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Intelligent vibration-based structural health monitoring systems: Methodological advances and challenges

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ABSTRACT

Ensuring the safety and longevity of engineering structures requires the development of robust and efficient damage detection strategies. Traditional structural health monitoring (SHM) methods, which often rely on time-consuming and potentially disruptive direct assessments, are increasingly being replaced by more intelligent and effective vibration-based SHM techniques. These advancements are primarily driven by improvements in sensor technology, computational power, and signal processing algorithms. This paper investigates the latest developments in intelligent vibration-based SHM systems, a rapidly evolving field that leverages structural vibration analysis for highly sensitive damage detection. It specifically explores the integration of optimization algorithms and artificial intelligence techniques to enhance the precision, efficiency, and real-time capabilities of damage detection systems. It also provides a comprehensive overview of state-of-the-art vibration-based methods, including modal analysis, frequency response functions, and signal processing techniques. Additionally, it highlights the role of optimization algorithms, machine learning, and innovative hybrid approaches in shaping the future of SHM.

1. Introduction

Structural health monitoring (SHM) is a multidisciplinary scientific field that incorporates computer science, electronics, materials science, and civil engineering [1], as illustrated in Fig. 1. The intersection of these diverse disciplines fosters the development of innovative solutions to complex problems where researchers explore various aspects of the field by combining perspectives from multiple disciplines. The Internet of Things (IoT) enables engineers to monitor sensor data in real time and assess the health of various facilities, including airlines, power transmission infrastructure, bridges, and other critical structures. Through the platform, users can remotely configure operating parameters for each sensor, such as sampling frequency, resolution, full-scale range, alarm thresholds, and activation levels. Data is transmitted via a wireless network, making the system both cost-effective and operationally efficient. This information is sent to a central hub for analysis, supporting decision-making in various scenarios. Overall, this process enhances the safety and longevity of infrastructures [2].

Recent advancements in signal processing, computing, and sensor technology have paved the way for developing vibration-based SHM techniques. Engineers can assess the health of a structure by analyzing changes in vibration characteristics, such as natural frequency and mode shapes. However, obtaining useful information can be challenging in some cases due to environmental noise and the complex behavior of structures. To address these challenges, researchers have employed various methods, including modal parameter identification, frequency response function analysis, signal processing, finite element model updating, optimization, statistical time series analysis, and machine learning. These techniques offer diverse approaches to identifying and locating damage in structures, tailored to the specific characteristics of each structure.

In recent years, it has become increasingly common to combine these methods to enhance the capabilities of SHM systems. Optimization algorithms have played a crucial role in improving damage-detection

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accuracy [3–16] and in the design of novel vibration-supression [17–23] and energy-absorption [24–36] structural systems across various scales. Alongside metaheuristic optimization algorithms, artificial neural networks (ANNs) [37–40] and a range of machine learning techniques have significantly contributed to the advancement of SHM systems by enhancing the identification of damage within structures. Notably, the scope of SHM technologies has expanded to include industries such as aerospace [41,42] and automotive [43–46].

This paper provides a comprehensive review of state-of-the-art vibration-based SHM methods, with a particular emphasis on the integration of optimization algorithms and artificial intelligence (AI) techniques. The subsequent sections cover foundational and advanced

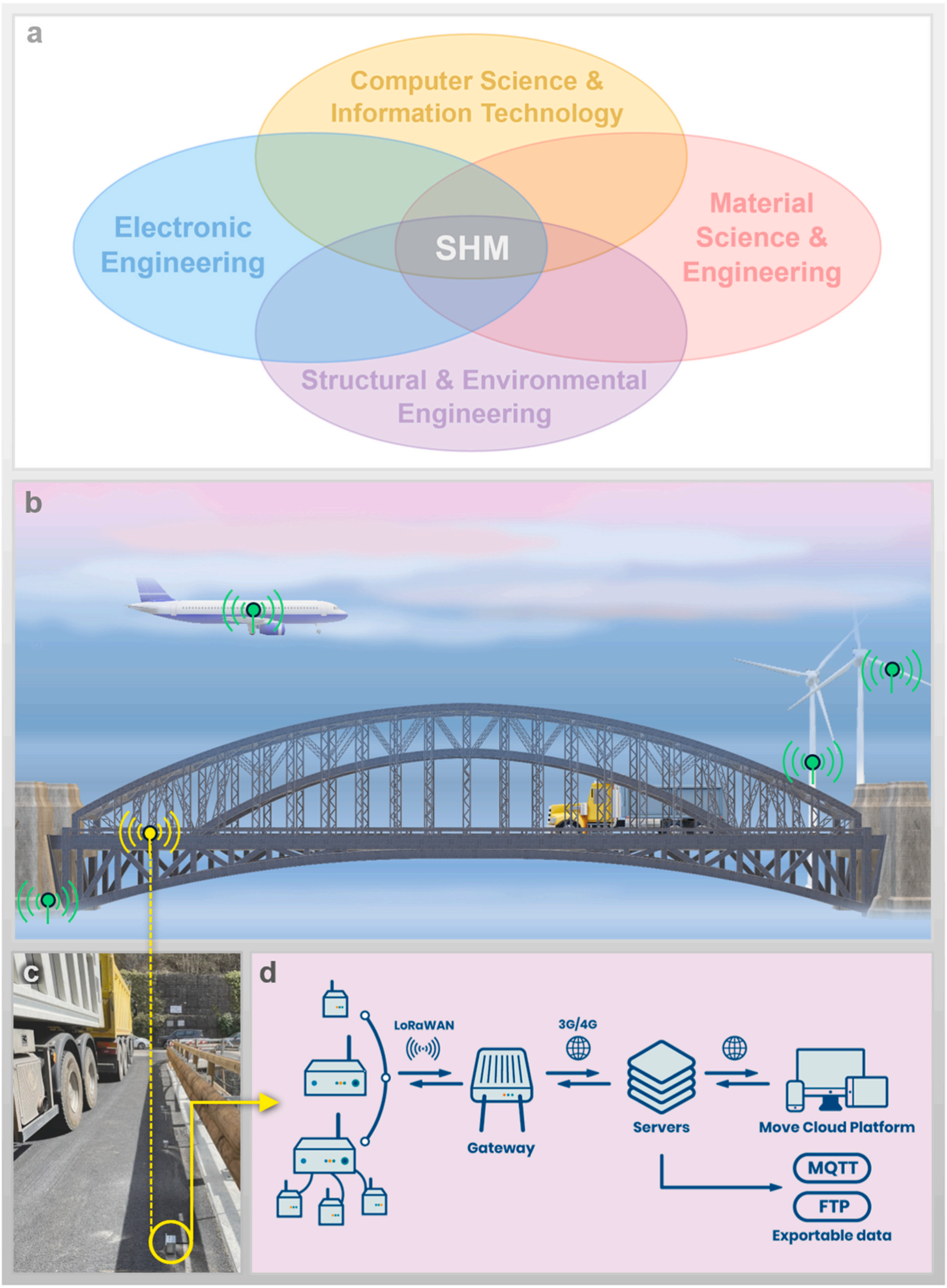

Fig. 1. An overview of SHM and its applications. (a) Disciplines involved in SHM. (b) Sensor applications across various structures and infrastructures. (c) Sensors deployed on a bridge (adapted from [2]). (d) Wireless monitoring system (adapted from [2]).

topics, including sensor technologies, feature extraction and discrimination methods, and Bayesian approaches. Key techniques such as modal analysis, frequency response function analysis, and signal processing are explored in depth, along with model updating and statistical time series methods. The paper also examines the role of optimization and machine learning in improving damage detection performance, and it highlights emerging learning strategies tailored to civil infrastructure. By critically analyzing current methodologies and identifying research gaps, this study aims to support the development of more accurate, intelligent, and robust vibration-based SHM systems and to guide future research directions in the field.

2. Sensor technologies in vibration-based SHM

One of the essential elements in advancing SHM, alongside algorithmic and methodological developments, is the use of innovative sensor technologies. Recent progress in this area has significantly enhanced SHM capabilities. Du et al. [47] provided an extensive review of fiber optic sensors applied to railway infrastructure monitoring, covering components such as rails, concrete sleepers, ballast, subgrade, bridges, tunnels, and even perimeter security (including landslide detection). Sarmadi et al. [48] focused on smartphone-based sensor technologies for applications such as modal identification, damage assessment, finite element model updating, and structural comfort evaluation, also reviewing vision-based approaches for displacement measurement and surface damage detection. Sofi et al. [49] highlighted wireless smart sensor networks and their integration with artificial intelligence for tasks such as damage detection, data analysis, anomaly detection, and cloud-based data storage. Ma et al. [50] examined various displacement measurement techniques for civil infrastructure, particularly in buildings and bridges, and analyze the challenges unique to each. Shen et al. [51] concentrated on terrestrial laser scanners (TLS) for deformation monitoring, emphasizing methods like multi-epoch point cloud comparisons and geometric change detection, while addressing the difficulty of monitoring irregular surfaces such as tunnels and landslide-prone zones.

Expanding on this, Yu et al. [52] reviewed LiDAR-based pavement inspection methods and compare terrestrial, airborne, and mobile laser scanning systems, highlighting mobile laser scanning (MLS) as the most effective for pavement SHM due to its balance of mobility and accuracy. Zhou et al. [53] further enhanced the utility of TLS by proposing a new beam vector (BV) model for scanner calibration, which significantly improves geometric accuracy, especially for hybrid scanner types, thereby increasing the reliability of 3D spatial data used in SHM. Additionally, Ge et al. [54] applied TLS and stereo feature matching for landslide monitoring, developing an improved point cloud alignment methodology using random sample consensus (RANSAC) and displacement matrices. This work supports the precision of deformation tracking across time intervals and offers valuable insights into 3D displacement analysis for large-scale structural or geotechnical hazards. Sakthivelpathi et al. [55] complemented these advancements by reviewing micro- and nano-structured capacitive sensors, which offer high sensitivity and low power consumption for measuring parameters such as strain and pressure. These sensors are increasingly used not only in SHM but also in wearables, robotics, and healthcare applications.

Building on these emerging trends, several novel sensing strategies have recently been introduced. For example, Hassan et al. [56] proposed wireless printed large-area strain sensors using additive 3D direct writing technology. These sensors enable dual-axis strain mapping with high durability under dynamic loads, showing minimal resistance variation over repeated cycles, making them especially suitable for continuous and long-term infrastructure monitoring. In the realm of vision-based sensing, Hou et al. [57] developed an anti-occlusion method for structural displacement estimation that maintains subpixel accuracy even when visual targets are temporarily blocked, thereby improving real-world applicability and robustness of optical measurement systems. Kumar et al. [58] demonstrated the feasibility of using MyShake-enabled smartphones for ambient vibration analysis of tall buildings, offering a scalable and accessible SHM approach for extracting modal parameters such as natural frequencies and damping ratios from crowd-sourced data. Bernardini et al. [59] introduced a new strain gauge-based method for detecting corrosion in steel truss bridges, proposing damage-sensitive features and a damage-extent index validated through numerical and experimental studies. This targeted sensing strategy allows for precise corrosion localization under operational conditions. Finally, Xu et al. [60] integrated fiber optic sensors with deep learning and hyperparameter optimization to identify temperature anomalies in earth-rock dams. Their approach addresses data quality issues using generative adversarial networks, illustrating the potential of AI-enhanced fiber sensing systems in challenging geotechnical SHM scenarios.

3. Methodological advances and challenges

Identifying cracks, deformations, and damages in traditional SHM relied solely on visual inspections. Although these methods were straightforward, they lacked the accuracy and sensitivity needed for effective damage detection. During the 19th century, several advanced techniques were introduced, including manometers, acoustic emission testing, and radiography [61]. Although these methods represented significant improvements, there remained a need for more advanced equipment and techniques. The mid-20th century marked a turning point with the advent of vibration-based SHM. In the field of vibration-based SHM, damage detection methods are generally categorized into two main groups: model-driven methods and data-driven methods. Model-driven approaches typically employ finite element method (FEM) along with optimization algorithms to identify the location and severity of damage by comparing simulated and actual responses. In contrast, data-driven methods rely on the direct analysis of sensor data or features extracted from it, using techniques such as statistical analysis, machine learning, or pattern recognition to detect anomalies.

In this paper, considering the two-stage structure of damage detection, namely, feature extraction and feature detection/classification, the reviewed methods are introduced and analyzed within this overarching framework. This classification scheme not only provides a better understanding of the role and performance of each approach but also plays a significant role in the design of long-term and automated structural health monitoring systems. This approach leverages the fact that the vibration characteristics of a structure, such as natural frequencies and mode shapes, are sensitive to changes in the structure's health. Structural damage can alter these characteristics.

Damage detection methods can be categorized as either destructive or non-destructive. Initially, researchers used both approaches to assess the extent and location of damage. In destructive methods, the damage location had to be estimated approximately and empirically, with tests limited to the specific area being assessed. However, evaluating the health of structures using destructive and field methods is costly and often ineffective. Destructive methods involve physically removing a sample of the material for testing. For example, in concrete structures, this might involve extracting a core sample to determine compressive strength, while in steel structures, a section of material may be removed to test tensile strength. The high cost of coring and the impracticality of sampling all structural elements have driven the development of non-destructive methods. Historically, structural damage was assessed only through visual inspections, but over time, and with technological advancements, new methods have been developed for this purpose. While these technologies offer significant advantages, they also have inherent limitations. Today it is possible to detect structural damage using non-destructive methods without harming the structural components. Non-destructive methods in SHM are divided into two broad categories: feature extraction and feature discrimination. Both are essential for achieving the final aim. The first step in investigating a problem is to extract relevant features and information from it. Various methods are used for this purpose, such as modal parameter-based methods, frequency response functions (FRFs), signal processing-based methods, statistical time-series models, and finite element model updating methods. For the subsequent step of using, classifying, and interpreting data, machine learning methods, optimization algorithms, and inverse problem techniques are applicable. Fig. 2 presents an overview of the methods used for detecting structural damage.

Vibration-based damage detection methods treat the structure as a dynamic system characterized by mass, stiffness, and damping. Damage within the structure can be detected through changes in these properties, which are influenced by frequency response and modal parameters. In vibration-based SHM, the vibration characteristics of the structure are analyzed to assess its health. These characteristics are typically categorized into three domains: time domain, frequency domain, and time-frequency domain. Time domain methods utilize time history responses, while frequency domain methods rely on modal parameters. Time-frequency domain methods combine elements of both, using time-frequency analysis tools.

3.1. Feature extraction

Feature extraction in vibration-based SHM involves identifying and deriving parameters that are sensitive to structural changes while being robust to environmental variability. This section presents a range of techniques including modal parameter estimation, signal decomposition, and statistical modeling. These techniques are used to obtain interpretable features from raw sensor data, serving as the foundation for subsequent damage identification processes.

3.1.1. Modal parameter-based methods

Modal parameter-based damage detection methods rely on changes in the vibration characteristics of the structure to detect damage. By analyzing variations in natural frequencies and mode shapes, engineers can identify potential damage locations and assess their severity [62]. This non-destructive approach is highly valuable for assessing the health of various structures.

3.1.1.1. Mode shapes. Mode shapes represent the altered geometry of a structure under specific vibration patterns. They offer valuable insights into the structure's stiffness and can help identify damage locations by analyzing changes in curvature patterns or displacements. One approach involves extracting operational deflection shapes from experimental data. For example, Yoon et al. [63] proposed a global fitting method that captures information about the state shapes by using the shape function of the analytical curvature factor, which is derived from an analytical operational deflection shape. This method has been effective in identifying damage to different types of structures. Cao et al. [64] addressed the challenge of detecting multiple damages in beams using curvature mode shapes. To mitigate noise sensitivity, they combined wavelet transform with a Teager energy operator, enhancing the robustness of curvature mode shapes.

Another effective approach is to examine the measured mode shapes directly. Xu et al. [65–67] introduced innovative methods for damage detection in beams and plates using measured mode shapes. These methods facilitated the development of non-model approaches for damage detection in beam and plate structures by leveraging measured mode shapes and constructed reference shapes. The effectiveness of these methods has been validated through numerical simulations across various damage scenarios.

Vision-based SHM provides a non-contact method for accurate displacement and damage assessment. Tan et al. [68] focused on using mode shapes for damage monitoring and detection. They introduced a method for measuring vibration displacement and detecting damage in truss structures by analyzing vibration videos. He and Zhou [69] studied mode shape reconstruction and the use of curvature mode shapes for damage diagnosis. Their method employs empirical mode decomposition to separate modal responses and Fourier series fitting to accurately represent the mode shapes.

Xu and Zhu [66] used the measured mode shapes to generate damage indices. By employing these mode shapes and the resulting damage index, their method enabled monitoring of the structure's health without requiring prior knowledge of the finite element model. Fawazi et al. [70] discussed the localization and amplification of crack effects in a beam using reconstructed mode shape data obtained from numerical modal analysis. The stationary wavelet transform was applied to the mode shape data to identify crack locations. Additionally, spline interpolation was used to increase the resolution of the mode shape data, thereby improving the accuracy of crack detection. Studies presented in [71] and [72] utilized deviations in displacement mode shape data to detect structural damage. Notably, the authors of [72] employed modal slope and curvature mode shape to monitor the structural state and identify the relevant parameters.

In the field of vibration-based bridge health monitoring, one promising technique involves using modal parameters, specifically mode shapes, to detect damage. Mode shapes reveal specific vibration patterns on a bridge, making them valuable indicators of structural integrity. Researchers have explored various methods in this area, each offering distinct advantages. One innovative approach utilizes vibrations generated by regular traffic. This technique reduces the need for extensive sensor deployment on the bridge, thereby minimizing noise and enhancing the efficiency of the monitoring process. These vibrations can be analyzed to detect subtle changes in the bridge's dynamic behavior, which may indicate early signs of damage.

Several studies have demonstrated promising results using these methods. Zhang et al. [73] developed a technique for detecting bridge deck damage based on mode shapes derived from vehicle vibration data. Other studies [74,75] have similarly focused on extracting bridge mode shapes through the vibration analysis of passing vehicles. As shown in

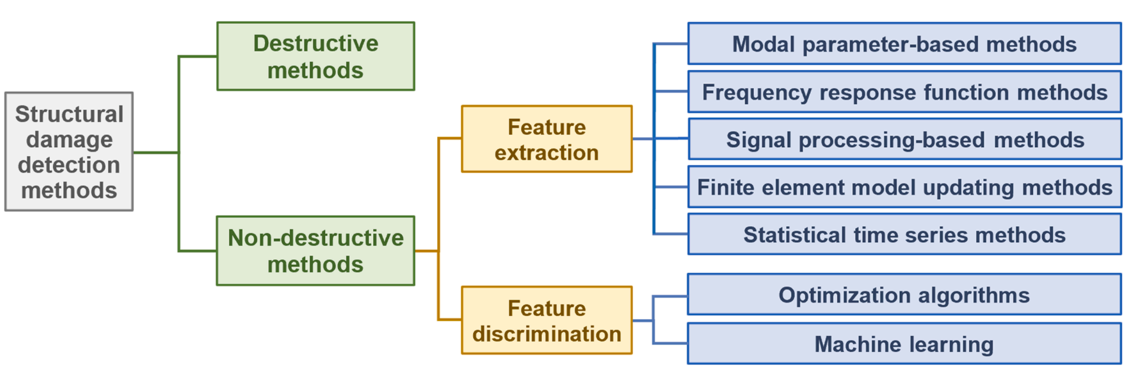

Fig. 2. Classification of structural damage detection methods.

