence of damage or deterioration. Techniques such as modal analysis, finite element modeling, and strain measurement can be employed to assess stiffness degradation and identify potential structural issues before they lead to failure. Some localization techniques rely on identifying irregularities in the deflected shape of the structure [34,79–81]. These methods are based on accurately determining the modal characteristics of the structure, and particularly the deflected shape. Achieving this requires high-spatial-resolution sensors, high-quality measurements, and reliable signal processing. One significant advantage of vibration-based damage identification methods is their ability to detect damage at a global level using sensors that may not be deployed close to the damage location, which is generally unknown. Stiffness loss estimation can be accomplished using response-only approaches, either by utilizing sensor data exclusively, or by employing physical-based models like finite element models. Most of these methods capitalize on the relationship between local stiffness loss and the corresponding variation of curvature, which serves as the damage-sensitive feature. This involves double differentiation of displacement data obtained from a dense and distributed network of sensors. However, using such dense sensor arrays can increase the overall cost of the monitoring system. Additionally, estimating curvature from noisy recorded responses can be challenging. To address these issues, some researchers have proposed methods that identify curvature variations without explicitly computing curvatures or by using numerical validation through finite element approaches. This is particularly useful when experimental data directly associated with damaged structures are limited. Fortunately, the availability of data recorded on benchmark structures offers an opportunity to validate the effectiveness of these methods for damage localization in real-world conditions. The interested readers are referred to [82] to learn more about individual methodologies based on modal and operational shapes, shape variation due to a loss of stiffness, methods based on curvature, and methods based on the indirect detection of curvature changes.

3.3. Corrosion Detection

Corrosion is a common problem in bridge structures, particularly in areas exposed to harsh environmental conditions or de-icing salts. Corrosion can weaken structural elements, leading to reduced load-carrying capacity and increased susceptibility to failure. Corrosion in metallic components of bridges, such as cables, reinforcements, connections, or girders, can significantly degrade bridge performance, necessitating the monitoring of corrosion to identify critical degradation requiring maintenance. Even though researchers have delved into this topic over the past two decades, it is important to recognize that the scientific literature may not be as extensive on this topic as it is for other issues. However, this should not mislead the reader into thinking that corrosion-related problems are any less critical or prevalent. Challenges related to corrosion losses and diagnostics on pre-stressed rebars or post-tensioned tendons do indeed exist and are commonly addressed through the utilization of conventional or advanced non-destructive evaluation methods. Monitoring corrosion using techniques such as electrical resistance sensors, ultrasonic testing, or visual inspection can help assess the extent of corrosion damage and prioritize maintenance or repair efforts. Early detection of corrosion allows for timely intervention to prevent further deterioration and ensure the long-term durability of bridges.

Morris et al. [83] investigated the effects of local variables on rebar corrosion and proposed a criterion for evaluating rebar corrosion based on concrete electrical resistivity measurements. The study involved two exposure conditions, a seashore environment and partial immersion in a saline solution, with variations in water-to-cement ratios and initial chloride ion additions. The results demonstrated that electrical resistivity can effectively assess the potential for steel corrosion, and that concrete mix design, environmental exposure conditions, and initial chloride concentration influence the rebar corrosion process. Notably, this study did not involve the monitoring or testing of specific bridges.

Deeble Sloane et al. [84] presented a strategy to monitor the eventual corrosion of high-strength steel wires in suspension bridges through a sensor network assessing the environmental conditions and deterioration of main cables indirectly. The strategy underwent testing on a full-scale mock-up cable, recording temperature, Relative Humidity (RH), and corrosion rate levels. The sensor network successfully provided valuable insights into the cable's interior environment. Although the observed trend was not consistent throughout the mock-up cable cross-section, RH values emerged as robust indicators of corrosion rate levels.

For in-depth study, the reader is referred to the pertinent literature addressing corrosion detection through electrochemical methodologies [85–87] and physical-based approaches [88,89].