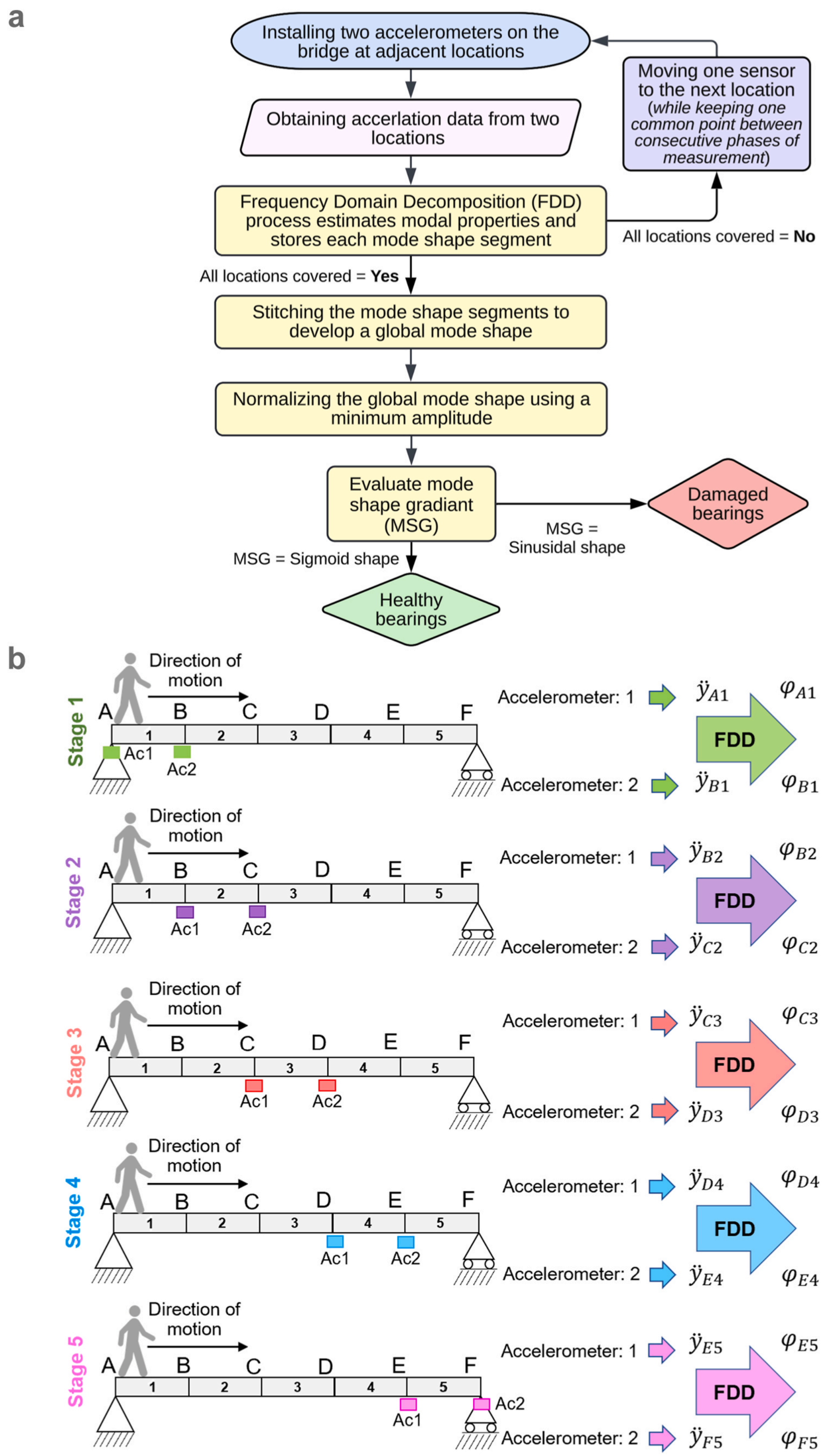

Fig. 3. (a) Flowchart of an approach for estimating the modal parameters of a bridge using progressively re-deploying sensors (adapted from [76]). (b) schematic representation of the proposed method applied to a bridge in five stages (adapted from [76]).

Fig. 3a, Khan et al. [76] presented an algorithm to estimate the mode shape of a bridge by combining data from different sections and then using these mode shapes and their variations to detect damage. Fig. 3b illustrates the schematic representation of the proposed concept, which was applied in five stages.

Furthermore, Qi and Au [77] demonstrated that vehicle vibrations can reveal bridge mode shapes that are sensitive to damage. Oshima et al. [78] proposed a new bridge evaluation method that utilizes mode shape analysis from passing vehicles to assess the bridge's health. Table 1 summarizes the key features and applications of the reviewed studies on modal parameter-based methods and mode shapes.

■ Challenges and future trends

Mode shape-based methods in structural health monitoring face several major challenges, such as the requirement for high sensor density to achieve spatial resolution, low sensitivity to minor damage, especially in low-strain regions, and susceptibility to noise in measured responses [63,65,66]. Installing a dense sensor network in large-scale structures like bridges or towers is often expensive or impractical, limiting the feasibility of such approaches in real applications. While some methods aim to reduce sensor requirements, no widely adopted or robust solution has emerged [68].

Additionally, environmental and operational variations such as temperature, humidity, and variable loading can significantly affect modal parameters, making it difficult to isolate damage-induced changes from these influences. Many techniques that perform well under laboratory or simulated conditions struggle with real-world constraints like noisy environments and installation limitations. Overcoming the gap between theoretical promise and practical deployment remains one of the central challenges in this domain.

3.1.1.2. Natural frequencies and mode shapes. Natural frequencies, which are the inherent vibrational frequencies of a structure, are fundamental parameters for damage detection. Changes in these frequencies often indicate structural deterioration or damage. For instance, Maes et al. [79] demonstrated the potential of using natural frequencies to monitor the health of a railway bridge by tracking its vibrations before, during, and after reinforcement. Maes et al. [79] also highlighted the challenges in differentiating between damage-induced changes and those caused by environmental factors, such as temperature variations. In response, Anastasopoulos et al. [80] investigated the effect of temperature, particularly frost, on a steel arch bridge. The results showed that while the natural frequencies were significantly affected by glaciation, the mode shapes remained relatively stable. These findings emphasize the importance of considering environmental conditions when using natural frequencies for damage detection.

Several studies have tackled the challenges posed by environmental factors through innovative methods. Zhao et al. [81] developed a system for monitoring the health of transmission towers using vibrations, with a focus on natural frequencies less impacted by wind speed. This system successfully identified changes related to damage. The proposed system by Zhao et al. [81] consisted of an acceleration sensor, a wind speed and direction sensor, an analyzer, and a monitoring center as illustrated in Fig. 4. Similarly, Marzo et al. [82] proposed adding mass to structures to analyze changes in natural frequencies caused by damage. This approach enhances the sensitivity of monitoring systems and improves the precision of damage detection.

The integration of numerical modeling with experimental data has also advanced the field. Muhammad et al. [83] compared operational modal analysis (OMA) results with finite element models for an ultra high performance fiber reinforced concrete (UHPFRC) bridge, finding close agreement in mode shapes but significant discrepancies in natural frequencies.

Beyond bridges and towers, natural frequencies and mode shapes have been applied to a variety of other structures. Zhao and Zhang [84] explored damage identification in truss structures using modal data. Natural frequencies were employed by Shifrin [85] and Choi and Han [86] for video-based structural analysis and crack identification in bars, respectively. A crucial factor in advancing this field has been the integration of numerical models with experimental data. Despite notable discrepancies in natural frequencies and mode shapes, Muhammad et al. [83] found comparable results when comparing operational modal analysis with finite element models for a UHPFRC bridge. Table 2 summarizes the references reviewed in this section.

■ Challenges and future trends

Natural frequencies and mode shapes are widely used in SHM due to their sensitivity to structural changes. However, distinguishing between damage-induced changes and those caused by environmental factors, such as temperature or wind, remains a key challenge. Studies like those by Maes et al. [79] and Anastasopoulos et al. [80] showed that environmental conditions can significantly affect natural frequencies, potentially leading to false damage detection. To address this, researchers have proposed solutions such as frequency filtering, mass addition techniques, and robust data analysis methods.

Future trends in this area focus on integrating multiple data sources and improving the accuracy of numerical models. For example, combining experimental results with finite element models, as performed by Muhammad et al. [83], helped validate damage detection, despite some observed discrepancies. Additionally, hybrid systems using video-based sensing or advanced signal processing, like those in the study by Choi and Han [86], are paving the way for more automated, reliable SHM frameworks that can better handle environmental variability.

3.1.2. Damping

Recent studies have shown that damping can be more sensitive than natural frequencies and mode shapes in certain damage detection scenarios. However, damping-based damage detection remains a developing research area that has yet to be fully explored [87]. While natural frequencies and mode shapes are widely used for damage detection, damping has received less attention due to the challenges associated with its measurement and analysis. Available evidence suggests that damage typically leads to increased damping in structures.

Early research by Bovsunovsky [88] explored the relationship between damping and crack formation. By comparing damping-based methods with frequency-based methods, the study demonstrated that changes in damping are more noticeable, particularly in structures that initially exhibit low damping. However, the effectiveness of this approach depends on factors such as the type of crack, its location, and the material properties. In this context, a criterion was proposed to evaluate the damage detection capability based on damping in certain instances.

Subsequent studies delved deeper into the relationship between damping and structural damage. Sehgal and Kumar [89] introduced a two-stage damage detection method that effectively combines stiffness and damping updates. By accurately identifying damage locations and severities, they demonstrated the potential of damping-based methods to enhance damage detection accuracy. Mustafa et al. [90] proposed an energy-based damping evaluation (EBDE) method for bridge damage localization, analyzing energy dissipation patterns. This approach reduces the number of required sensors while effectively identifying damage locations, showing significant promise.

Recent research has broadened the application of damping-based damage detection across various structures. For instance, Liu et al. [91] introduced a method for the simultaneous detection of defects caused by both stiffness reduction and damping in buildings. This approach overcomes the limitations of traditional methods, which typically focus on a single type of damage. The accuracy of damage

Table 1
Summary of modal parameter-based methods (mode shapes).

References	Year	Sensor type	Excitation method	Response type	Structure scale	Description
Yoon et al. [63]	2010	Accelerometer (PCB Piezotronics)	Forced excitation (electric impulse hammer)	FRF acceleration	Multiple: lab-scale steel beams, composite beams, composite plate, and large-scale composite hull	Operating mode shapes derived from experimental data.
Cao et al. [64]	2014	Scanning laser vibrometer (SLV, Polytec PSV−400)	Harmonic excitation using electromechanical shaker	Velocity mode shapes	Lab-scale (1-m steel beam with cracks)	Tackled multiple damage detection in beams using curvature mode shapes.
Xu et al. [65]	2014	▪ Scanning laser vibrometer (Polytec PSV−500) ▪ Single-point laser vibrometer (Polytec OFV−353)	▪ Acoustic excitation using speakers (OMA) ▪ Impact hammer (EMA for material property identification)	Velocity mode shapes and natural frequencies	Lab-scale (114.4-mm beam)	Directly measured mode shapes for beams and plates.
Xu et al. [66]	2017	Scanning Laser Doppler Vibrometer (SLDV) – Polytec PSV−500	▪ Impact hammer (PCB 086-D80) for EMA ▪ Acoustic excitation using a speaker for MS measurement	Velocity (used to extract Mode Shapes and Frequencies)	Medium lab-scale plate: 400 mm × 500 mm × 4.75 mm	Directly measured mode shapes for beams and plates.
Xu et al. [67]	2014	N.A.	N.A.	Mode shapes	Small-scale (ABS cantilever beam, L=114.4 mm)	Non-model-based methods use mode shapes and wavelet transforms to locate embedded horizontal cracks.
Tan et al. [68]	2023	▪ High-resolution video camera (1920 ×1080, 120 fps) ▪ Vision-based tracking (FAST + homography)	Ambient excitation (natural or operational loading)	▪ Vibration displacement (vision-tracked) ▪ Mode shapes (from OMA)	Medium-scale lab model (56 nodes and 160 elements): ▪ Truss spans: 12 upper / 14 lower ▪ Element length ≈ 0.39–0.4 m	Vision-based method for partial mode shapes of truss bridges.
He and Zhou [69]	2019	N.A.	N.A.	▪ Numerical displacement index (NDI) ▪ Damage indices (based on stiffness loss)	Full-scale steel bridge: ▪ Two-span continuous girder bridge ▪ Span length: 27.43 m (≈19.20 m + 8.23 m) ▪ Interior and exterior girders modeled	Curvature mode shape separated modal responses for damage diagnosis and utilize Fourier series for accurate representation.
Fawazi et al. [70]	2023	N.A.	N.A.	Mode shape data (vibration mode shapes)	Beam scale (single beam, 1250 mm length)	Enhanced damage detection uses mathematical transformations on reconstructed mode shape data to improve crack detection.
Kim et al. [71]	2013	Uniaxial accelerometer (DYTRAN model 3055B1)	▪ Impact hammer (Brüel & Kjær model 8204) ▪ Roving hammer method	▪ Frequency response functions (FRF) ▪ Modal displacements ▪ Proper orthogonal modes (POM)	Lab-scale beam: ▪ Length: 800 mm ▪ Cross-section: 50 mm × 4 mm ▪ Damages at 300 mm and 540 mm from fixed end	Utilized deviations in displacement mode shape data to identify structural damage.
Ali and Bandyopadhyay [72]	2020	N.A.	N.A.	▪ Modal slope ▪ Modal curvature (from limited DOFs in FE model)	Not specified (generalized finite element model, element-level identification)	Utilized deviations in modal slope and curvature mode shapes for structural condition monitoring and parameter identification.
Zhang et al. [73]	2024	Moving vehicle (as sensor)	Stationary vehicle (shaker excitation)	Vehicle acceleration (used to construct mode shapes)	Medium-scale bridge (25 m span)	Used a vehicle's vibration data to detect bridge deck damage by analyzing mode shapes.
Jian et al. [74]	2020	Accelerometers (on trailers) - simulated	Indirect excitation by moving tractor–trailer model	▪ Bridge mode shapes (via trailer responses) ▪ Wavelet-based FRF-like extraction	Full-scale box girder bridge 30-m long, 15.3-m wide, 1.6-m high, 477.6 t (simulated)	Proposed a novel method for identifying bridge mode shapes by utilizing the dynamic responses of a passing vehicle.
Yang et al. [75]	2014	Accelerometer on vehicle only	Indirect excitation by test vehicle motion	▪ Vehicle acceleration processed via FFT, filtering, and Hilbert transform ▪ Bridge mode shapes extracted	Numerical simulation of 30-m bridge (20 beam elements, vehicle-bridge interaction)	Presented an algorithm for extracting mode shapes from the vibrations generated by passing vehicles.
Khan et al. [76]	2022	Wireless triaxial MEMS accelerometers (redeployed in five stages)	Passing trains (ambient/ forced vibrations)	▪ Global 1st mode shape estimated via frequency domain decomposition (FDD) ▪ Damage localization via mode shape gradient	Full-scale railway bridge (18.3-m span, steel beams); before and after rehab (Ireland)	Presented a method to estimate the global mode shape of a bridge by combining data from various segments.
Qi and Au [77]	2016	Accelerometers on moving vehicle only	Impact excitation (drop mass on vehicle) during passage	▪ Bridge mode shapes extracted via Hilbert transform of vehicle	Numerical model of a simply-supported bridge (30-m span, 30 elements)	Highlighted that vehicle vibrations themselves can reveal

(continued on next page)

Table 1 (*continued*)

References	Year	Sensor type	Excitation method	Response type	Structure scale	Description
				response ■ Damage localization using Coordinate MAC + wavelet analysis		a bridge's mode shapes, which are sensitive to damage.
Oshima et al. [78]	2014	Accelerometers on passing vehicle	Vehicle self-weight only, no active excitation	■ Mode shapes estimated from vehicle response. ■ Damage types: support immobilization and center beam stiffness reduction. ■ Accuracy is high for severe damage and no noise, but low robustness to noise.	Numerical model of 2D beam-vehicle interaction	New method using mode shapes from passing vehicles for bridge assessment.

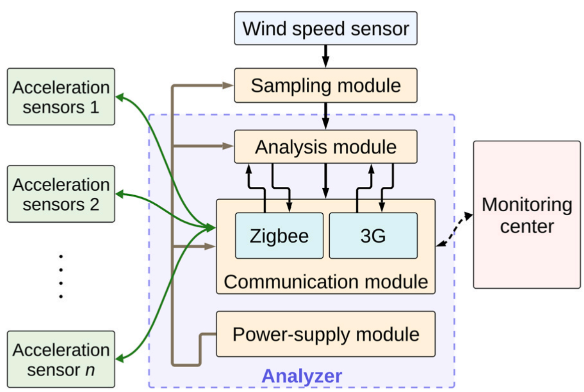

Fig. 4. Block diagram of a SHM system proposed for transmission line towers. (adapted from [81]).

detection is significantly influenced by the choice of damping models. In particular, Souza et al. [92] examined the impact of different damping models on damage detection within a Bayesian framework. Although this study did not substantially improve damage localization due to variations in damping models, it underscores the potential importance of this factor in different structural contexts.

Furthermore, understanding the amplitude-dependent nature of damping is crucial for improving damage detection. Gohar et al. [93] demonstrated that incorporating amplitude-dependent damping characteristics can strengthen the correlation between damping changes and the presence of damage. Numerous studies [94–96] have emphasized the high sensitivity of damping in detecting damage, especially when compared to conventional parameters like natural frequencies and mode shapes. Several studies [96–98] also introduced novel methods to utilize damping for damage detection in different structural systems. Souza et al. [92] further examined the impact of various damping models on the accuracy of damage detection. Gohar et al. [93] highlighted the importance of considering amplitude-dependent damping, while Hummel et al. [99] explored the feasibility of using affordable sensors for structural evaluation and damping detection.

The integration of damping into damage detection processes holds significant potential. However, challenges remain with the precise quantification of damping and the influence of environmental factors. Table 3 summarizes methods for estimating damping using modal parameters, highlighting various techniques and their key features.

■ Challenges and future trends

Using damping to detect structural damage is still uncommon because damping is difficult to measure accurately. It can vary with temperature, ambient noise, and how the structure is used. Additionally, the models currently employed are often too simplistic to clearly reflect actual damage.

In the future, improved modeling and emerging techniques such as machine learning may enhance damage detection. Combining damping with other indicators, such as stiffness or mode shapes, can increase reliability. Furthermore, advances in sensors and smart materials may make these methods more practical and cost-effective for use in real-world structures.

3.1.3. *Frequency response function*

The frequency response function (FRF) is valuable for identifying structural damage. Its non-invasive nature, high sensitivity to damage, and ability to provide comprehensive data make FRF an attractive option for engineers. However, precise analysis of FRF data requires specialized knowledge, and understanding the potential limitations of this method is essential. Huang et al. [100] proposed a novel approach to enhance vibration control and damage detection in buildings equipped with vibration control systems. This study used FRF analysis to determine the stiffness of structural components, comparing the FRF data of the building with and without semi-active friction dampers. The comparison of FRF data from both damaged and healthy building models revealed changes in vibration patterns, particularly in natural frequencies and overall response. These changes can be used to identify the location and extent of the damage.

Although some studies have directly utilized FRF data, Esfandiari et al. [101] employed principal component analysis (PCA) to simplify complex data and concentrate on major changes. By applying PCA to the FRF data, this approach successfully detected the precise location and extent of damage in truss and frame models, even in the presence of measurement inaccuracies. Nevertheless, PCA's accuracy decreases in complex structures, and its accuracy might be further affected by errors resulting from measurements and models. In order to address these difficulties, Padil et al. [102] combined a non-probabilistic method with PCA to create a stronger damage index based on compressed FRF data. By applying this method to computer simulations and testing it on an actual bridge, it was found to effectively minimize uncertainties and enable precise damage detection.

Recent advances in FRF-based structural damage identification have involved comparative algorithms. For example, the differential evolution (DE) algorithm has shown exceptional accuracy in detecting damage, even amidst noise [103]. Zhan et al. [104] introduced a technique that combines FRF with cross signature assurance criterion (CSAC) indices to accurately identify and quantify damage in supported beams. This method proves more robust against systematic testing errors and effectively detects both individual and multiple damages. Additionally, Soliman et al. [105] validated the accuracy of a vibration-based damage detection system using FRF data in bolted connection structures, demonstrating the impact of damage on dynamic characteristics.

The accuracy of structural damage identification has been improved by incorporating mode shape data into particle swarm optimization (PSO) along with FRF data [106]. Furthermore, Zenzen et al. [107]

Table 2
Summary of modal parameter-based methods (natural frequencies and mode shapes).

References	Year	Sensor type	Excitation method	Response type	Structure scale	Description
Maes et al. [79]	2022	▪ 12 Accelerometers (deck and arches) ▪ 14 Strain gauges ▪ 2 Laser displacement sensors ▪ Environmental sensors (temperature, humidity, wind, etc.)	Ambient train loads	▪ Natural frequency shifts from long-term vibration data ▪ Environmental effect filtering via linear regression and Robust PCA ▪ ROC curve analysis for detection performance	Full-scale bowstring railway bridge, 115-m span, located between Leuven and Brussels (includes actual retrofitting and FE-simulated subtle damage)	Natural frequency-based SHM for railway bridge.
Anastasopoulos et al. [80]	2022	Fiber-Bragg grating (FBG) strain sensors	Ambient/Operational (output-only) excitation	Strain (strain mode shapes and natural frequencies)	Full-scale bridge	Influence of temperature on natural frequencies and strain mode shapes.
Zhao et al. [81]	2019	Accelerometers	Ambient (wind) and artificial (tower leg lifting using hydraulic jack)	Acceleration (used to extract natural frequencies)	Full-scale (110 kV transmission tower)	Vibration-based SHM for transmission towers using natural frequencies.
Marzo et al. [82]	2024	Vibration (Modal) Sensors	External mass application (80 kg) at various nodal points	Natural frequencies and mode shapes	Both 2D and 3D steel warehouse models	Mass addition method for enhancing damage detection using natural frequencies.
Muhammad et al. [83]	2024	Accelerometers (calibrated, DAQ-connected)	Ambient vibrations (wind, traffic, environmental sources)	Acceleration (for modal parameter extraction via OMA)	Full-scale (single-span 39.35 m UHPFRC pedestrian bridge)	Comparison of OMA and FEM for UHPFRC bridge using natural frequencies and mode shapes.
Zhao and Zhang [84]	2012	N.A.	N.A.	Modal data: natural frequencies and mode shapes	Numerical model (6-span planar truss, 31 elements)	Damage identification in truss structures using modal data.
Shifrin [85]	2016	N.A.	Ambient or forced vibration	Natural frequencies from longitudinal vibration (rods) and transverse vibration (beams)	Rods and simply-supported beams with rectangular cross-section (laboratory scale)	Crack detection in rods using natural frequencies.
Choi and Han [86]	2018	Vision-based camera (Photron SA3, 1000 fps) + laser Doppler vibrometer (LDV) for verification	Impact hammer excitation	Natural frequencies and mode shapes extracted from video motion magnification and LDV vibration measurements	Laboratory-scale cantilever beams	Video-based damage detection using natural frequencies.

proposed a hybrid approach that combines FRF with the bat algorithm (BA), demonstrating superior performance over the genetic algorithm (GA) in terms of both accuracy and computational efficiency for detecting damage in beam and truss structures. Ruiz et al. [108] achieved high accuracy in detecting and localizing damage in beam-type structures by utilizing FRF analysis combined with machine learning classifiers.

Hassani [109] proposed a method that utilizes the response surface method (RSM) with FRF curvature as the response variable, effectively detecting both single and multiple damage cases in numerical evaluations. Furthermore, Sukri et al. [110] employed the cross-correlation difference matrix, based on FRF data, to identify damage in building structures, demonstrating the adaptability of this method for various infrastructure applications. Panigrahi et al. [111] improved the precision of damage identification in noisy signals by combining mutual information with an enhanced reptile search algorithm. Several investigations [112–116] have focused on determining local damage through the examination of frequency and mode shape.

Table 4 summarizes various methods for estimating damping using FRF, highlighting various techniques and their attributes.

- Challenges and future trends

Although FRFs are highly useful for detecting structural damage, several challenges remain. Analyzing FRF data requires expert knowledge, and in real-world structures, factors such as noise, measurement errors, or modeling inaccuracies can significantly reduce accuracy, especially in large or complex systems. Additionally, applying advanced techniques like PCA or machine learning can be difficult without sufficient data or appropriate experimental setups.

Looking ahead, integrating FRF data with intelligent algorithms, such as AI or optimization methods, will likely enhance the ease and reliability of damage detection. Improvements in sensor technology and computing power will also support more accurate data collection and faster processing. Importantly, increased testing on real structures, rather than solely in simulations, will be essential to build trust and validate these methods in practical applications.

3.1.4. Signal processing-based methods

Signal processing-based methods are essential tools in SHM due to their ability to detect structural defects with high sensitivity and accuracy. These methods analyze the dynamic responses of the structure to extract hidden information, providing a deeper understanding of its structural integrity [117]. Methods such as wavelet transform (WT) [118–122], Hilbert-Huang transform (HHT) [123–127], and discrete wavelet transform (DWT) [128–130] are extensively used for this purpose. These advanced techniques can detect subtle changes in structural responses that may indicate damage, even under complex loading conditions. By transforming and analyzing the frequency and time-domain characteristics of the signals, these methods can accurately identify, locate, and measure damage, thereby facilitating prompt and reliable maintenance decisions.

In signal processing-based SHM methods, feature discrimination follows feature extraction and involves distinguishing features from damaged and undamaged structures. Since these features do not always have a clear physical meaning, statistical models using machine learning are often employed. When data from both healthy and damaged states are available, supervised learning methods tend to perform best. Otherwise, unsupervised methods are applied. These models help determine whether damage is present, its location, severity, and the remaining useful life of the structure. They also aim to minimize false alarms. In SHM, such models are used for both protective and predictive

Table 3
Summary of modal parameter-based methods (damping).

References	Year	Sensor type	Excitation method	Response type	Structure scale	Description
Cao et al. [87]	2017	N.A.	N.A.	N.A.	N.A.	A comprehensive overview of various damping estimation methods.
Bovsunovsky [88]	2019	N.A.	N.A.	Damping characteristics (analytical)	Beam (theoretical scale)	Damping changes linked to crack formation.
Sehgal and Kumar [89]	2021	Accelerometer (uniaxial), instrumented hammer	Impact hammer test	Natural frequencies, mode shapes, receptance functions, and damping	Lab-scale cantilever beam (mild steel, 540 ×49 ×6 mm^3)	Combined stiffness and damping updates for damage identification.
Mustafa et al. [90]	2018	Piezoelectric accelerometers and servo velocimeters	Ambient (car-running test), free vibration extracted from traffic-free intervals	Modal damping ratios, mode shapes, and frequencies	Full-scale steel truss bridge (Warren-type, 70.77 m span)	Used energy dissipation (damping) for damage localization.
Liu et al. [91]	2019	N.A.	N.A.	Complex eigenvalues and eigenvectors	Numerical (5-story shear-type building)	Identified damping defects in addition to stiffness reduction.
Souza et al. [92]	2019	Accelerometers (PCB Piezotronics 336 C, 336C31)	Impact hammer (20 impacts per test, SIMO setup)	Modal data (natural frequencies, damping ratios via STFT)	Experimental (aluminum beam, 1464 mm long)	Investigated impact of different damping models on damage detection.
Gohar et al. [93]	2023	Accelerometers	One-point concentrated load (static and dynamic)	Free vibration response (used for ERA and CWT), damping ratios, mode shapes, natural frequencies	Small-scale (RC slab specimens: 1800×1200×200 mm)	Emphasizes amplitude-dependent damping for improved damage correlation.
Sinha and Chakraborty [94]	2022	Accelerometer (B&K Delta Tron 4507)	Impact hammer (B&K 8206–002), single-point roving	FRF, natural frequencies, mode shapes, and damping factors (via FFT + curve fitting)	Experimental (400 mm × 300 mm × 10 mm FRP plate)	Damping changes more sensitive than frequency changes for damage detection in FRP plates.
Curadelli et al. [95]	2008	Accelerometers (KYOWA AS-GB, 100 mV/g)	Free vibration after loading (RC beam); shaking table (3D frame)	Instantaneous frequencies and damping coefficients (via wavelet transform)	Experimental (1) RC Beam: 5.6 m × 0.2 m × 0.1 m; Experimental (2) 3D aluminum frame: 6-story, 0.5 m height	Damping as a sensitive damage indicator in SHM.
Arora [96]	2018	Accelerometer	Impact hammer at 5 locations	FRF; damping matrix identification	Experimental: Aluminum cantilever beam (600 ×50 ×20 mm); modeled as 5 frame elements	Damping-based damage identification approaches.
Zhang [97]	2022	Accelerometer (measuring vertical acceleration)	Excitation force (random process) imposed at point D0	Vertical acceleration response	One-span steel truss (structural scale)	Novel method for setting reasonable damping coefficients for damage identification.
Rouhi et al. [98]	2024	■ RFDA (resonant frequency damping analysis) with microphone or accelerometer (implied) ■ Axial extensometer (used in fatigue tests)	■ Impulse excitation technique (IET) ■ Cyclic tension-compression fatigue loading	■ Damping parameter from vibration response (via FFT and time decay), Natural frequency ■ Hysteresis loops (elastic/plastic strain energy and damping ratio)	■ Small-scale lab specimen (CFRP coupons) ■ Small-scale lab specimen (CFRP coupons)	Damping parameter increases with low-velocity impact damage in CFRP.
Hummel et al. [99]	2021	MEMS accelerometers (ADXL355)	Impact hammer (known force) and ambient vibrations (unknown force)	Acceleration (converted to displacement via integration)	Small-scale 4-story steel frame (lab-scale physical model)	Low-cost sensors for damping assessment.

monitoring [131].

Montejo [132] suggested using continuous wavelet transform (CWT) to enhance damage identification, particularly in the presence of random excitations, overcoming the limitations of conventional approaches. The correlation-based pattern recognition technique, which utilizes both fast Fourier transform (FFT) and CWT, has proven highly effective. Notably, CWT provides superior resolution compared to other methods [133]. Beheshti Aval et al. [134] combined empirical state analysis with artificial neural networks (ANN) to develop a method for detecting and evaluating damage in multi-story buildings during earthquakes. The high precision of this technique highlights the significant potential of such methods. Additionally, the use of fast S-transform in conjunction with convolutional neural networks (CNN) has proven effective in filtering data and promptly identifying damage in real-time [135]. Kankanamge et al. [136] reviewed the application of WT in SHM, highlighting its superiority over FFT in analyzing non-stationary signals for modal identification and damage detection. Through case studies on a steel girder bridge in the U.S. and a cable-stayed bridge in China, they demonstrated WT's effectiveness in extracting modal parameters and detecting subtle structural changes.

Amezquita-Sanchez and Adeli [137] suggested that the Fast S-Transform, Complete Ensemble Empirical Mode Decomposition, Synchrosqueezed Wavelet Transform, and Empirical Wavelet Transform are suitable methods for SHM. Building on previous work, we believe these techniques, although already applied, still hold considerable potential and deserve further exploration. Yang et al. [138] applied a complete ensemble empirical mode decomposition (CEEMD)–wavelet denoising method to bridge monitoring data. Tested on the Guozigou Bridge, it showed better noise reduction and signal preservation than traditional methods, using temperature, deflection, and strain signals. Sanchez et al. [139] applied the synchrosqueezed wavelet transform (SWT) method for SHM on the IASC-ASCE benchmark steel frame. SWT effectively identified natural frequencies with very low error, improving detection of closely spaced frequencies typical in symmetric civil structures. Dong et al. [140] proposed a modified empirical wavelet transform (EWT) for processing acoustic emission (AE) signals in SHM of composite structures. Their method, based on a local window maxima (LWM) algorithm, enhances spectral separation by identifying meaningful empirical modes

Table 4
Summary of FRF methods.

References	Year	Sensor type	Excitation method	Response type	Structure scale	Description
Huang et al. [100]	2012	N.A.	Controlled excitation (with semi-active friction dampers adding known stiffness) and possibly external excitation (full or single point)	Frequency response functions (FRFs), possibly also natural frequencies and mode shapes	Numerical model of a 5-story shear building (simulation study)	FRF for building damage detection.
Esfandiari et al. [101]	2020	Not explicitly mentioned (likely accelerometers or displacement sensors)	Numerical excitation at selected DOFs using finite element (FE) simulation	Principal components of FRFs (via PCA) and natural frequencies	Numerical simulation of a 2D truss and a frame structure	PCA analysis of FRF data for damage localization and severity.
Padil et al. [102]	2020	Accelerometer (implied – vibration data measured)	Roving impact hammer (modal test)	FRF	Laboratory-scale steel truss bridge (5000 mm × 1000 mm × 866 mm)	Improved damage index using FRF.
Gökdağ [103]	2013	N.A.	N.A.	FRF	N.A.	Algorithm comparison for FRF-based damage.
Zhan et al. [104]	2021	ICP (piezoelectric) accelerometer	Impact hammer	FRF	Laboratory-scale beam	FRF and CSAC for damage quantification.
Sulaiman et al. [105]	2017	Accelerometers	Impact hammer	▪ Frequency response function (FRF) ▪ Impulse response function (IRF)	Simplified car hood model (lab-scale)	FRF for bolted joint damage assessment.
Mohan et al. [106]	2013	N.A.	Vertical unit force (beam) and horizontal unit force (frame)	FRF and natural frequencies	Small-scale structures (Cantilever beam and plane frame)	PSO with FRF for enhanced damage detection.
Zenzen [107]	2018	-	Harmonic excitation	FRF	Beam-like and truss structures (small to medium-scale, simulated in FE)	Bat algorithm and FRF for damage identification.
Ruiz et al. [108]	2024	FRF measurement	Impact excitation (using an impact hammer or a similar method)	FRFs	Beam-type structure (laboratory-scale aluminum beams)	Machine learning with FRF for damage detection.
Hassani [109]	2024	N.A.	Dynamic force excitation at reduced degrees of freedom; optimized excitation frequency ranges near resonance	Condensed frequency response functions (CFRFs)	Composite laminated plates (numerical model), finite element (FE) scale	FRF curvature for damage identification.
Sukri et al. [110]	2024	N.A.	Impact Force	FRF curvature	Simply-supported beam (numerical model)	FRF for damage detection in buildings.
Panigrahi et al. [111]	2024	Strain gauges	Applied force (200 N; near sensor); Impulsive load / no load; Random/ambient excitation and added mass	Strain	Laboratory-scale beam Laboratory-scale beam 1/10 scaled prototype; Scaled-down building (1.5 m × 2 m plan)	Improved FRF methods for noise-affected data.

related to damage. Experimental validation using pencil-lead breaks on CFRP plates and three-point bending tests on GFRP specimens demonstrated the method's superior performance in isolating damage-related signal components compared to the original EWT. Karimpour and Rahmatalla [141] introduced the extended empirical wavelet transformation (EEWT), a novel method for extracting accurate global and local modal information under transient excitation. EEWT enables precise structural model updating (SMU) with minimal sensor usage by incorporating a new objective function based on modal transmissibility. The method was experimentally validated on a simply supported beam and a scaled highway bridge model using both impact and shaker excitations. Results demonstrate EEWT's superior performance compared to traditional EMPE methods, especially in capturing local modal properties under transient loads. Its effectiveness highlights EEWT's potential as a robust tool for structural health monitoring and updating.

Delgadillo and Casas [142] introduced a method for detecting damage in real bridges using an advanced signal decomposition technique, improved completed ensemble EMD with adaptive noise (ICEEMDAN), combined with unsupervised machine learning. The method is designed to work with nonlinear and time-varying vibration signals caused by traffic. After decomposing the signals, symbolic features were extracted and grouped using clustering to identify damage. The results showed that this approach could be effective for practical bridge health monitoring. Entezami and Shariatmadar [143] proposed a hybrid method that also uses ICEEMDAN, but in combination with auto-regressive moving average (ARMA) modeling to extract damage-sensitive features from non-stationary vibration signals under ambient excitations. An automatic selection process was used to choose the most relevant IMFs based on their energy. The ARMA residuals were used as features, and multivariate distance correlation was applied to locate the damage. The method was tested on both numerical (shear building) and experimental (steel frame) models with different damage cases.

Sarmadi et al. [144] applied an energy-based damage localization method using ensemble empirical mode decomposition (EEMD) and Mahalanobis-squared distance (MSD) on vibration signals from a laboratory-scale steel frame under ambient excitation. They demonstrated that their approach effectively identified damage locations despite non-stationary vibration conditions. Mousavi et al. [145] applied complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) to analyze vibrations for detecting damage in a steel truss bridge. It improves signal separation and combines features into indices that accurately locate damage. Lab tests confirm its effectiveness

The local time-frequency transform (LTFT) has garnered attention for its exceptional time-frequency resolution and its capability to reduce noise. This method is particularly effective for detecting damage in reinforced concrete structures through vibration analysis [146]. The use of wavelet transform has been extensively investigated in numerous studies. For example, Saadatmorad et al. [147] introduced an innovative technique that combines 2-D discrete wavelet transform with radial basis function networks (RBFNs) to detect damage in marine fiberglass composite panels. This method effectively addresses the noise problem, which can impact the accuracy of damage detection at lower damage levels. In another study, Saadatmorad et al. [148] introduced a new criterion for wavelet selection, significantly improving damage detection accuracy in metal structures by identifying the most suitable wavelet function. In addition, Abdushkur et al. [149] emphasized the importance of selecting the appropriate type of digital signals for wavelet conversion to enhance the accuracy of fault and damage detection.

Several studies have combined wavelet transform techniques with other methodologies to enhance damage detection. Chérrez et al. [150] proposed a technique that integrates wavelet de-noising with 2-D continuous wavelet transform (CWT) to assess crack properties in thin-walled composite beams. This method provides accurate results even in the presence of noise. Additionally, Saadatmorad et al. [151] investigated the identification of delamination in multilayer composite plates by employing a combination of 1D and 2D discrete wavelet transforms, which improved detection accuracy.

Wavelet transform applications have expanded to a wide range of materials and structural types. For instance, Zhu et al. [152] proposed using the continuous wavelet transform (CWT) to develop an index for detecting cracks in functionally graded materials (FGMs) beams. This method accurately identifies crack locations and estimates their depth. In another study, Saadatmorad et al. [153] investigated the application of wavelet transform and modal form covariance for precise damage detection in multilayer composite beams reinforced with nanoparticles.

Furthermore, alternative pioneering techniques have been explored. For example, Fallahian et al. [121] presented a damage identification technique that utilizes the discrete wavelet transform and ensemble pattern detection models. This approach demonstrates the capability to identify even little damage in complex structures. Similarly, Miao et al. [154] proposed an advanced technique that integrates wavelet transform with neural networks, resulting in improved speed and precision in damage detection. Besides, thorough evaluations have also been crucial in this field. A comprehensive review by Guo et al. [155] explored the development and applications of wavelet analysis, highlighting both its advantages and challenges for future research. Additionally, empirical studies, such as the one conducted by Janeliukstis et al. [156], used non-contact scanning laser vibrometry combined with continuous wavelet transform techniques to accurately identify and pinpoint structural degradation in beam structures.

Future studies could investigate integrating several methodologies, such as WT and HHT, to enhance accuracy and robustness. Additionally, there is a need for techniques that effectively manage noise, especially in complex structures, and for adaptable strategies suitable for larger and more sophisticated systems. Furthermore, integrating signal processing with machine learning, including using wavelet transformations in conjunction with neural networks, represents a highly promising approach to improve the speed and accuracy of damage identification.

Table 5 summarizes the references discussed for damage detection through signal processing, highlighting various analytical techniques.

■ Challenges and future trends

Despite the success of signal processing methods in detecting structural damage, several challenges remain. Many of these techniques are highly sensitive to noise, which can significantly reduce their accuracy, especially under real-world conditions such as earthquakes or strong winds. Selecting the appropriate wavelet function or signal type is also not straightforward and can greatly influence the results. Furthermore, many methods have only been validated on small-scale or laboratory models, and their effectiveness on large, complex structures remains uncertain. Another limitation is that the necessary data, such as acceleration or vibration signals, can be difficult to collect and may require costly equipment, like laser vibrometers.

Looking ahead, combining multiple signal processing techniques, such as wavelet transform (WT) and Hilbert-Huang transform (HHT), may enhance both accuracy and adaptability. There is also increasing interest in integrating these approaches with machine learning tools, such as neural networks, to improve the speed and reliability of damage detection. Real-time monitoring using deep learning models like convolutional neural networks (CNNs) and fast S-transforms shows great promise, particularly in handling noisy data. Future research should focus on improving the robustness of these methods for large-scale structures and ensuring their reliability under varying loading and environmental conditions.

3.1.5. Finite element model updating methods

FEM updating methods are highly promising techniques for detecting structural damage. These methods focus on minimizing discrepancies between model predictions and real-world data by iteratively adjusting the FEM property matrices, such as mass, stiffness, and damping [157]. By analyzing changes in these parameters, FEM updating can identify the presence, location, and severity of damage. However, the accuracy of these methods depends on the quality of the initial FEM model and the engineer's understanding of the various outcomes of the updating process [158].

In the field of vibration-based SHM, FEM updating plays a crucial role in enhancing the accuracy of computer-generated structural models by incorporating real-world data. Several studies [159–162] have reported advancements in vibration-based SHM through various techniques for refining FEMs using real-world data, leading to more precise structural health assessments. Schommer et al. [159] provided a comprehensive overview of FEM updating procedures, discussing common methods, advantages, and limitations. They emphasized the importance of selecting an appropriate approach based on the specific structure and available data. Girardi et al. [160] developed a method specifically for updating FEMs of buildings using modal analysis, while in a subsequent study, Girardi et al. [161] proposed a method for updating FEMs that finds a globally optimal solution for unknown parameters, such as material properties. Ereiz et al. [162] introduced a novel SHM method combining both static and dynamic data in the FEM updating process.