3.4. Fatigue Crack Length

Fatigue cracks develop in bridge components subjected to repeated loading and unloading cycles, such as vehicular traffic or wind-induced vibrations. Monitoring fatigue crack length is essential for assessing the progression of damage and predicting the remaining fatigue life of the structure. The initiation and propagation of these cracks stem from stress concentration induced by minor defects in the material. The nucleation and accumulation of such defects culminate in the development of fatigue cracks. The early stages of these cracks are typically characterized by minute dimensions, rendering their detection challenging. Additionally, depending on the loading conditions and structural configurations, these cracks may progress swiftly, thereby compromising structural integrity [90].

It is crucial to note that if bridges undergo inadequate inspection and maintenance, fatigue cracks have the potential to evolve into critical threats, particularly for fracture-critical bridges [91]. This underscores the imperative need for vigilant monitoring and proactive maintenance practices to avert catastrophic failures in bridge structures.

Timely detection of fatigue cracks helps to initiate appropriate maintenance interventions. Techniques such as non-destructive testing (e.g., ultrasonic testing, magnetic particle inspection) and visual inspection can be used to measure and monitor fatigue crack length over time. By tracking crack growth rates and identifying critical crack lengths, engineers can implement appropriate maintenance and repair strategies to mitigate the risk of structural failure. Presently, visual inspection stands as the predominant method for fatigue cracks detection in highway bridges within the United States [92]. Nonetheless, this approach is characterized by its inherent drawbacks, including high costs, labor intensiveness, and susceptibility to errors owing to the minute dimensions of cracks and the minimal contrast between the crack and its adjacent metallic surface [93].

Various advanced technologies have been proposed for monitoring the initiation and/or propagation of fatigue cracks, encompassing methods such as acoustic emission [94], piezoelectric sensors [95], Lamb wave techniques [96], and vibration analysis [97].

Despite their potential, these methodologies are confronted with challenges, including intricate setups, sophisticated data processing algorithms, and susceptibility to noise, underscoring the need for continued refinement and development in this domain.

3.5. Sensors and the Issue of Drift

The reliability of sensors is crucial for a successful implementation of SHM and its effective integration with regular inspections. As sensors age along with the monitored structure, they may experience a drift phenomenon, which is a gradual and often linear or exponential decrease in accuracy. Thus, sensor drift refers to the gradual change in sensor output over time due to environmental factors, aging, or calibration errors. Sensor drift can compromise the accuracy and reliability of SHM systems, leading to false alarms or missed detections of damage. If not properly monitored, drift can lead to unnoticed inaccuracies, potentially causing false positives or, in worst-case scenarios, false negatives. False positives trigger on-site inspections to verify alarms, while false negatives may result in critical damage being overlooked until the next bridge inspection cycle.

Engineers and SHM specialists face the challenge of developing methods and strategies to address or eliminate drift due to sensor aging without incurring high costs that negate the economic advantages of wireless sensors over wired technology. Although wireless sensors have become relatively inexpensive, labor costs associated with replacing them can be significant, and, in certain cases, it poses a considerable safety risk.

While there is currently no standardized approach to correct drift, various methods have been researched. Calibrating sensors regularly and implementing temperature compensation techniques can help mitigate sensor drift. Temperature variations can affect sensor performance, so incorporating temperature sensors or using temperature compensation algorithms can adjust for these effects. Redundancy and fault-tolerant sensor configurations can also improve the reliability of SHM systems in the presence of sensor drift. By using multiple sensors to monitor the same structural parameter, discrepancies or drift in individual sensor readings can be identified and corrected. Advanced signal processing techniques, such as adaptive filtering or system identification methods, can be employed to estimate and compensate for sensor drift in real time. These techniques continuously monitor sensor outputs and adjust calibration parameters or filter settings accordingly to maintain accuracy.

Another method involves clustering sensors in specific regions rather than using individual sensors [97]. By evaluating the detections from all sensors in the cluster and determining a uniform baseline, sensors can be recalibrated to a reference "zero-line", establishing the detectable threshold from that point. This recalibration can be achieved manually using remote computers or by utilizing auto-calibrating sensors. Additionally, the approach relies on recognizing skewed data and excluding them from the results to prevent errors. Implementing these methods is essential for maintaining sensor accuracy and the overall effectiveness of SHM systems.