Cheng et al. [163] integrated fractal theory with model updating for damage detection in large steel arch bridges, offering a two-tiered approach that is robust against environmental factors. Zhou et al. [164] introduced a new method using L1 regularization for damage detection in beam-like structures, achieving more precise damage localization with fewer frequency data points, making it potentially more efficient. Shimpi et al. [165] and Fang Dong et al. [166] employed response surface methodology to enhance model accuracy for historical masonry bridges and continuous beam bridges, respectively. Both studies applied vibration testing and sensitivity analysis to identify optimal structural parameters, with the response surface method creating surrogate models to efficiently update FEMs and assess damage.

Sun et al. [167] proposed a novel method for bridge damage localization and quantification by integrating deep learning with FEM simulations. This approach used dynamic response data to calculate damage indices, significantly improving computational efficiency for damage severity quantification compared to traditional FEM simulations. In a comparative study, Rosati et al. [168] evaluated the effectiveness of the Douglas-Reid and response surface methods for model updating of historical structures, applying these methods to the Tower of the Nations, a reinforced concrete building in Naples, Italy.

Jiang et al. [169] presented a data-driven algorithm that combines the scaled boundary finite element method (SBFEM) with deep learning for crack detection in large structures. SBFEM efficiently simulated wave propagation in defective structures, while a dilated causal convolutional neural network accurately identified crack details, demonstrating robustness to noise. Similarly, Yang et al. [170] combined boundary element methods with neural networks for damage identification in plates, and Pagani and Enea [171] utilized CNNs and advanced structural theories for damage detection in composite structures.

Lyu et al. [172] developed a novel method incorporating a reference

Table 5
Summary of signal processing-based methods.

References	Year	Sensor type	Excitation method	Response type	Structure scale	Response type
Montejo [132]	2011	N.A.	Deterministic (e.g., 3 Hz sinusoidal) and random (e.g., earthquake-like)	High-frequency response (via DWT, HHT, CWT, andhigh-pass filtering)	Small-scale (3-story shear building)	Proposed CWT for damage detection under random excitations.
Qiao et al. [133]	2012	Wireless Accelerometer (G-Link by MicroStrain)	Impulse (steel ball drop)	Acceleration (vibration)	Small-scale (3-story lab structure, ~91.4 cm tall)	Compared FFT and CWT for pattern recognition in damage detection.
Aval et al. [134]	2020	Accelerometers	Filtered white noise via a Butterworth filter	Acceleration response	1/4-scale 4-story steel frame (IASC–ASCE benchmark)	Combined empirical mode decomposition and ANN for damage detection and assessment during earthquakes.
Ghahremani et al. [135]	2021	Accelerometers	Chirp sinusoidal signal	Acceleration	3-story plexi frame	Used fast S-transform and CNN for real-time damage detection.
Kankanamge et al. [136]	2020	Wireless Accelerometers	Ambient vibration	Acceleration	Full-scale (bridge)	Modal identification of a steel girder bridge using CWT. CWT outperformed FFT in capturing time-frequency dynamics.
Yang et al. [138]	2024	▪ Temperature/ humidity sensors ▪ Image-based deflection system ▪ Vibration strain gauges	N.A.	Temperature, humidity, deflection, and strain	Full-scale bridge	Denoised signals (using CEEMD + Wavelet)
Sanchez et al. [139]	2020	N.A.	Ambient vibrations	Dynamic response (natural frequencies)	4-story 3D steel frame structure	SWT method detects damage in a 4-story steel frame from vibration data
Dong et al.[136, 140]	2018	Acoustic Emission Sensors	Pencil lead breaks (PLBs), three-point bending	Acoustic Emission Signal	Laboratory Scale (CFRP and GFRP plates)	A modified EWT based on local window maxima (LWM) is proposed to improve AE signal decomposition for identifying damage mechanisms in composite structures.
Karimpour & Rahmatalla [141]	2022	Accelerometers	Impact hammer (transient), electrodynamic shaker (steady state)	Time-domain and frequency-domain signals	Small-scale lab models	EEWT extracts global and local modal info under transient loading; validated on beam and scaled bridge with transient and steady excitation
Delgadillo and Casas [142]	2022	N.A.	Traffic-induced vibration	Vibration signal	Full-scale truss bridge	Damage detection in bridges using ICEEMDAN and unsupervised learning on traffic vibrations
Entezami and Shariatmadar [143]	2019	Accelerometers	Ambient excitation	Acceleration (time histories)	Lab-scale steel frame and numerical model	Damage localization via ICEEMDAN, ARMA, and distance correlation under ambient vibrations
Sarmadi et al. [144]	2019	FBA and EPI accelerometers	Ambient vibration (wind, pedestrians, traffic)	Acceleration (vibration signals)	Laboratory-scale 4-story steel frame model	Steel structure damage localization using ambient vibration and EEMD-based energy features
Mousavi et al. [145]	2022	Accelerometers	Band-limited white noise applied vertically at mid-span through a shaker	Vibration acceleration signals	Laboratory-scale steel truss bridge (14 bays, 5.6 m span length)	Steel truss vibration signals analyzed by CEEMDAN to detect damage; method proven effective in lab tests.
Liu et al. [146]	2023	▪ Capacitive accelerometer (Model: Silicon Designs 2260–010) ▪ Piezoelectric Sensor	Instrumented hammer impact	Vibration acceleration signal	Reinforced concrete T-girder large scale (lab)	Highlighted LTFT for damage detection in reinforced concrete structures.
Saadatmorad et al. [147]	2022	Laser Doppler vibrometer (LDV)	Vibration (modal excitation)	Vibration amplitude (mode shape signals)	Laboratory-scale laminated composite plate (RLCP)	Combined 2-D DWT and RBFN for damage detection in composite plates.
Saadatmorad et al. [148]	2024	Accelerometer	Modal impact hammer	Acceleration / Mode Shapes	Laboratory-scale beam (40 cm)	Introduced a wavelet-based damage detection method with an optimized wavelet selection criterion (WSC).
Abdushkour et al. [149]	2024	N.A.	N.A.	Mode shape (from simulation)	Beam (numerical)	Emphasized the importance of signal type in wavelet transform for damage detection.
Chérrez et al. [150]	2021	N.A.	Modal analysis (numerical excitation)	Mode shapes and natural frequencies (displacement modes)	Thin-walled composite beam (elliptical cylinder), small-scale / laboratory-scale (simulated)	Measured crack-type damage features using wavelet de-noising and 2-D CWT.
Saadatmorad et al. [151]	2022	N.A.	N.A.	Mode shape (from FE model)	Numerical model (composite laminated plates)	Combined 1-D and 2-D DWT for delamination detection.
Zhu et al. [152]	2019	N.A.	Free vibration / modal analysis (analytical excitation via Timoshenko beam theory)	Mode shapes (displacement field) analyzed via wavelet transform	Laboratory scale (numerical simulation of small beams, e.g., L = 0.2 m)	Proposed a damage index for crack identification in FGM beams using CWT.

(continued on next page)

Table 5 (*continued*)

References	Year	Sensor type	Excitation method	Response type	Structure scale	Response type
Saadatmorad et al. [153]	2024	Laser Doppler Vibrometer (non-contact laser Doppler)	Impact load (to induce damage)	Mode shapes (vibration response)	Laminated composite beam (meso scale / beam scale)	Used wavelet transform and covariance of mode shapes for damage detection.
Fallahian et al. [121]	2022	Accelerometers	Hydraulic shaker (2–12 Hz, random signal)	FRFs and displacement	Full-scale bridge (I-40 Bridge)	Combined DWT and ensemble pattern recognition for damage detection.
Miao et al. [154]	2020	N.A.	N.A.	Rotation mode shapes (numerical)	Numerical model of a 3-span continuous beam	Optimized damage identification using wavelet transform and neural network.
Guo et al. [155]	2022	N.A.	N.A.	N.A.	N.A.	Reviewed wavelet analysis and its applications.
Janeliukstis et al. [156]	2017	▪ Scanning laser vibrometer ▪ Ultrasonic pulse-echo sensor	▪ Periodic chirp and sine wave signals ▪ Drop-weight impact (for damage only)	▪ Vibration velocity (transformed to deflection shapes) ▪ Echo signal (for imaging damage)	▪ Beam and plate structures (lab scale) ▪ Beam structures (lab scale)	Used continuous wavelet transform and mode shape curvature for damage localization.

signal for operational modal analysis and damage detection in beams. Several studies have utilized vibration-based data and machine learning classifiers for effective damage detection. Perfetto et al. [173] used guided wave-based neural networks trained with FEM data to accurately pinpoint damage in flat panels made from different materials. Zhou et al. [174] also combined FEM with CNNs for real-time damage detection in high-pile wharf structures.

Baybordi and Esfandiari [175] introduced a FEM updating method focused on sensitivity analysis, simplifying the calculation of how structural parameters affect acceleration responses. Their approach demonstrated greater accuracy and noise resistance compared to traditional methods. In another study, Baybordi and Esfandiari [176] used time-domain response data to establish a linear connection between structural changes and their effects, proving effective in various damage scenarios. Ganjdoust et al. [177] worked on composite structures using an inverse FEM approach to minimize errors between experimental and numerical strain measurements, successfully detecting both internal and external defects like delamination.

Conversely, He et al. [178] developed a damage detection method independent of FEM, using deflections from the modal flexibility matrix as damage indicators. This technique showed sufficient accuracy with fewer sensors. Zacharakis and Giagopoulos [179] proposed a method that combines vibration analysis with metaheuristic algorithms, such as PSO, to accurately localize damage by adjusting stiffness and mass parameters to match the dynamic response of the damaged structure. Naranjo-Pérez et al. [180] introduced a hybrid algorithm combining the unscented Kalman filter (UKF) with harmony search (HS) to improve FEM updating in civil engineering, overcoming traditional computational challenges. Kao et al. [181] presented a two-step approach for updating structural models using ANN and an enhanced particle swarm optimization (EPSO) algorithm. Furthermore, Teng et al. [182] proposed a real-time damage detection method using CNNs to map vibration signals to structural conditions, achieving high accuracy with FEM-generated training data. Similarly, Zara et al. [183] improved ANN methods for detecting damage in composite structures by using optimization algorithms like Jaya and whale optimization algorithm (WOA) to enhance training and accuracy.

Rezaiee-Pajand et al. [184] proposed a sensitivity-based SMU method for updating mass and stiffness matrices using modal data. A hybrid sensitivity function, combining modal strain and kinetic energies, improves robustness and accuracy. To address noisy or incomplete data, they introduce a hybrid regularization scheme that combines the Lanczos bidiagonalization (LBD) algorithm with Tikhonov regularization, with optimal parameters selected via generalized cross-validation. The method is validated on a steel truss and the I-40 Bridge in New Mexico, showing superior performance compared to classical Tikhonov and LSQR methods.

FEM updating methods, including RSM, FRF, and Bayesian approaches, improve damage detection by addressing challenges like incomplete data and measurement noise. For example, RSM with D-optimal designs emphasizes the need for fewer samples while maintaining accuracy. Fang and Perera [185] demonstrated this in various structural scenarios, proving its efficacy for detecting both single and multiple damages. For instance, combining operational vibration measurements with FEM updating can estimate fatigue damage in large-scale industrial structures [186]. Giagopoulos et al. [186] proposed integrating vibration measurements into high-fidelity FEMs, enabling dense fatigue mapping and correlating well with experimental results, thereby supporting the development of effective maintenance strategies. A Bayesian approach using complex modal data for model updating was introduced by Henikish et al. [187], incorporating uncertainties in modal parameters, eliminating the need for mode matching, and using a Metropolis-within-Gibbs (MWG) sampler for posterior probability density function (PDF) simulation. This approach proved effective in both simulated and experimental studies, providing a probabilistic framework for damage detection.

Heung-Fai et al. [188] proposed a robust Bayesian framework for SMU and damage detection. By employing Markov chain Monte Carlo (MCMC) sampling, they effectively addressed uncertainties in model parameters and measurement noise. The method's ability to handle unidentifiable problems represents a significant contribution, enabling damage localization and quantification even in challenging scenarios.

Li et al. [189] developed a damage detection method that combines a modal strain energy sensitivity function with an iterative regularization algorithm called iteratively reweighted norm–basis pursuit denoising (IRN-BPD). Their approach accurately identified and quantified structural damage using incomplete and noisy modal data. Two case studies, a 6-DOF mass–spring system and the I-40 bridge, demonstrate its effectiveness and robustness.

Zeng et al. [190] presented a real-time, likelihood-free Bayesian method for damage detection and model updating using a convolutional neural network-based probabilistic parametric estimator (PPE). The approach directly estimated posterior statistics from raw acceleration data without needing likelihood evaluations. Its performance was validated on a numerical steel pedestrian bridge (Fig. 5) and a real-world cable-stayed bridge under ambient vibrations, outperforming Normalizing Flow and Polynomial Chaos Expansion in both accuracy and speed.

The review paper [191] covered Bayesian finite element model updating techniques, focusing on uncertainty quantification, model updating methods, and applications in structural health monitoring and damage detection.

Recent advancements in FEM updating methods have significantly addressed key challenges, such as measurement noise, data incompleteness, and computational efficiency. Techniques like substructural analysis [192–201], Bayesian inference [187,202–208], and adaptive meta-modeling [209] collectively contribute to more accurate and reliable damage detection methodologies. These studies highlight the importance of integrating robust statistical and computational methods

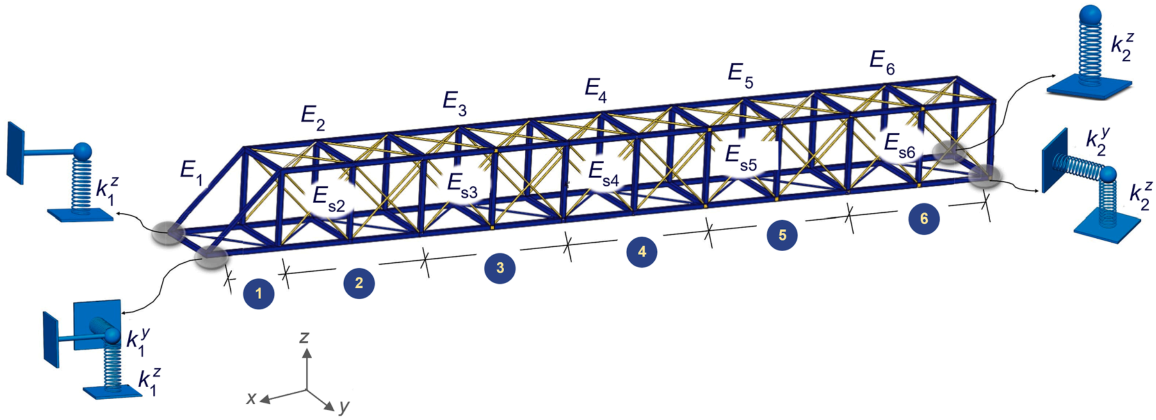

Fig. 5. Overview of a steel pedestrian bridge (adapted from [190]).

to enhance the practical applicability of FEM updating in SHM, supporting the continuous evolution of SHM practices. Several studies have focused on substructural approaches for efficient and accurate model updating, aligning with the computational benefits of substructural analysis [192,193]. To handle incomplete data, Shadan et al. [210] introduced a method robust against missing information using sensitivity equations, which complements RSM in minimizing data needs. Addressing noise in measurements is another key area of development. Xin et al. [204] proposed a Bayesian approach that effectively handles noise through uncertainty quantification, achieving accurate updates even with significant noise. Similarly, Ni et al. [203] presented a method using a Gaussian surrogate model that achieves high accuracy in parameter identification. Pedram et al. [211] employed power spectral density (PSD) functions to update FEMs, particularly for plate and shell structures. This method used PSD functions in the frequency domain, deriving an exact sensitivity equation and ensuring robustness against measurement and mass modeling errors. Computational efficiency is also crucial, particularly for large-scale structures. Zhou and Tang [209] developed a framework using adaptive multi-response Gaussian process (MRGP) for efficient model updating, similar to RSM's focus on reducing sample requirements.

Stochastic approaches, particularly those leveraging Bayesian frameworks and genetic algorithms, have been explored by Yang et al. [212]. Their two-stage stochastic model updating method combines multi-population migrant genetic algorithms with Metropolis-Hastings algorithms, addressing parameter uncertainties and enhancing the likelihood of achieving global optima, as demonstrated in the context of heavy-haul railway bridges.

Future research in FEM updating could benefit from integrating emerging artificial intelligence (AI) techniques like reinforcement learning and generative adversarial networks (GANs) to enhance accuracy and damage detection. Developing hybrid approaches, such as combining Bayesian inference with machine learning, could improve robustness against noise and incomplete data. Efforts should also focus on making FEM updating scalable for large structures and applicable in real-time SHM scenarios, with potential advancements through interdisciplinary collaboration. Table 6 summarizes methods for FEM updating, highlighting different techniques and their applications.

■ Challenges and future trends

Despite significant advances, FEM updating methods still face several challenges that limit their full potential in SHM. One major challenge is the dependency on the initial FEM accuracy and the quality of measured data, which directly affect the robustness of the updating process. Incomplete, noisy, or inconsistent data from sensors can introduce uncertainty and degrade damage detection accuracy. Additionally, computational cost remains a concern for large-scale or complex structures, where model updating can become prohibitively expensive without efficient algorithms or surrogate modeling techniques. Handling environmental and operational variability is another persistent difficulty, as changes in temperature, humidity, or load conditions can mask or mimic damage effects, complicating the identification process.

Recent developments in stochastic approaches, such as Bayesian frameworks and metaheuristic optimization algorithms, have improved robustness to noise and parameter uncertainty [187,212]. However, practical implementation in real-time SHM systems is still limited due to the computational intensity of these methods and the need for better integration with field data. Furthermore, the scalability of FEM updating techniques to very large or complex infrastructure, such as bridges or industrial plants, remains a challenge that necessitates innovative model reduction and parallel computing strategies. Looking forward, the integration of advanced AI methods with traditional FEM updating shows promising potential. Hybrid approaches that combine machine learning, deep learning, and reinforcement learning with Bayesian inference may enhance damage localization accuracy and improve resilience against incomplete and noisy data. Incorporating multi-sensor fusion and real-time data streams could enable continuous FEM updating for proactive maintenance and early damage detection.

Another future direction involves enhancing user accessibility through automated FEM updating tools and cloud-based platforms that reduce the expertise required and facilitate large-scale applications. Interdisciplinary collaboration combining civil engineering, computer science, and data analytics will be critical in developing scalable, efficient, and robust FEM updating methods suitable for the diverse needs of modern infrastructure monitoring.

3.1.6. Statistical time series methods

Time series-based methods for SHM, such as auto-regressive (AR), autoregressive with exogenous input (ARX), and auto-regressive moving average (ARMA) models, fit historical data to extract damage-sensitive features while accounting for operational and environmental variations. These methods effectively handle uncertainties and are often better suited for automated SHM than traditional model updating methods. The process generally involves three key steps: capturing random signals, building statistical models, and making decisions for damage diagnosis.

A variety of approaches have been explored for damage detection in structures using AR models. Zhu et al. [213] pioneered this method by correlating changes in ARMA model coefficients with variations in structural stiffness, using sparse regularization to address the challenges of underdetermined systems. Subsequent research has built on this foundation, focusing on enhancing the robustness and applicability of AR-based methods.

Kauss et al. [214] integrated AR models with differential evolution

Table 6
Summary of FEM updating methods.

Reference	Year	Sensor type	Excitation method	Response type	Structure scale	Description
Schommer et al. [159]	2017	■ Displacement transducers ■ Not explicitly stated	■ Static loading (mass placement) ■ Dynamic: swept sine excitation (constant force amplitude)	■ Displacement (deflection/sagging) ■ Eigenfrequencies and mode shapes	■ Full-scale (46-m beam) ■ Full-scale (46-m beam)	Provided a comprehensive overview of FEM updating procedures.
Girardi et al. [160]	2021	SARA SS20 seismometric stations (seismometers)	Ambient vibration monitoring (ambient vibrations, operational conditions — no artificial excitation, natural ambient excitation)	Dynamic properties: natural frequencies, damping ratios, mode shapes (experimental modal properties estimated via operational modal analysis techniques SSI–cov and EFDD)	Full-scale historic masonry tower (Matilde donjon, 26 m high, in Livorno, Italy)	Developed a method for updating FEMs of buildings using modal analysis.
Girardi et al. [161]	2020	Sensors used for modal analysis (not specifically detailed)	Ambient vibration or natural excitation (modal analysis)	Frequency response (modal frequencies)	Building scale (including historical buildings, arches, domes, towers)	Proposed a method for updating FEMs that finds a globally optimal solution for unknown parameters.
Ereiz et al. [162]	2021	N.A.	N.A.	N.A.	N.A.	Introduced a novel method in the FEM updating process.
Cheng et al. [163]	2021	Strain gauges, Accelerometers	Ambient (in-service conditions)	Strain (Level 1), Acceleration (Level 2)	Large steel arch bridge	Combined fractal theory and model updating for damage detection in large steel arch bridges.
Zhou et al. [164]	2015	Accelerometer	Instrumented hammer	Vibration frequency response (modal frequencies)	Cantilever beam (single structural element, beam scale)	Leveraged L1 regularization for FEM updating.
Shimpi et al. [165]	2024	Integrated piezoelectric accelerometers (ICP)	Ambient vibration testing (ambient excitation)	Vibration response (accelerations)	Full bridge (macro scale)	Employed response surface methodology in FEM updating.
Fang Dong et al. [166]	2024	Three-dimensional acceleration sensors	Ambient vibration (environmental vibration testing)	Dynamic characteristics: natural frequencies, vibration modes	Continuous beam bridge (large-scale bridge structure)	Utilized response surface methodology for FEM.
Sun et al. [167]	2024	Inclination sensors	White Gaussian noise (100 Hz)	Dynamic response (inclination)	Two-span continuous girder bridge (numerical scale, FEM-based)	Combined deep learning with FEM simulations.
Rosati et al. [168]	2024	Force Balance Accelerometers	Output-only Ambient Vibration (Operational Modal Analysis, OMA)	Dynamic modal parameters (natural frequencies, mode shapes)	Full-scale historic building (Tower of the Nations, reinforced concrete building)	Compared Douglas-Reid and response surface methods for FEM.
Jiang et al. [169]	2024	Not explicitly stated (assumed displacement/velocity sensor)	Signal generator with Hanning-windowed waveform (fs = 2314 Hz, fc = 3660 Hz)	Horizontal dynamic displacement response	Large-scale / Massive structures	Merged SBFEM and deep learning for FEM updating.
Yang et al. [170]	2024	Strain gauges (BEM-based simulation)	Static loading (for boundary strain analysis)	Boundary strain (simulated and/or measured)	Plate (Laboratory scale)	Integrated boundary element methods and neural networks for FEM.
Pagani and Enea [171]	2024	N.A.	Bending, Torsion, Uniaxial Traction (numerical loading)	Displacement and Strain Field (numerical images)	Thin-walled beam and composite laminate (numerical model)	Leveraged convolutional neural networks for FEM.
Lyu et al. [172]	2024	CSLDV (continuously scanning laser Doppler vibrometer) and single-point LDV	Random (white-noise) excitation using a shaker	Vibration velocity (used to estimate damped natural frequencies and undamped mode shapes)	Laboratory-scale beam	Introduced a demodulation method for FEM.
Perfetto et al. [173]	2021	Piezoelectric (PIC255 PZT)	Chirp signal (50–500 kHz)	Lamb wave propagation	Laboratory-scale plate (287 mm × 287 mm × 2 mm)	Used guided wave-based ANNs for FEM.
Zhou et al. [174]	2022	N.A.	Sudden unloading load	Displacement (longitudinal, lateral, and vertical components)	Large-scale (High-pile wharf foundation)	Combined FEM with 1D CNNs.
Baybordi and Esfandiari [175]	2024	B&K accelerometers (model 5)	PCB modal hammer (model 086C03)	Acceleration (time-domain)	Small-scale laboratory model (aluminum frame, 66.75 cm height)	Proposed sensitivity-based approach for FEM.
Baybordi and Esfandiari [176]	2022	Displacement sensors (possibly with velocity sensors as well, as both are mentioned in the error analysis)	Impulsive, harmonic, and periodic excitation	Time history response (displacement and velocity)	Numerical truss model (small-scale structure with 12 nodes and 25 elements)	Employed sensitivity analysis and time-domain data for FEM.
Ganjdoust et al. [177]	2023	Strain rosettes, FBG (fiber Bragg grating) sensors	Mechanical loading (tensile, bending, torsion, axial)	In-plane strain components (ε_{11}, ε_{22}, γ_{12}); displacement; von Mises strain	Small-scale lab specimens (plates, shells, T-beams, composite panels)	Applied inverse FEM to composite structures.
He et al. [178]	2021	N.A.	Ambient vibration from parked vehicles	Mode shapes, estimated deflection	Beam structure	Used the modal flexibility matrix for damage detection.

(continued on next page)

Table 6 (*continued*)

Reference	Year	Sensor type	Excitation method	Response type	Structure scale	Description
Zacharakis and Giagopoulos [179]	2022	Triaxial accelerometers	Random excitation (shaker)	Output-only Transmittance Functions	Small-scale composite beam	Combined metaheuristic algorithms with FEM.
Naranjo-Pérez et al. [180]	2021	Accelerometers	Forced vibration using proof-mass actuators	FRFs / modal Properties (frequencies and modes)	Laboratory-scale footbridge (15-m steel frame)	Presented a hybrid algorithm combining the UKF with HS to improve FEM updating in civil engineering.
Kao et al. [181]	2024	Wired single-axis and wireless multi-axis accelerometers	White noise with zero mean	Natural frequencies (in strong and weak axes)		Introduced a two-step approach for updating structural models using ANN and an enhanced PSO.
Teng et al. [182]	2020	Accelerometer	Hammer impact	Acceleration (vibration signals)	Laboratory-scale steel frame	Utilized CNNs for real-time FEM updating.
Zara et al. [183]	2023	Impact hammer (PCB Hammer Type 086C03), Accelerometer (PCB M352C66)	Impact hammer (force excitation)	FRF, natural Frequencies, Mode Shapes	Beam-scale (specimens of GFRP composite beams)	Improved ANN for FEM updating in GFRP structures.
Rezaiee-Pajand et al. [184]	2021	Accelerometers	Hydraulic shaker with 9863 kg reaction mass (9.79 kN force)	Acceleration	Full-scale	I−40 bridge; twin-span steel/concrete bridge tested before demolition
Fang and Perera [185]	2011	N.A.	Numerical	Modal frequencies	Numerical	Employed RSM with D-optimal designs for FEM.
Giagopoulos et al. [186]	2019	Accelerometers	Operational	Acceleration	Full-scale (real-life)	Integrated vibration measurements for FEM-based fatigue estimation.
Henikish et al. [187]	2023	Accelerometers	Impact loading	Acceleration time history	Small-scale (3-story lab structure)	Applied Bayesian approach for FEM updating.
Heung-Fai et al. [188]	2018	Accelerometers	Ambient vibration (electric fan simulating wind)	■ Acceleration (translational modes) ■ Acceleration (horizontal on columns, vertical on beams)	■ Laboratory-scale, 4-story steel shear building model ■ Laboratory-scale, 2-story steel frame with bolted connections	Offered a robust Bayesian framework for structural model updating and damage detection.
Li et al. [189]	2023	N.A.	N.A.	Modal data (frequencies, modes)	Small (mass–spring), Full-scale (I−40 bridge)	Numerical study using a 6-DOF system and a detailed I−40 bridge FE model.
Zeng et al. [190]	2025	Uniaxial and Biaxial Accelerometers	Ambient (Gaussian White Noise)	Acceleration (dynamic)	Medium and large	Steel pedestrian and cable-stayed bridges tested with CNN-based likelihood-free inference for fast, accurate damage detection and model updating.
Kiran et al. [191]	2025	N.A.	N.A.	Time-history data, frequency response functions, and modal characteristics	N.A.	Review of Bayesian FE model updating techniques, uncertainty quantification, model updating methods, and application in SHM and damage detection.
Zhu et al. [192]	2021	Accelerometers	Impulsive force (at Node 4; *Y*-direction)	Acceleration response	Small-scale (experimental cantilever beam) and large-scale (e.g., high-rise building with >20,000 DoFs)	Used substructural analysis for FEM.
Ni et al. [203]	2022	Accelerometers	Hammer excitation	Horizontal floor responses	Small-scale steel frame (4 floors)	Utilized Gaussian surrogate model for FEM.
Xin et al. [204]	2019	Accelerometer	Harmonic base excitation	Acceleration response	Laboratory-scale (High voltage switch structure with 3 porcelain pillars)	Handled noise with Bayesian approach for FEM.
Zhou and Tang [209]	2021	Displacement sensor (*z*-direction FRF)	Harmonic excitation with unit amplitude (frequency sweep)	Frequency response function (FRF) in the *z*-direction	Small-scale benchmark structure (multi-plate model with 3510 DOFs)	Employed adaptive MRGP for FEM.
Shadan et al. [210]	2016	Accelerometers/ displacement sensors (implied by FRF usage)	Harmonic excitation near resonance frequencies	■ Frequency response functions (FRFs) ■ Natural Frequencies	Truss (small-scale, numerical model)	Addressed missing information in FEM updating.
Pedram et al. [211]	2018	Displacement sensors (translational DOFs only)	Point force excitation at selected nodes	Power spectral density (PSD) of displacements	Midsize structures (e.g., 1 m x 1 m plate, 3.2-m shell)	Used PSD functions for FEM updating.
Yang et al. [212]	2024	■ Accelerometers (implied by vibration measurements) ■ Accelerometers (implied by dynamic load response) + static load monitoring	■ Pulse hammer ■ Passing trains (dynamic), static loads from heavy vehicles	■ Dynamic response (natural frequencies) ■ Natural frequencies, displacements	■ Laboratory-scale (6000-mm concrete beam) ■ Full-scale (real bridge: Yellow River Bridge)	Introduced a two-stage stochastic approach for FEM.

(DE) optimization to enhance damage identification accuracy, particularly in the presence of environmental disturbances. Tang et al. [215] advanced the field further by combining CNNs with AR models for automated feature extraction, outperforming traditional methods such as multi-layer perceptron (MLP) and random forest.

Goi and Kim [216] introduced a damage indicator derived from multivariate AR models, demonstrating superior performance over univariate models in detecting various damage patterns. This approach was validated through field experiments, underscoring its practical applicability. Silva et al. [217] extended the use of AR models to composite plate structures, employing piezoelectric sensors for data acquisition. Figueiredo et al. [218] highlighted the importance of selecting the appropriate model order, comparing techniques such as the Akaike information criterion (AIC) and partial autocorrelation function.

While AR models have shown promise, alternative feature extraction methods have also been explored. Pan et al. [219] compared singular value decomposition (SVD)-based feature extraction with AR and vector autoregressive (VAR) models, demonstrating that SVD effectively handles noise. Additionally, a multi-level machine learning approach using AR spectrum features was proposed in [220] to address challenges related to limited sensor data and environmental variations.

Optimization of AR model coefficients is another crucial aspect of damage detection. Hoell and Omenzetter [221] focused on optimizing these coefficients for wind turbine blade damage detection, comparing various methods, including genetic algorithms. Krishnan et al. [222] introduced a real-time damage detection framework that combines recursive principal component analysis (RPCA) with time varying auto-regressive modeling (TVAR), eliminating the need for baseline data.

Gharehbaghi et al. [223] presented a supervised learning approach for detecting damage and deterioration in building structures using AR time-series models. Their method effectively addressed challenges posed by noise and demonstrated strong potential for accurate detection of structural conditions.

These studies demonstrate the versatility and effectiveness of AR-based methods for damage detection across various structural systems. Future research may focus on further enhancing the robustness and accuracy of these methods and exploring their integration with other advanced techniques for comprehensive SHM. Table 7 summarizes various statistical time series methods, outlining different approaches and their applications for damage detection.

■ Challenges and future trends

Statistical time series methods like AR and ARMA have shown promise in structural health monitoring, but several challenges remain.

Table 7
Summary of statistical time series methods.

References	Year	Sensor type	Excitation method	Response type	Structure scale	Description
Zhu et al. [213]	2020	■ Accelerometer ■ Accelerometer	■ Hammer with rubber tip ■ Hammer	■ Free-decay acceleration ■ Free-decay acceleration	■ Laboratory-scale (1-m long) ■ Small-scale frame model	ARMA model-based damage detection with sparse regularization.
Kauss et al. [214]	2024	■ Accelerometers ■ Accelerometers	■ Electrodynamic shaker (random load) ■ N.A. (ambient/environmental loads)	■ Acceleration (vibration signals) ■ Acceleration (vibration signals)	■ Laboratory scale (3-story frame) ■ Real scale (Z24 bridge)	Improved damage identification using AR models and DE optimization.
Tang et al. [215]	2020	Accelerometers	Shaker (2 V, 5 V, 8 V input)	Acceleration	3-storied frame structure	Automated feature extraction for damage detection using CNNs and AR models.
Goi and Kim [216]	2017	■ Uniaxial accelerometers ■ Optical sensors (for timing)	■ Ambient vibration (vehicle load) ■ N.A.	■ Vertical acceleration response ■ Vehicle entry/exit detection	■ Full-scale (real bridge) ■ Full-scale (real bridge)	Damage indicator based on multivariate AR models.
Silva et al. [217]	2019	PZT (SMART Layer)	Five-cycle tone burst at 250 kHz	Lamb wave time-series data	Aeronautical composite panel (lab scale)	AR model application for damage detection in composite plates.
Figueiredo et al. [218]	2011	Accelerometers Load cell	Electrodynamic shaker Electrodynamic shaker	Acceleration Force (input)	Laboratory Laboratory	Model order selection for accurate AR model-based damage detection.
Pan et al. [219]	2019	Accelerometers	Electrodynamic shaker	Acceleration (dynamic)	Laboratory-based frame structure	SVD-based feature extraction compared to AR and VAR models.
Entezami et al. [220]	2022	Accelerometer	Shaker (random excitation)	Acceleration	Laboratory-scale truss (Wooden Bridge)	Multi-level machine learning with AR spectrum features for damage detection.
Hoell and Omenzetter [221]	2016	Accelerometers	Aerodynamic excitation	Vibration (acceleration)	Large composite wind turbine blade (full blade scale)	Optimized AR model coefficients for wind turbine blade damage detection.
Krishnan et al. [222]	2018	Honeywell accelerometers TEDS by HBMTM	Scaled ground motion (1999 Chi-Chi earthquake), white noise, El Centro earthquake, Gaussian broad-band excitation, ambient vibration	Acceleration	Laboratory aluminum beam (120 cm long), two-story bench-scale model with TMD, full-scale 17-story UCLA factor building	Real-time damage detection using RPCA and TVAR modeling.
Gharehbaghi et al. [223]	2020	Accelerometers (piezoelectric in damage case, accelerations recorded in deterioration case)	Ambient and forced vibrations (ambient excitation from real building data in deterioration case; hydraulic shaker in damage case)	Acceleration response time series	3-story building (deterioration case) / 3-story metal bookshelf (damage case)	Supervised learning for damage and deterioration detection in buildings using AR time-series models.

These models can be sensitive to environmental or operational changes, making it difficult to distinguish actual damage from external influences. Model selection is crucial and greatly affects performance. Many techniques still depend on baseline data from undamaged structures, which is not always available. Noisy sensor data and inconsistencies across sensors, especially in large systems, can also reduce accuracy. Additionally, real-time implementation can be limited by processing demands.

Future directions include integrating AR models with machine learning, particularly deep learning, to automatically identify patterns and improve damage detection. Using multi-sensor models that track changes across time and space may enhance performance. Research is likely to focus on eliminating the need for baseline data, improving noise robustness, and boosting computational efficiency, making time series methods more practical for real-world use.

3.2. Feature discrimination

Feature discrimination focuses on interpreting the extracted features to detect, localize, or quantify structural damage. In this section, various methodologies such as statistical decision-making, pattern recognition, and machine learning-based classifiers are discussed, emphasizing how they leverage the extracted features to distinguish between healthy and damaged states, particularly in the context of long-term automated monitoring systems.

3.2.1. Optimization algorithms

Optimization methods have become a fundamental tool for solving engineering problems. Their effectiveness in finding the best solution within constraints has led to a significant increase in the development and application of new algorithms across various engineering disciplines [224–229]. This trend reflects the growing complexity of engineering challenges, which often require solutions that balance multiple objectives and factors.

Studies [230–238] collectively demonstrated the potential of various optimization and machine learning techniques for structural damage detection. However, challenges such as noise sensitivity and computational efficiency remain areas for future research. Das and Dhang [239] introduced a multi-stage optimization method for detecting damage in truss and frame structures with limited sensors. By using the iterated improved reduction system (IIRS) for modal reduction and hybrid teaching-learning based optimization-particle swarm optimization (ITLBO-PSO), the method accurately identified damage even in noisy environments, outperforming nine other algorithms in terms of precision and computational cost.

Aval and Mohebian [240] proposed the modal force information-based optimization (MFIBO) for damage detection in structures. MFIBO used modal force information to efficiently identify damage, outperforming metaheuristic algorithms in both accuracy and computational efficiency, even under noisy conditions. Mishra et al. [241] evaluated ten metaheuristic algorithms for damage detection in truss structures and found teaching-learning based optimization (TLBO) to be superior, delivering high precision with reduced computation time and function evaluations, even in noisy environments. Kahya et al. [242] applied the Harmony Search algorithm for damage detection in composite beams, demonstrating effectiveness with moderate to severe damage. However, the method showed reduced accuracy when detecting multiple minor damages in the presence of noise, suggesting that improvements could be made through algorithm hybridization or enhanced objective functions.

Le et al. [243] introduced an improved approach based on the modal assurance criterion (MAC) and the modal strain energy (MSE) method. In vibration-based SHM, two key metrics, MAC and the coordinate modal assurance criterion (COMAC), are commonly used to compare a structure's mode shapes between healthy and potentially damaged states. Given their widespread use in SHM, a comprehensive discussion of their definitions, mathematical formulations, and practical interpretations is presented.

MAC provides a general measure of similarity between two mode shapes. A MAC value of 1 indicates a perfect match, while values closer to zero suggest greater differences. However, MAC cannot pinpoint the location of the damage.

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

In Eq.(1), φ_i^d and φ_i^u are damaged and undamaged j-th mode shape, respectively. In Eq.(1), MAC values varies between 0 and 1. A value of 1 signifies the shapes are identical, while values closer to 0 indicate a greater difference.

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

In Eq.(1), x_j represents the coordinate of the j-th point. COMAC builds upon MAC by considering each point (coordinate) within the mode shapes, allowing for a more detailed comparison that highlights specific areas where the shapes differ significantly. By analyzing these localized discrepancies, COMAC can suggest potential damage locations. Since COMAC is a normalized value, it ranges between 0 and 1. A COMAC value close to 1 at a particular point suggests the structure is healthy in that area, whereas a value significantly lower than 1 may indicate damage at that location. Although COMAC provides more detailed information than MAC, its calculations are computationally more expensive.

Gomes and Giovani [244] presented a hybrid method for damage detection in laminated composites. Their two-step approach used mode shape data to locate damage and sunflower optimization (SFO) to assess its severity. This method effectively identified and quantified damage while improving efficiency and reducing computational costs. Dehcheshmeh et al. [245] applied moth-flame optimization (MFO) for damage detection in civil structures, using an objective function based on modal strain energy and static displacements. The method efficiently handled noise and limited data.

Several studies [246–251] employed hybrid optimization approaches to enhance the robustness of damage detection. Alexandrino et al. [237] used a multi-objective genetic algorithm (MOGA) integrated with neural networks and fuzzy decision-making to handle the inverse problem of damage identification, ensuring solutions were not overly sensitive to small variations. Similarly, Tran-Ngoc et al. [252] addressed the local minima issue in ANN training by combining GA with the cuckoo search (CS) algorithm, achieving faster convergence and higher accuracy. In contrast, Ho et al. [253] proposed a hybrid approach using the marine predator algorithm (MPA) with feedforward neural networks (FNNs). This method focused on optimizing the neural network learning process and demonstrated superior performance in handling noise and improving prediction accuracy. Its effectiveness in reducing discrepancies between simulated and real data highlights the importance of novel swarm intelligence algorithms in SHM.