3.6. Impact of Environmental Factors and Operational Conditions

The impact of environmental factors and operational conditions on the effectiveness of SHM techniques is indeed a critical aspect that requires thorough consideration. Variations in temperature, humidity, and traffic loads can significantly influence the performance and reliability of vibration-based monitoring methods discussed in the review.

Environmental factors such as temperature variations and humidity levels can affect the material properties of structures, leading to changes in their dynamic response characteristics. For instance, temperature fluctuations can cause thermal expansion and contraction, leading to alterations in structural stiffness and damping properties. Similarly, variations in humidity levels can affect the moisture content of materials, thereby influencing their mechanical behavior and structural response to dynamic loads.

Operational conditions, such as varying traffic loads, induce changes in the structural loading patterns, resulting in fluctuations in the dynamic response of the monitored system. High traffic loads can impose dynamic forces on the structure, leading to increased structural vibrations and potentially affecting the accuracy of vibration-based SHM methods in detecting damage or anomalies. Given the significant influence of these environmental and operational factors on SHM techniques, there is a clear need for standardized protocols to account for these variables in SHM practices. Standardized protocols would provide guidelines for monitoring and controlling environmental conditions during data acquisition, as well as methodologies for incorporating operational load variations into the analysis of structural health.

By establishing standardized protocols, researchers and practitioners can ensure consistency and reliability in SHM assessments across different environmental and operational conditions. This would enhance the accuracy and effectiveness of vibration-based monitoring methods, ultimately contributing to the advancement of SHM practices and the maintenance of infrastructure safety and integrity.

However, in the context of railway bridges, it is worth noting that the impact of changes in operational conditions may be somewhat mitigated compared to other types of bridges. Unlike highway or road bridges, where traffic loads can vary significantly due to factors such as vehicle type, speed, and volume, the operational conditions for railway bridges tend to be more standardized. Railway traffic typically involves trains with relatively consistent configurations and loading patterns, especially in comparison to the diverse mix of vehicles found on highways or roads. As a result, the dynamic loading induced by trains on railway bridges tends to exhibit less variability, which can lead to more predictable structural responses. The standardized nature of railway traffic can influence the reliability of vibration-based monitoring methods for railway bridges, as the structural dynamics are subject to more uniform loading conditions. This can simplify the interpretation of monitoring data and enhance the accuracy of damage detection algorithms, as the effects of varying operational conditions are less pronounced.

As a final comment, understanding the influence of environmental factors and operational conditions on the reliability of vibration-based SHM techniques is essential for developing robust monitoring strategies. Standardized protocols tailored to account for these variables would facilitate more accurate and consistent SHM assessments, thereby improving the reliability and effectiveness of structural health monitoring practices.

3.7. Emerging Technologies and Methodologies

Emerging technologies in SHM can be identified in fiber optic sensors and wireless sensors, which are currently revolutionizing the way structural health is monitored and maintained. Fiber optic sensors and wireless sensors represent promising technologies for structural health monitoring, offering enhanced sensitivity, flexibility, and efficiency compared to traditional monitoring techniques. As these technologies continue to advance, they are expected to play a significant role in ensuring the safety and longevity of critical infrastructure worldwide.

Fiber optic sensors are increasingly being utilized in SHM due to their numerous advantages. These sensors use optical fibers to detect changes in strain, temperature, pressure, and other parameters within structures. Fiber optic sensors offer high sensitivity, enabling the detection of small changes in structural conditions. Multiple sensors can be multiplexed along a single fiber, allowing for distributed sensing over long distances. Fiber optic sensors are immune to electromagnetic interference, making them suitable for use in harsh environments. Moreover, they are resistant to corrosion, making them suitable for long-term monitoring applications. Another significant advantage is that fiber optic sensors can provide real-time data, allowing for an immediate response to structural changes or failures.

Wireless sensors are another emerging technology that is gaining traction in SHM [98]. These sensors eliminate the need for physical wiring, offering several benefits. First, they are easier to install compared to traditional wired sensors, reducing installation time and costs. They also enable remote monitoring of structures, allowing engineers to assess structural health without being physically present at the site. Another significant advantage is that wireless sensor networks can be easily scaled up or down, making them suitable for monitoring structures of varying sizes and complexities. Many wireless sensors are designed to operate on low power, extending their battery life and reducing maintenance requirements. Finally, wireless sensors facilitate the collection and transmission of data to centralized servers or cloud platforms, enabling easy access to monitoring data for analysis and decision making.