Further studies [254,255] demonstrated the use of neural networks in damage detection with different optimization strategies. Rautela and Gopalakrishnan [254] applied convolutional and recurrent neural networks (CNN and RNN) with ultrasonic guided waves for real-time damage detection and localization, showing that deep learning could effectively manage uncertainties and noise in SHM. In contrast, Khatir et al. [255] enhanced neural network performance using the arithmetic optimization algorithm (AOA) for functionally graded material (FGM) plates, achieving high precision in damage quantification.

Zar et al. [256] introduced a hybrid method for damage detection in arch dams, combining radial basis function neural networks (RBFNN) with the Jaya algorithm (JA). This approach, which requires only one parameter, integrated dynamic elastic modulus and modal data for rapid damage identification, demonstrating significant time savings and robustness against noise. Huang et al. [257] proposed improving structural damage identification (SDI) through an adaptive simulated annealing particle swarm optimization-convolutional neural network (ASAPSO-CNN) with data augmentation. By adding noise to training signals and forming a four-dimensional input matrix for the CNN, an adaptive fitness function optimized accuracy, model complexity, and training efficiency. Tested on a beam model and a steel truss bridge, the method showed strong performance and robustness compared to other techniques [257]. This highlights the growing trend of integrating robust optimization algorithms with advanced neural network architectures to enhance SHM's accuracy and reliability.

Table 8 summarizes various optimization methods, highlighting their underlying techniques and applications.

■ Challenges and future trends

Even though optimization methods are powerful tools for detecting structural damage, several challenges remain. One major issue is noise in the measurement data, which can make it difficult for algorithms to accurately identify the location or size of the damage. Additionally, some optimization methods require significant time and computational resources, especially when dealing with large or complex structures. This can slow down the process and limit the practical use of these methods in real-world applications. Detecting small or multiple instances of damage is also more difficult, particularly when signals are weak or overlapping.

Future research is anticipated to focus on the integration of diverse algorithmic approaches to enhance both the performance and efficiency of structural damage detection methods. The development of hybrid techniques has the potential to mitigate errors and improve the reliability of diagnostic outcomes. Moreover, the incorporation of advanced artificial intelligence methodologies, particularly deep learning, coupled with real-time data acquisition is expected to significantly augment both the speed and precision of damage identification processes. Emerging optimization strategies inspired by swarm intelligence, which emulate collective behaviors observed in nature, also exhibit considerable promise. Collectively, these advancements are expected to contribute toward the development of faster, more accurate, and more robust damage detection systems capable of operating effectively under conditions of noise and data complexity.

3.2.2. *Machine learning methods*

Machine learning and its applications have become increasingly prevalent across various engineering fields, including concrete bridges and buildings [258–260], steel structures [261–263], and vibration control [264–266]. These data-driven approaches allow algorithms to learn structural behavior from historical data, effectively utilizing this knowledge to identify damage in new structures. Machine learning techniques can be applied in supervised, unsupervised, semi-supervised, and reinforcement learning scenarios. In the context of SHM, supervised learning involves training algorithms with data from both undamaged and damaged conditions. In contrast, unsupervised learning uses only data from undamaged conditions. Semi-supervised learning combines both labeled and unlabeled data to build predictive models, improving performance compared to supervised methods that rely solely on labeled data. Reinforcement learning enables agents to learn optimal decision-making policies by interacting with the environment and receiving rewards or penalties based on their actions.

3.2.2.1. Supervised methods. Supervised learning in SHM leverages labeled datasets containing information on both undamaged and damaged structural conditions. The objective is to train algorithms to identify relationships between sensor data (input) and the corresponding structural state (output), enabling the prediction of damage in previously unseen data [267]. In this context, most supervised learning techniques rely on discriminative models, where classifiers are trained to learn boundaries between healthy and damaged states. Entezami et al. [268] proposed a novel methodology that applies supervised classifiers such as linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), naive Bayes, and decision trees to damage-sensitive features extracted from AR and PCA models. This approach trains classifiers on data representing both undamaged and damaged structural states before maintenance, enabling effective damage detection and condition assessment of maintained structures. While Entezami et al. [268] focused on structural systems, similar classification strategies have also been applied to mechanical components. Goyal et al. [269] employed a support vector machine (SVM) classifier to detect and classify bearing faults using features extracted from vibration signals. The classifier, particularly the linear SVM, demonstrated high accuracy, validating the effectiveness of the proposed non-contact sensor.

Vibration-based damage detection has been extensively studied using various machine learning techniques. For instance, Harsha et al. [270] employed the ANN and adaptive neuro-fuzzy inference system (ANFIS) to predict damage location based on natural beam frequencies. Sarmadi and Entezami [271] developed a hybrid approach, combining both unsupervised and supervised learning techniques to overcome the issue of limited data, which is common in civil engineering applications. Traditional machine learning methods, such as decision trees and SVM, have also been used for assessing damage severity and classifying damage types based on beam dynamic response data [272,273].

Fig. 6a illustrates the process of supervised learning methods [273]. Data collection is the initial step in analyzing raw data in these methods. The model learns from labeled data, and features are extracted. The data is divided into two parts: training and testing datasets. Then, a machine learning algorithm is applied to build the model. Fig. 6b shows a neural network, where input data is used to predict an output [274]. Fig. 6c presents a damage detection flowchart using a deep neural network, which operates in two phases: offline and online [274]. In the offline phase, the initial parameters of the neural network are set and adjusted based on the training data. The online phase involves real-time monitoring, where data is collected and used by the trained neural network to predict the damage condition.

Recent advancements in SHM have increasingly leveraged deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks for multiclass damage detection and localization [274–277]. These deep learning models are particularly effective at identifying complex patterns in vibration data, enabling more accurate and nuanced damage identification [278]. To address this, researchers have explored integrating physics-based models with machine learning frameworks within digital twin environments [279,280]. These hybrid approaches aim to improve damage assessment reliability by combining empirical data with theoretical insights.

Beyond vibration-based methods, Qiao et al. [281] introduced a novel approach for rapid building damage assessment using high-resolution remote sensing (HRRS) imagery. Their method combines a fully convolutional neural (FCN) network with superpixel segmentation to effectively detect damaged building areas. This approach demonstrates the potential of deep learning for post-disaster assessment.

In terms of specific machine learning techniques, Sepahvand [282] applied nonlinear SVM for damage detection in structures with subtle changes in natural frequencies. Collectively, these studies showcase the evolving landscape of machine learning applications in SHM, from traditional algorithms to sophisticated deep learning models, highlighting the importance of incorporating domain knowledge for accurate and reliable damage detection.

To bridge the gap between research and practical applications, Agarwal et al. [283] proposed a combined framework of FEM updating and deep learning for damage detection, localization, and quantification. Dogan et al. [284] employed deep transfer learning for damage

Table 8
Summary of optimization methods.

References	Year	Sensor type	Excitation method	Response type	Structure scale	Description
Shakya et al. [230]	2019	N.A.	Simulated damage via stiffness reduction (elastic modulus reduction)	Frequency response function (FRF), natural frequencies	Multiple scales: - Cantilever Beam (simple) - 2D Planar Truss (moderate) - Double-Story Building (moderate) - 2D Frame (complex/large)	Combined the ACO with the Hooke-Jeeves pattern search for optimizing frequency response functions.
Nguyen-Thoi et al. [231]	2018	N.A.	N.A.	Modal data (natural frequencies, mode shapes)	Large-scale (72-bar truss, Steel portal frame)	Used a two-stage process with the damage locating vector (DLV) method and DE to localize and quantify damage.
Ghannadi and Kourehli [232]	2019	Accelerometers	Electrodynamic shaker	Acceleration (Time histories)	Experimental (3-story LANL structure)	Proposed the MFO algorithm using the modal assurance criterion and natural frequency.
Chen and Yu [233]	2020	Modal acceleration sensors (PCB, ICP 333B30)	Impact hammer (PCB force hammer)	Frequencies and mode shapes (via Experimental Modal Analysis)	Laboratory-scale (simply supported beam, 1.2 m span)	Integrated an improved Nelder-Mead algorithm with the Ant Lion Optimizer to enhance damage detection accuracy.
Huang et al. [234]	2019	Accelerometers	Ambient or controlled excitation	Resonant frequencies, mode shapes, modal damping	Large-scale (bridge)	Combined Particle Swarm Optimization and Cuckoo Search to address temperature variations in damage identification.
Kaveh and Zolghadr [235]	2017	N.A.	Ambient or controlled vibration (implied by modal analysis)	Modal data (natural frequencies, mode shapes)	Numerical models of structures (e.g., beam models); small to medium scale	Introduced a guided modal strain energy-based approach using the Tug-of-War Optimization algorithm.
Kim et al. [236]	2019	N.A.	N.A.	Natural frequencies and mode shapes	Numerical models of planar and space truss structures	Employed the Differential Evolution algorithm for damage detection in truss structures using reaction forces and singular value decomposition.
Alexandrino [237]	2020	Virtual stress sensors (BEM-based) at interior points	No physical excitation (quasi-static elastostatic simulation)	Mean stress at selected interior points	Laboratory-scale plate with hole (1 m × 1 m)	Used an MOGA integrated with neural networks
Camacho Navarro [238]	2019	Piezoelectric (PZT)	▪ Guided wave via 5-cycle, 80 kHz burst ▪ Guided wave excitation ▪ Guided wave excitation	▪ Guided wave signals / Cross-correlation analysis ▪ Guided wave signals / Cross-correlation analysis ▪ Guided wave signals / Cross-correlation analysis	▪ Small-scale lab structure ▪ Lab-scale aircraft component ▪ Lab-scale turbine blade	Modified the RAPID algorithm for damage localization using the normalized Q-index metric and elliptical distribution.
Das and Dhang [239]	2022	N.A.	N.A.	Natural frequencies and mode shapes (modal data)	Small-to-medium-scale numerical models (e.g., 31-bar and 47-bar planar trusses, 63-bar space truss, 25-bar space truss)	Introduced a multi-stage optimization method using IIRS for modal reduction and hybrid ITLBO-PSO, outperforming nine other algorithms.
Aval and Mohebian [240]	2021					Proposed MFIBO using modal force information for efficient damage detection.
Mishra et al. [241]	2020	Accelerometers	Ambient or free vibration (implied)	Natural frequencies and mode shapes (dynamic response)	Large-scale spatial truss structures (72-bar and 120-bar)	Evaluated 10 metaheuristic algorithms, finding TLBO to be superior in precision and computational cost.
Kahya et al. [242]	2022	N.A.	N.A.	Vibration characteristics (natural frequencies and mode shapes)	Beam scale (laminated composite beam, ~381 mm length)	Used the Harmony Search algorithm for damage detection in composite beams, suggesting improvements with algorithm hybridization or enhanced objective functions.
Le et al. [243]	2022	N.A.	N.A.	Modal strain energy (MSE), MAC	Plate scale (numerical model)	Introduced an improved approach using the MAC and COMAC for SHM.
Gomes and Giovani [244]	2022	N.A.	Numerical	Mode shapes and modal curvature (MSDBI), natural frequencies	Laminated composite plate (small-to-medium scale)	Used mode shape data and SFO in a two-step approach for damage detection in laminated composites.
Mohamadi et al. [245]	2022	N.A.	Numerical	Modal strain energy (MSE), static displacements, natural frequencies, mode shapes	Civil engineering structures: steel truss, steel frame, eight-story shear frame (small to mid-scale structural systems)	Utilized Moth-Flame Optimization for damage detection based on modal strain energy and static displacements.
Mei et al. [246]	2023	N.A.	Modal excitation (implied via simulation or dynamic loading)	Curvature mode shapes (first-order mode used	Small-scale models: steel pipe (1D beam elements)	Employed hybrid optimization approaches to enhance robustness in damage detection.

(continued on next page)

Table 8 (*continued*)

References	Year	Sensor type	Excitation method	Response type	Structure scale	Description
					and cantilever plate (2D plate elements)	
Entezami et al. [247]	2023	Uniaxial Accelerometers	Ambient vibration (traffic-induced, wind, environmental factors)	Acceleration time histories (vibration response)	Full-scale bridges (Z24 Bridge, Yonghe Bridge)	Utilized hybrid optimization methods for improved damage detection accuracy and robustness.
Meruane and Heylen [248]	2011	Tri-axial accelerometer	Excitation based on driving point residues (DPRs)	Modal response (global and local modes)	Laboratory-scale (3D space frame, 3 m × 0.5 m × 0.5 m)	Focused on hybrid optimization strategies for SHM.
Ding et al. [249]	2016	Not explicitly stated	Not explicitly stated	Natural frequencies only (no mode shapes)	Laboratory-scale (beam: 2.0 m × 25 mm × 19 mm)	Discussed hybrid optimization techniques for SHM.
Yang et al. [250]	2016	■ Laser vibrometer (OFV−503) ■ Laser vibrometer (OFV−503) ■ Eddy current displacement sensor	■ Harmonic excitation ■ Harmonic excitation ■ Operational excitation (rotating)	■ Mode shape (via Hilbert/FT) ■ Mode shape (via Hilbert/FT) ■ ODS (via Hilbert/FT)	■ Small-scale (cantilever beam) ■ Small-scale (blower wheel) ■ Small-scale (rotor shaft system)	Explored hybrid optimization strategies in SHM.
Cha and Buyukozturk [251]	2015	Not explicitly stated	Numerical modal analysis (FEM), simulated excitation	Incomplete mode shapes (global translational components in X and Y directions), natural frequencies	3D modular steel structures (four-story, irregular, asymmetric)	Employed hybrid optimization methods for enhanced SHM accuracy.
Tran-Ngoc et al. [252]	2021	N.A.	Free vibration (modal)	Natural frequencies, mode shapes	Plate and beam (lab-scale)	Combined GA with CS to address local minima issues in ANN training for faster convergence and higher accuracy.
Ho et al. [253]	2021	Accelerometer	Impact hammer (unidentified force)	Vibration (acceleration), modal data (frequencies and mode shapes)	Laboratory-scale beams (1 m steel beam), numerical models (simply supported beam, two-span continuous beam, free-free beam)	Proposed the MPA with FNNs for optimizing neural network learning processes.
Rautela and Gopalakrishnan [254]	2021	Ultrasonic guided waves	Ultrasonic excitation	Time-series and time-frequency (via wavelet transform)	Small-scale structures	Utilized CNN and RNN with ultrasonic guided waves for real-time damage detection.
Khatir et al. [255]	2021	N.A.	Frequency response function (FRF)	Frequency-based (FRF curves used to calculate damage indices)	Plate structure (functionally graded material (FGM) plates)	Improved neural network performance using the AOA for Functionally FGM plates.
Zar et al. [256]	2023	N.A.	Dynamic loading (simulated)	Modal parameters (natural frequency, mode shape), DEM (Dynamic Elastic Modulus)	Large-scale (arch dam)	Combined RBFNN with the JA for damage detection in arch dams.
Huang et al. [257]	2024	Acceleration sensors	Simulated vehicle moving load (experimental model); Field vibration tests (real bridge)	Vibration (acceleration) signals	Experimental model: three-span continuous beam (~22 m) Real-world case: steel truss bridge (main span ~59.2 m)	Introduced an ASAPSO-CNN for enhanced SHM accuracy.

classification in reinforced concrete elements, while Ahmadian et al. [285] explored the extreme gradient boosting (XGBoost) and stacking for enhancing SHM performance.

Karyofyllas and Giagopoulos [286] presented a condition monitoring (CM) framework using SVM models trained on data generated from numerical simulations of a multi-body dynamics (MBD) model. This approach demonstrated high accuracy and robustness in fault classification. Rakesh Katam et al. [287] combined natural frequencies with SVM for damage detection in cantilever steel beams, addressing limitations associated with using frequencies alone.

Studies presented in [267,270–287] collectively contribute to the advancement of machine learning-based SHM by addressing various challenges, exploring different data sources and machine learning techniques, and demonstrating practical applications in real-world structures. Future research should focus on further integrating physics-based models with machine learning, developing more robust and interpretable models, and addressing the challenges of data scarcity and variability in real-world scenarios.

3.2.2.2. Unsupervised methods. Unsupervised learning, a cornerstone of machine learning, has gained significant traction in SHM due to its ability to uncover hidden patterns within unlabeled data. Unlike supervised methods, which rely on explicitly labeled damage states, unsupervised techniques excel at identifying anomalies that may indicate structural degradation. Several benchmark structures have been employed to evaluate these methods [288].

Unsupervised learning, as outlined in [267], deals with unlabeled data, where the damage state is not explicitly identified. The algorithm seeks to uncover hidden patterns or relationships within the data, potentially enabling the identification of anomalies or deviations that could indicate damage. In this context, unsupervised damage detection is often based on discriminative modeling, where algorithms differentiate between normal and abnormal structural behaviors without requiring labeled inputs.

For example, Hou et al. [289] proposed an unsupervised graph anomaly detection method based on discriminative embedding similarity to identify slipping in viscoelastic sandwich cylindrical structures (VSCSs). The method learns normal data patterns by embedding adjacency and attribute matrices using graph attention networks and vision transformers. Anomalies are then detected by evaluating reconstruction errors and embedding similarity deviations. Experimental results under sinusoidal and random vibration excitations, using acceleration and eddy current sensors, demonstrate high detection accuracy without requiring labeled anomaly data. Similarly, Xiaoming et al. [290] introduced an unsupervised vision-based method for detecting and localizing structural anomalies using reverse knowledge distillation. A pretrained

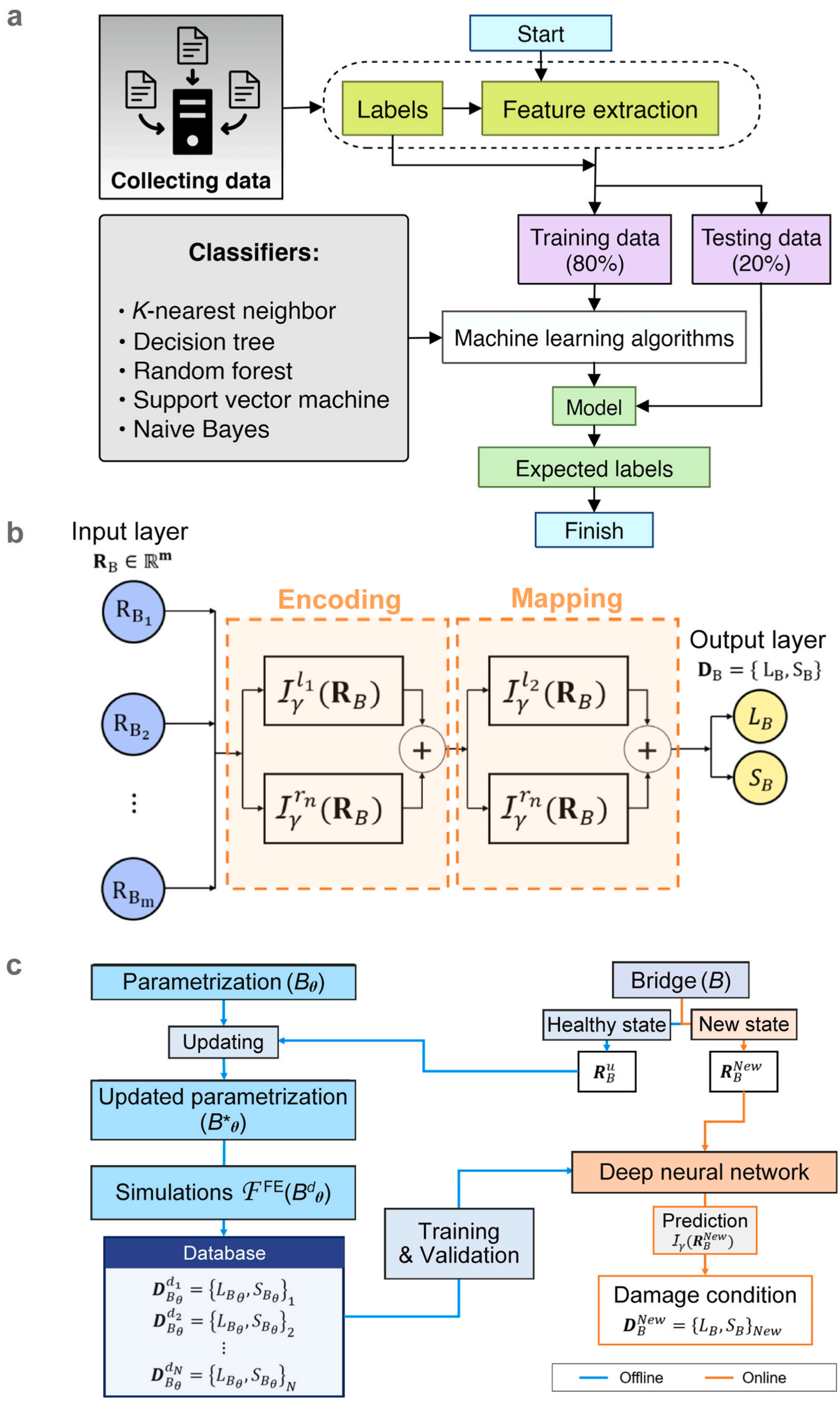

Fig. 6. (a) A supervised machine learning process (adapted from [273]). (b) A damage detection workflow using a deep neural network (adapted from [274]). (c) A neural network prediction model (adapted from [274]).

ResNet teacher guided a smaller student model to learn features of undamaged concrete structures from images without labeled data. Anomalies were identified by comparing features between the models. Deeper ResNet backbones, especially ResNet152, showed the best performance. The method removes the need for manual labeling but cannot yet quantify damage size or type.

Researchers have explored diverse approaches within this domain. Nick et al. [291] integrated modal parameters with artificial neural networks to accurately detect damage in steel frames. Hosseini Lavasani and Mahdipour [292] used decision trees and Bayesian optimization to identify damage in buildings, demonstrating robustness to noise. Whiteman et al. [293] successfully applied convolutional neural networks to predict damage states in reinforced concrete structures, even in the presence of noise. Bayane et al. [294] focused on real-time damage detection in bridges (Fig. 7b) using anomaly detection algorithms, showcasing the method's effectiveness in handling abrupt changes in structural behavior. Fig. 7a illustrates the seven-step process of anomaly detection algorithms. First, a loading event is detected. Second, measurements are recorded and reset. Third, the data is cleaned and prepared for feature extraction. Fourth, features are extracted. Fifth, the extracted feature is added to the feature matrix of similar past events, and the matrix is normalized. Sixth, an anomaly is detected using the chosen algorithm. Finally, decisions are made based on the anomaly detection results.

The scarcity of labeled damage data underscores the importance of unsupervised learning in SHM. To address this challenge, researchers have turned to autoencoder-based techniques. Silva et al. [295] employed stacked autoencoders to extract informative features from modal parameters. Spínola Neto et al. [296] conducted a comparative study of different autoencoder architectures, demonstrating the potential of these models for structural change identification. Feijóo et al. [297] applied autoencoders to offshore wind turbine foundations, achieving robust performance under varying operational conditions.

Deep learning has also made inroads into unsupervised SHM. Rastin et al. [298] utilized deep convolutional autoencoders to detect and quantify structural damage directly from raw vibration signals. Shang et al. [299] employed a deep convolutional denoising autoencoder to extract damage features resilient to noise and environmental variations. These studies highlight the potential of deep learning in capturing complex patterns within structural data. Future research should prioritize combining unsupervised methods with physics-based models to improve accuracy and make the decision-making process of these models more transparent. Additionally, exploring multi-sensor data and developing techniques to understand how these models make decisions are essential for advancing the field.

3.2.2.3. Semi-supervised methods. Semi-supervised learning offers a practical approach to damage detection by combining labeled and unlabeled data. While many semi-supervised techniques in SHM are based on discriminative models aiming to learn decision boundaries between structural states generative models have also proven effective. For instance, Bull et al. [300] proposed a semi-supervised classification method for structural health monitoring using Gaussian Mixture Models and Expectation Maximisation. It improves damage detection accuracy by combining labelled and unlabelled data, reducing the need for costly fully labelled datasets. Tested on simulated and experimental data, the method achieved around 3.8 % lower classification error than fully supervised approaches, even with only 2.5–3 % labelled data.

Fig. 8 shows semi-supervised learning, demonstrating how a model uses both labeled and unlabeled data to enhance its accuracy. Lai and Nagarajaiah [301] introduced a semi-supervised method for vibration-based damage detection by establishing a baseline undamaged model. This approach avoids the need for pre-labeled damage data. Building upon this, Dang et al. [302] proposed a framework combining graph neural networks and contrastive learning to effectively utilize both labeled and unlabeled data.

Composite structures present unique challenges in damage detection. Moradi et al. [303,304] developed a semi-supervised approach using acoustic emission data to construct health indicators. Their method effectively combines feature extraction, dimensionality reduction, and predictive modeling. Fig. 8 shows the utilized neural network structure, showcasing a multi-layer long short-term memory (LSTM) network proposed for feature fusion [303].

Huang and Burton [305] integrated supervised and semi-supervised learning for seismic damage assessment. By combining historical data with real-time information, they created a dynamic and adaptable framework. To further advance semi-supervised methods, future research should focus on developing innovative techniques that effectively exploit the potential of unlabeled data. This includes exploring new data fusion methods, improving model interpretability, and addressing challenges related to data quality and quantity.

3.2.2.4. Reinforcement methods. Reinforcement learning (RL) offers a unique approach to damage detection by framing the problem as a decision-making process. Unlike supervised learning, which relies on labeled data, RL agents learn to make optimal decisions through trial and error, maximizing rewards while interacting with the environment. Fig. 9 depicts reinforcement learning, where a model improves by engaging with its environment and adapting according to the rewards and penalties it receives.

Khazaeli and Goulet [307] pioneered the application of RL to SHM by formulating damage detection as an anomaly detection problem. They utilized Bayesian dynamic linear models to distinguish normal behavior from potential damage indicators, while RL optimized the decision-making process. Hake et al. [306] extended this concept by combining RL with imitation learning to detect damage in infrastructure. The system shown in Fig. 9a utilizes multiple sensors to detect damaged areas in port structures. It integrates sensor data and applies deep learning to identify these damaged regions. The method effectively distinguishes between structural changes caused by damage and those resulting from external factors. Fig. 9b provides an overview of the automated damage detection process, emphasizing the importance of accurate input models, point clouds, and the use of CNNs for feature extraction and damage identification.

RL's ability to optimize decision-making processes has attracted attention in various SHM applications. Cao et al. [308] addressed the challenges of multi-objective optimization in damage identification by combining RL with traditional optimization techniques. Huang [309] integrated RL with dilated CNNs and differential equation models to enhance the accuracy and reliability of SHM data analysis.

To further advance the field, future research should focus on developing hybrid RL approaches that combine the strengths of model-based and model-free methods. Additionally, exploring the application of RL in real-time damage detection and prognosis is crucial. Table 9 highlights references to machine learning methods that have already been presented.

■ Challenges and future trends

Machine learning techniques have contributed significantly to structural damage monitoring; however, several challenges remain. A major issue is the scarcity of labeled damage data, which complicates effective model training. Additionally, variations in environmental conditions and operational usage can lead to ambiguous results. Many deep learning models function as black boxes, making it difficult to interpret their decision-making processes, which may reduce engineers' confidence in their application.

Future research should focus on integrating machine learning with physics-based models to enhance reliability. Hybrid methods that combine data-driven and model-based approaches are particularly

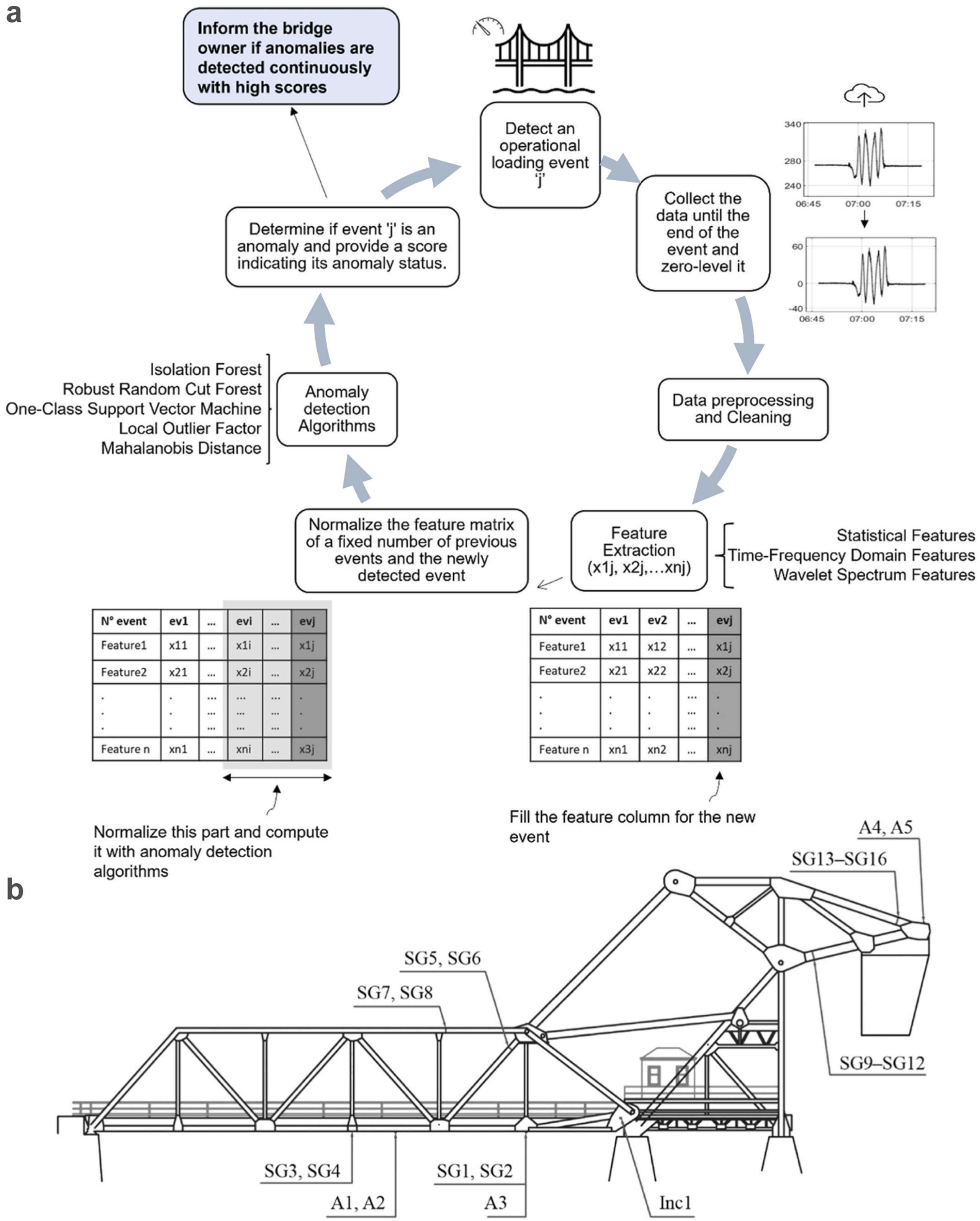

Fig. 7. (a) Seven-step anomaly detection process. (b) Real-time bridge damage detection. (adapted from [294]).

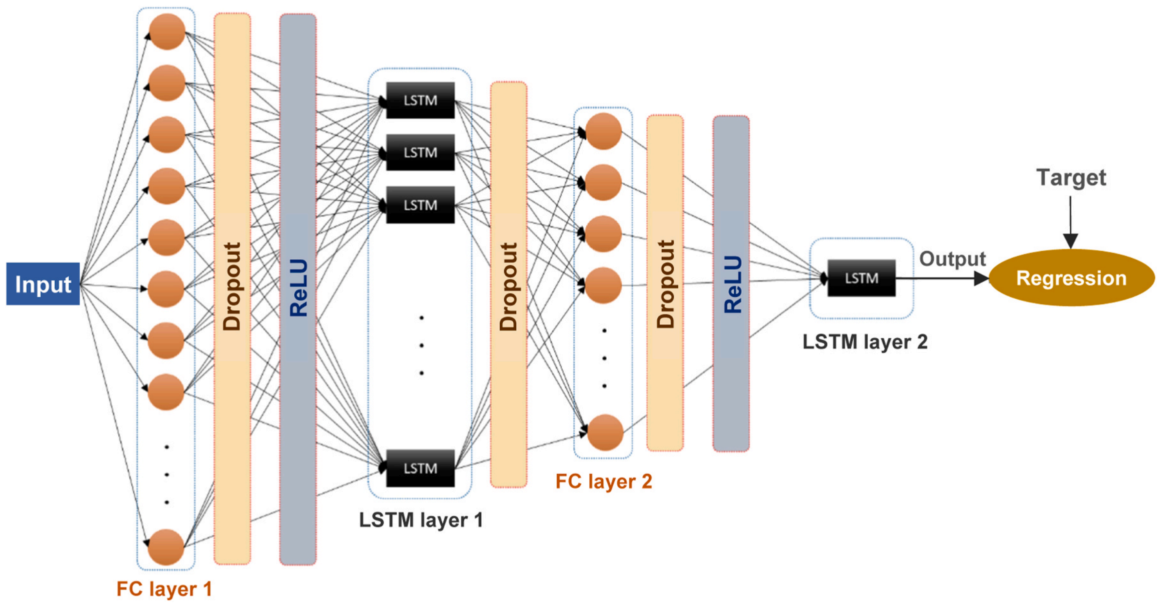

Fig. 8. A multi-layer LSTM network structure for feature fusion.
(adapted from [303]).

promising for improving accuracy and robustness. Employing techniques that require minimal labeled data, fusing information from multiple sensors, and incorporating reinforcement learning can also lead to more intelligent and adaptive monitoring systems.

3.3. Bayesian methods

Bayesian methods have emerged as powerful tools for SHM due to their ability to handle uncertainty and incorporate prior knowledge. By combining prior information with observed data, these methods provide probabilistic estimates of damage states, thereby enhancing decision-making under complex conditions.

Early studies focused on applying Bayesian methods to specific structural components and types of data. Yin et al. [310] demonstrated the effectiveness of Bayesian methods in conjunction with finite element model reduction for addressing high-dimensional problems. Hou et al. [311] explored Bayesian inference for damage detection using incomplete modal data. Zhang et al. [312] showcased the robustness of Bayesian approaches under challenging operational conditions.

Subsequent research expanded the application of Bayesian methods to more complex structural systems and data types. Xiang et al. [313] applied Bayesian stochastic subspace identification for damage detection. Barman et al. [314] integrated Bayesian data fusion with optimization techniques to improve efficiency and accuracy. Drangsfeldt and Avendaño-Valencia [315] incorporated hierarchical Bayesian models to enhance damage localization. Ásgrímsson et al. [316] introduced a novel hierarchical Bayesian model that incorporates spatial correlation of damage, improving the precision of damage detection. Kiran and Bansal [317] developed a multi-scale Bayesian approach for comprehensive damage assessment.

Despite these advancements, challenges such as computational efficiency and model complexity persist. Future research should focus on developing scalable Bayesian algorithms, exploring hybrid approaches with other machine learning techniques, and addressing the integration of Bayesian methods with real-time monitoring systems. Table 10 details Bayesian methods used in damage detection, outlining different approaches and their applications.

■ Challenges and future trends

Bayesian methods have demonstrated significant potential in the field of structural health monitoring, primarily due to their capacity to effectively manage uncertainty and incorporate prior knowledge to enhance damage detection. Despite these advantages, several challenges remain. Bayesian approaches are often computationally intensive and methodologically complex, particularly when applied to large-scale or intricately detailed structural systems. These computational demands limit their feasibility for real-time applications, as many existing Bayesian models struggle to deliver timely results under such constraints.

Future research should focus on creating more efficient Bayesian algorithms that can easily handle larger systems and work smoothly with live monitoring data. Combining Bayesian approaches with other machine learning methods could also improve the accuracy and reliability of damage detection. Another important direction is developing models that better capture how damage patterns relate across different parts of a structure and over time. Additionally, incorporating discriminative models which directly learn the boundary between damaged and undamaged states could enhance the interpretability and performance of Bayesian frameworks. Solving these challenges will make Bayesian methods more practical and trustworthy for real-world structural health monitoring.

3.4. Emerging learning strategies for enhanced damage detection in civil structures

While the main learning algorithms have been thoroughly reviewed, it would be valuable to briefly acknowledge emerging strategies that address ongoing challenges such as limited labeled data, environmental effects, real-time performance, and model generalization. This addition could offer a more forward-looking perspective and highlight promising directions for future research in vibration-based SHM.

Several recent studies have advanced SHM by proposing innovative unsupervised and semi-supervised machine learning techniques to detect damage in civil structures under variable Environmental And Operational (E/O) conditions. [318,319] used long- and short-term modal frequency data from the Z24 and Yonghe Bridges to validate their models. Although they applied different learning strategies, Entezami et al. [318] combining regularized Gaussian mixture model (RGMM) supported by nearest neighbor graphs (NNGs) called here

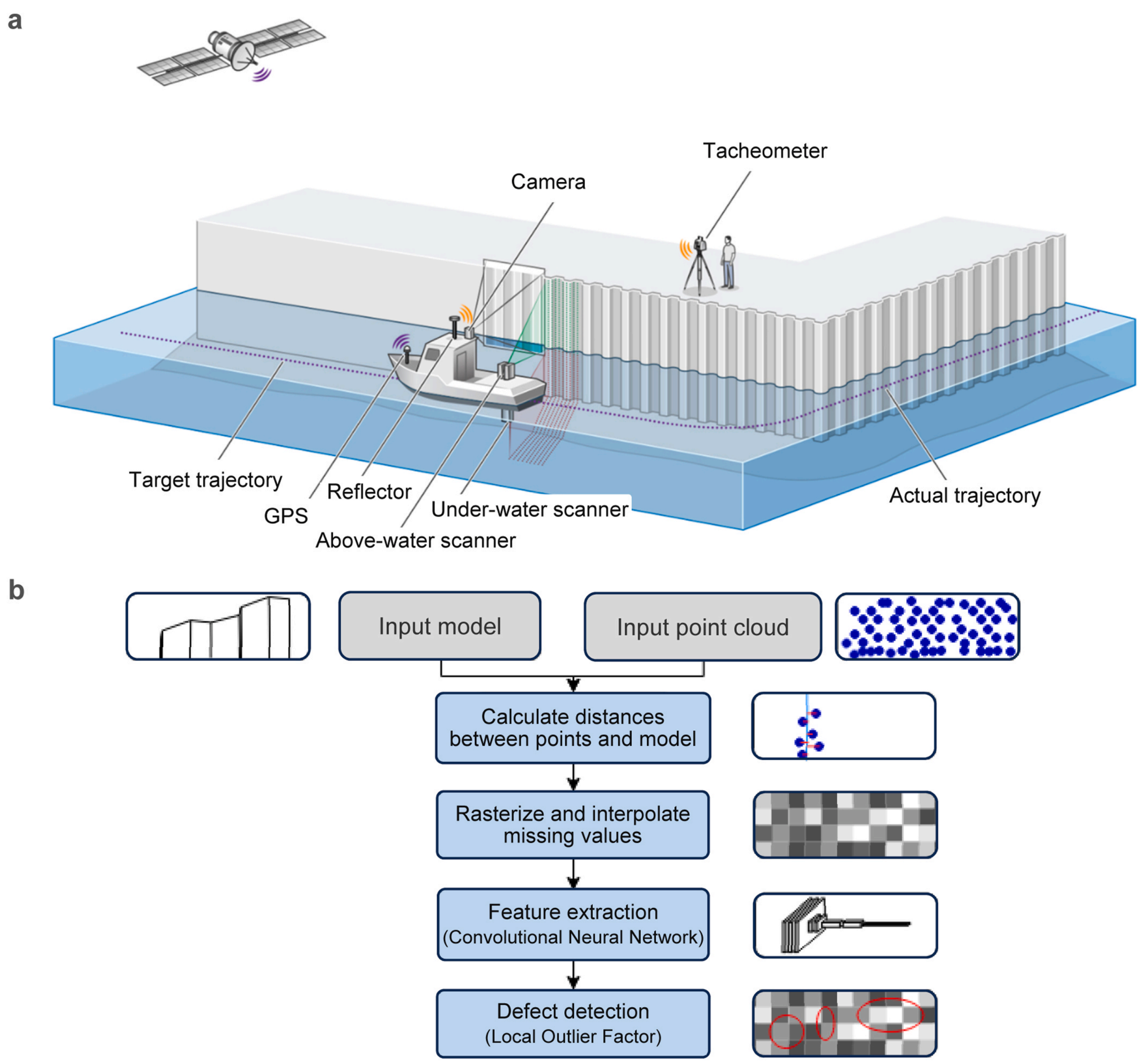

Fig. 9. (a) Multi-sensor system for port structure 3D mapping (adapted from [306]). (b) Flowchart of the automatic damage detection process (adapted from [306]).