Emerging methodologies in SHM are leveraging cutting-edge technologies such as IoT (Internet of Things) integration, big data analytics, deep learning, and Artificial Intelligence (AI) to enhance the accuracy, efficiency, and reliability of monitoring systems. IoT integration involves the incorporation of interconnected sensors, actuators, and devices into structural systems to collect and exchange data in real time. Sensors deployed throughout structures continuously gather data on various parameters such as strain, vibration, temperature, and corrosion. This real-time data collection enables engineers to monitor structural health remotely, detect anomalies, and identify potential issues before they escalate into critical failures. IoT integration facilitates predictive maintenance strategies, helping to optimize asset management and reduce downtime and maintenance costs. This has recently been achieved using big data analytics, which involves the processing and analysis of large volumes of data generated by SHM systems to extract valuable insights and patterns. Sophisticated algorithms and techniques are applied to identify correlations, trends, and anomalies in the data collected from sensors. By analyzing historical and real-time data, big data analytics can predict structural behavior, assess performance degradation, and optimize maintenance schedules. Other technologies are emerging in the field of AI which encompass various techniques including machine learning, expert systems, and natural language processing applied to SHM. AI algorithms can analyze sensor data to diagnose structural health issues, recommend maintenance actions, and optimize structural performance. AI-powered decision support systems assist engineers in interpreting complex data and making informed decisions regarding maintenance, repair, and retrofitting of structures. By leveraging AI, SHM systems can become more autonomous and adaptive, enabling proactive management of structural assets and mitigating risks. Deep learning, a subset of AI, involves training neural networks with large data sets to recognize patterns and make predictions. In SHM, deep learning algorithms are employed to analyze sensor data, identify structural defects, and predict potential failures. Deep learning models can automatically learn complex relationships within the data, enabling more accurate and reliable predictions compared to traditional methods. These models can also adapt and improve over time as they are exposed to more data, leading to continuous enhancements in predictive capabilities.

Overall, the integration of IoT, big data analytics, deep learning, and artificial intelligence is transforming the field of structural health monitoring, enabling more proactive, data-driven approaches to maintenance and asset management. The challenges highlighted in the previous section, such as establishing damage thresholds and mitigating sensor drift in vibration-based SHM applications, require a multi-faceted approach involving experimental testing, numerical modeling, data-driven methods, sensor calibration, and advanced signal processing techniques. Emerging technologies like fiber optic sensors and wireless sensors, combined with emerging technologies like IoT integration, big data analytics, and deep learning offer promising avenues for overcoming these limitations and advancing the capabilities of SHM systems in real-world applications.

4. Conclusions

A comprehensive review of vibration-based condition monitoring techniques revealed a plethora of diverse algorithms that make use of data in the time, frequency, and modal domains. However, the scientific literature highlights the need for a homogenization of approaches to utilizing measured vibration data for damage detection, localization, and quantification. Particularly, there is a notable disagreement among researchers regarding the sensitivity and measurability of modal parameter shifts caused by localized damage. Furthermore, there has not been a universal algorithm proposed that can effectively identify any type of damage in all types of structures. Similarly, the development of an algorithm capable of accurately predicting the remaining service life of a structure remains an open challenge. Some algorithms have demonstrated success in locating damage in a singular location, while others have limitations in terms of the number of damage locations they can effectively address.

Finally, despite some recent remarkable contributions, the alarm thresholds are still an open challenge, because despite their essential role in ensuring both structural safety and satisfactory serviceability being very clear, there is a notable lack of guidance available to engineers regarding their practical application, and in most cases the followed approach is based on experience gained in the field.

As the field of Structural Health Monitoring continues to advance, researchers and engineers are actively working to address these challenges and develop more comprehensive and versatile algorithms that can enhance the overall effectiveness of damage detection and structural health assessment.

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