RGMM-NNG clustering with non-parametric Reverse Gaussian mixture function (RGMF) anomaly detection, and Sarmadi et al. [319] using semi-parametric extreme value theory with probabilistic self-clustering, both achieved notable robustness against environmental effects without relying on pre-labeled data or fixed thresholds. These similarities in experimental setup and dataset choices highlight the growing trend toward generalized anomaly detection frameworks that prioritize adaptability and data-driven decision-making.

In comparison, the method proposed by Entezami et al. [320] introduced unsupervised meta-learning (UML) to further tackle E/O variability, missing data, and scalability challenges. Similar to [318, 319], Entezami et al. [320] also validated the performance using Z24 Bridge data, emphasizing modal frequency shifts due to temperature changes. What distinguishes [320] is its segmentation and subspace learning strategy using locally robust Mahalanobis distances, allowing for improved anomaly detection over time. A similar focus on modal features is seen in [321], where a hybrid Gaussian mixture models (GMMs) and discriminative reconstruction-based dictionary learning (DRDL), referred to as the GMM-DRDL method, isolated damage-induced changes from environmental noise, again highlighting a preference for modal data and well-known experimental benchmarks.

Expanding beyond bridges, Ghiasi et al. [322] addressed the domain of railway track monitoring by proposing an unsupervised domain adaptation (UDA) framework for detecting geometrical defects using drive-by vibration data collected from sensors mounted on high-speed trains. This approach differs by transferring knowledge across different railway lines without labeled data in the target domain, demonstrating improved detection accuracy and practical applicability in large-scale, real-world settings. Unlike the bridge-focused studies primarily using modal frequencies, Ghiasi et al. [322] incorporated multi-sensor fusion including accelerometers, GPS, lasers, and cameras, reflecting a more heterogeneous data environment but similarly emphasizing the need to overcome challenges from unlabeled, variable data.

[323,324] explored active learning and transfer learning strategies respectively to address the scarcity of labeled damage data. While Bull

Table 9
Summary of machine learning methods.

Reference	Year	Sensor type	Excitation method	Response type	Structure scale	Description
Chun et al. [267]	2020	Piezoelectric acceleration sensor (MODEL2304A)	Impact by dropping a 136.10 g rubber ball from 200 mm height	Acceleration (time-domain signal), natural frequency, standard deviation, decay rate	Laboratory-scale aluminum alloy I-beams (2 m long)	Supervised learning for predicting damage state using labeled data.
Entezami et al. [268]	2020	■ Acceleration ■ Acceleration	■ Uniform random load ■ Random vibration	■ Vertical acceleration time history ■ Acceleration time history (time-domain)	■ Numerical ■ Small-scale (laboratory)	■ A 5-m long simply supported beam modeled in ABAQUS using Euler–Bernoulli theory and Rayleigh damping ■ Aluminum frame tested under 17 structural states, including nonlinear breathing crack simulation
Goyal et al. [269]	2020	Non-contact vibration sensor (compared with an accelerometer)	Rotating machinery operation under various load conditions	Vibration signal (time-domain), features extracted via DWT and statistical methods	Component-level (bearing in rotating machines)	A low-cost, non-contact vibration sensor developed and tested for detecting various bearing defects using SVM-based fault classification.
Harsha et al. [270]	2023	N.A.	N.A.	Natural frequency (Hz)	Beam (structural element scale)	Supervised learning for damage location prediction using ANN and ANFIS.
Sarmadi and Entezami [271]	2021	Accelerometers	Electrodynamic shaker	Acceleration time history	Laboratory-scale (3-story frame)	Supervised and unsupervised learning for damage detection and validation.
Mariniello [272]	2021	Accelerometers	Vibration-based (ambient or simulated dynamic loading)	Modal properties: natural frequencies and mode shapes	Element level (down to single element), story level, joint level, hinge level	Supervised learning with decision tree ensembles (DTEs) for precise damage detection and localization in SHM.
Sousa et al. [273]	2023	Accelerometer (PCB 353B03)	Impact hammer (PCB 086CO3)	FRF, natural Frequency	Laboratory-scale cantilever beam (0.38 m length)	Supervised learning with DTEs for precise damage detection and localization in SHM.
Fernandez-Navamuel et al. [274]	2022	Uniaxial Force-Balance Accelerometer (permanent); Tri-axial 18-bit Strong Motion Recorder (ambient test)	Ambient vibrations (traffic and wind)	Vertical accelerations; dynamic response (eigenfrequencies and eigenmodes)	Full-scale bridge	Supervised deep learning with autoencoders for bridge damage identification using Finite Element simulations.
Sony et al. [275]	2022	Accelerometers	Shaker (band-limited white noise for QUGS; two shakers for Z24 bridge)	Acceleration	QUGS: Laboratory-scale grandstand (steel frame) Z24: Full-scale concrete bridge	Supervised learning with windowed LSTM for damage detection and localization in civil structures using vibration data.
Rautela et al. [276]	2021	Piezoelectric transducers	Ultrasonic guided waves (toneburst, 5-cycle)	Time-domain signal changes (amplitude and phase), statistical features (RMSD, correlation)	Laboratory-scale composite panel (500 ×500 ×2 mm)	Supervised learning with CNNs for damage detection and localization in composite panels using ultrasonic waves.
Jiang et al. [277]	2024	Smartphone camera (visual sensor)	Passive (natural lighting, ambient conditions)	Image data (pixel-level images)	Concrete structures such as bridges, pavements, campus roads, indoor corridors (meter scale, structural elements scale)	Supervised learning with CNNs for detecting and localizing concrete surface defects using visual elements and geotags.
Seventekidis and Giagopoulos [278]	2023	Accelerometer	Impact (along the x direction)	Acceleration time response	Lab-scale	Investigation of model error impact on damage identification accuracy using machine learning.
Ritto and Rochinha [279]	2021	Displacement sensors	Axial force at free end (10 kN)	Displacement (primary), can also include velocity, acceleration, or deformation	Slender bar (1D continuum), small-scale	Integration of physics-based models with machine learning frameworks within digital twin environments.
Farnod et al. [280]	2022	N.A.	Load (static force) applied at beam tip ($f = (0, -100$ kN))	Displacement field (simulated/measured)	Beam scale (cantilever beam, 1 m × 0.2 m)	Physics-based modeling framework combined with data-driven optimization to infer damage characteristics.
Qiao et al. [281]	2024	High-resolution remote sensing (HRRS) imagery	Earthquake (natural disaster – passive excitation)	Optical (RGB) imagery, interpreted via CNN/FCN outputs	Urban building scale (city-scale: Port-au-Prince, Haiti)	Supervised learning with FCN for rapid building damage assessment using pre- and post-disaster HRRS imagery.
Sepahvand [282]	2021	Not explicitly stated	Experimental modal analysis (e.g., impact hammer or shaker)	Natural frequencies (eigenfrequencies)	Component scale (fiber-reinforced composite samples)	Supervised learning with SVM for damage detection in structures with small

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Table 9 (*continued*)

Reference	Year	Sensor type	Excitation method	Response type	Structure scale	Description
						variations in natural frequencies.
Agarwal et al. [283]	2021	Accelerometers	Frequency-based excitation (10–110 Hz)	Transmissibility functions (TFs)	Small-scale (e.g., 8-DOF lab-scale models)	Supervised learning with deep CNN for damage detection, localization, and quantification using finite element model updating.
Dogan et al. [284]	2023	Camera (Imaging)	N.A.	Image of damage	Building elements (e.g., columns, beams, shear walls in RC buildings)	Supervised learning with deep transfer learning for damage classification of RC elements using labeled images.
Ahmadian et al. [285]	2024	▪ Accelerometers (including double-axis accelerometers) installed on cables, towers, bridge body spans ▪ Accelerometers (4 sensors per floor, oriented in the *x* and *y* directions)	▪ Natural ambient loads (traffic, wind, environmental effects) during normal operation; measured vibrations and structural responses ▪ Simulated gravitational load (floor slabs weight) + two sets of filtered excitations modeling environmental effects (filter cutoff 100 Hz)	▪ Acceleration signals (frequency, amplitude, energy) ▪ Acceleration time histories	▪ Full-scale real-world megastructure (510 m cable-stayed bridge) ▪ Laboratory-scale, 1:4 quarter-scale steel structure (3.6 m height)	Supervised learning with XGBoost and Stacking for enhanced damage detection and classification.
Karyofyllas and Giagopoulos [286]	2024	Uniaxial Accelerometers (Kistler 8640A10)	Rotating motion via electric drive motor	Acceleration (vibration) in the *x* and *y* directions	Lab-scale (CFRP transmission shaft)	Supervised learning with SVM for damage detection using data from numerical simulations of an MBD model.
Katam et al. [287]	2024	ADXL 335	Initial impact (free vibration)	Time series acceleration data → converted to frequency domain via FFT	Laboratory-scale (cantilever beam: 700 mm length)	Supervised learning with SVM combining frequencies and damage information for improved detection in cantilever steel beams.
Eltouny et al. [288]	2023	▪ Accelerometers; environmental sensors ▪ Accelerometers; environmental sensors ▪ Tri-axial MEMS Accelerometers ▪ Tri-axial Accelerometers ▪ Accelerometers ▪ Accelerometers	▪ Ambient (including environmental conditions) ▪ Ambient (traffic-induced and environmental) ▪ Ambient + event-based (traffic, mainly buses) ▪ Ambient (wind, highway vibrations) ▪ Controlled (shaker excitation) ▪ Controlled (bumper-induced nonlinearities, mass/stiffness variation)	▪ Acceleration; environment ▪ Acceleration; environment ▪ Acceleration ▪ Acceleration ▪ Acceleration ▪ Acceleration	▪ Full-scale (real bridge) ▪ Full-scale (real bridge) ▪ Full-scale (real bridge) ▪ Full-scale (real bridge) ▪ Lab-scale (simulator) ▪ Lab-scale (test frame)	Benchmark structures for unsupervised learning in SHM.
Hou et al. [289]	2024	Acceleration, Eddy Current	Vibration, Displacement	Viscoelastic sandwich cylindrical	N.A.	Three-layer composite with metal and silicon foam layers; slipping anomaly detection
Xiaoming et al. [290]	2024	N.A.	N.A.	Visual anomaly localization via feature similarity between models	Concrete structures (images at structural component scale, not full buildings)	Unsupervised anomaly detection using pretrained ResNet teacher and student decoder with image data. Detects damage from image features without labels.
Nick et al. [291]	2023	Vibration sensors (implied via modal analysis)	Ambient or experimental loading (e.g., applied load causing vibration)	Modal parameters (modal flexibility, modal strain energy)	Component scale (beam) and Structural scale (steel frame of industrial shed)	Unsupervised ANN for damage detection in steel frames.
Hosseini Lavasani and Mahdipour [292]	2023	Accelerometers	Ambient vibration (Gaussian white noise, 10 s signals)	Acceleration	Small-scale model (four-story steel braced-frame structure)	Decision trees and Bayesian optimization for unsupervised building damage detection.
Whiteman et al. [293]	2024	▪ Accelerometers ▪ Accelerometers	▪ White noise (WN) base excitation (numerical and experimental) ▪ Ambient microtremors (measured from California's Central Valley)	▪ Absolute acceleration (main), displacement ▪ Noisy acceleration	▪ Full-scale 5-story RC building ▪ Full-scale 5-story RC building	Unsupervised CNN for damage prediction in reinforced concrete structures.
Bayane et al. [294]	2024	▪ Strain gauges (SG1–SG16) ▪ Accelerometers (A1–A5) ▪ Inclinometer (Inc1) ▪ Weather station	▪ Operational loads (train passages, bridge motion) ▪ Operational loads (train passages, bridge motion) ▪ Operational loads (bridge	▪ Strain ▪ Acceleration ▪ Angular displacement/ incline ▪ Temperature, wind speed, etc.	▪ Full-scale (real bridge) ▪ Full-scale (real bridge) ▪ Full-scale (real bridge) ▪ Full-scale (real bridge)	Anomaly detection for real-time unsupervised bridge damage detection.

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Table 9 (*continued*)

Reference	Year	Sensor type	Excitation method	Response type	Structure scale	Description
			motion) ■ Environmental conditions			
Silva et al. [295]	2021	Accelerometers	Ambient vibration (passive)	Vibration response (acceleration); natural frequencies estimated	Full-scale civil structure (Z−24 Bridge)	Stacked autoencoders for unsupervised feature extraction from modal parameters.
Spínola Neto et al. [296]	2024	■ Accelerometer ■ Accelerometer ■ Accelerometer	■ Impact (pendulum) ■ Ambient vibration (wind, traffic, etc.) ■ Forced vibration	■ Acceleration ■ Acceleration ■ Acceleration	■ 2D Laboratory Frame ■ 3D Yellow Frame (4-story) ■ Z24 Bridge (real-scale)	Comparative study of autoencoder architectures for unsupervised structural change identification.
Feijóo et al. [297]	2021	Triaxial accelerometers (PIEZOTRONIC 356A17)	Inertial shaker with white noise signal (simulating environmental wind effect)	Vibration-response only (output-only data)	Scaled laboratory model (2.7 m high offshore wind turbine model)	Autoencoders for unsupervised damage detection in offshore wind turbine foundations.
Rastin et al. [298]	2021	■ Accelerometer ■ Accelerometer	■ Independent loading (y-dir) ■ 10 kN dynamic load	■ Acceleration ■ Acceleration	■ Small-scale (Lab) ■ Medium-scale (numerical model based on a real bridge)	Deep convolutional autoencoders for unsupervised damage detection/quantification.
Shang et al. [299]	2021	Accelerometers	Gaussian white noise (ambient excitation)	Acceleration responses	Numerical and experimental beam models (lab-scale)	Deep convolutional denoising autoencoder for unsupervised damage feature extraction.
Lai and Nagarajaiah [301]	2019	■ Accelerometers and strain gauges ■ Accelerometers ■ Accelerometers	■ Shake table (random excitation 0–50 Hz), impact hammer ■ Rail-mounted random base excitation (20–150 Hz), internal pounding ■ Real earthquake ground motion (Northridge)	■ Acceleration, force (impact), and strain ■ Acceleration ■ Acceleration	■ 3-story steel frame (HK PolyU) ■ Three-story aluminum frame (LANL) ■ Fire command and control (FCC) building (1994 Northridge EQ)	Semi-supervised method for vibration-based damage detection.
Dang et al. [302]	2023	Vibration sensors (16 total)	White noise loads at floor centers	Vibration signals (measured)	Medium-scale (4-story steel frame)	Graph neural networks and contrastive learning for semi-supervised SHM.
Moradi et al. [303]	2023	■ AE (acoustic emission) ■ DFOS (distributed fiber optic sensing) ■ FBGs (fiber Bragg gratings) ■ LWDS (Lamb wave detection system) ■ DIC (digital image correlation) ■ Camera	■ Passive (no external excitation; relies on internal damage events) ■ Passive (strain-based) ■ Passive (optical sensing) ■ Active (wave excitation and response) ■ Passive (optical, uses load-induced deformation) ■ Passive (visual monitoring)	AE hit features: amplitude, rise time, duration, energy, counts, and RMS ■ Full-field surface strain/displacement ■ Visual damage detection / crack propagation (qualitative)	■ Composite skin-stiffener panels (laboratory scale, aircraft-grade) ■ Composite skin-stiffener panels (not detailed) ■ Composite skin-stiffener panels (limited to 2019 campaign) ■ Composite skin-stiffener panels (2019 campaign only) ■ Composite skin-stiffener panels ■ Composite skin-stiffener panels	Semi-supervised approach for developing health indicators in composite structures.
Moradi et al. [304]	2023	Acoustic emission (AE)	Passive (no excitation; detects energy released from damage)	AE signals (statistical features of emitted stress waves)	Component level (composite panels with stiffener)	Principal component analysis for feature dimensionality reduction in health indicator development.
Huang and Burton [305]	2022	N.A.	Earthquake ground motion (PGV data interpolated from seismic recordings)	Damage state of pipe segments (damage/no damage classification)	Pipe network (distributed infrastructure system)	Combined supervised and semi-supervised learning for seismic damage assessment.
Khazaeli and Goulet [307]	2024	■ Inclinometers ■ Extensometers ■ Thermometers	■ Ambient loads (e.g., traffic, temperature changes) ■ Ambient loads (e.g., traffic, temperature) ■ Environmental temperature changes	■ Angular displacement (inclination) ■ Elongation (strain/displacement) ■ Temperature measurement	Bridge spans (large civil infrastructure)	RL for anomaly detection in structural responses.
Hake et al. [306]	2022	Terrestrial Laser Scanner (Z + F Imager 5016)	Passive (no active excitation; uses reflected laser light)	3D Point Cloud (converted to depth images)	Large-scale infrastructure (quay wall, bridges, high-rise buildings, tunnels)	RL and imitation learning for damage detection in infrastructure.
Cao et al. [308]	2023	Piezoelectric transducer	Frequency-sweeping voltage input	Admittance (harmonic response)	Segment-level (divided into multiple structural segments; small-scale damage detection)	RL for multi-objective optimization in structural damage identification.
Huang [309]	2024	N.A. (Pre-recorded data used)	N.A. (Not part of this numerical study)	SHM data anomalies (e.g., trend, drift, missing data, outliers)	Large-scale structure (long-span cable-stayed bridge)	RL with dilated CNNs and differential equation model for SHM data analysis.

Table 10
Summary of Bayesian methods.

References	Year	Sensor type	Excitation method	Response type	Structure scale	Description
Yin et al. [310]	2017	Accelerometers	Impact hammer	Modal parameters (natural frequencies, mode shapes)	Laboratory-scale steel frame (two-story bolt-connected)	Bayesian methods with finite element model reduction.
Hou et al. [311]	2021	Accelerometers (Bruel & Kjaer)	Instrumented hammer (impact excitation)	Vertical acceleration of beams and horizontal acceleration of columns	Small-scale experimental model (3-story steel frame, 0.5 m story height)	Bayesian methods for damage detection using incomplete modal data.
Zhang et al. [312]	2021	Accelerometers (5 V/g)	Ambient vibration, vehicle-induced, shaker, hammer	Acceleration (vertical)	Medium-scale (truss bridge), Small-scale (lab frame)	Bayesian methods for robust damage detection under challenging conditions.
Xiang et al. [313]	2024	Accelerometers	Operational vibration (ambient excitation)	Vibration data (acceleration)	Tower (offshore wind turbine)	Bayesian stochastic subspace identification for damage detection.
Barman et al. [314]	2021	N.A.	N.A.	Natural frequencies and mode shapes	Small-scale	Bayesian data fusion with optimization for damage detection.
Drangsfeldt and Avendaño-Valencia [315]	2024	Accelerometers	N.A.	Vibration response (used for DSFs)	Laboratory-scale wind turbine blade	Hierarchical Bayesian models for damage localization.
Ásgrímsson et al. [316]	2022	Accelerometers / Raw sensors	Ambient / Operational loads	Raw sensor data sequences / Reconstruction error	Bridge scale	Hierarchical Bayesian model for damage detection with spatial correlation.
Kiran and Bansal [317]	2024	Strain gauges (measured strains)	Dynamic excitation (natural vibration modes)	Strain mode shapes and natural frequencies	Structural system (2D truss, plate, FE model scale)	Multi-scale Bayesian approach for damage assessment.

et al. [323] used online probabilistic active learning evolving from one-class to multi-class classifiers validated on Z24 bridge data, Soleimani-Babakamali et al. [324] leveraged domain adaptation and contrastive learning to transfer damage detection knowledge from rotating machines to framed structures, achieving near-supervised accuracy without target labels. These methods underscore a shared focus

Table 11
4. Summary of emerging strategies and methods.

References	Year	Sensor type	Excitation method	Response type	Structure scale	Description
Entezami et al. [318]	2025	▪ Single-axis accelerometers ▪ Temperature and wind sensors	▪ Ambient (Operational) ▪ N.A.	▪ Modal frequencies ▪ Environmental data	▪ Full-scale bridges ▪ Full-scale bridges	▪ Z24 (concrete box girder bridge) and Yonghe (cable-stayed bridge); used for long-term SHM validation ▪ Used for capturing temperature and wind effects on bridge response
Sarmadi et al. [318]	2023	Accelerometers	Ambient (Operational)	Acceleration (used to extract modal frequencies)	Large-scale	Two large-scale structures: Z24 concrete box-girder bridge (Switzerland) and Yonghe cable-stayed bridge (China); used for validating anomaly detection.
Entezami et al. [320]	2023	Accelerometers	Ambient vibration (OMA)	Acceleration (Modal Frequencies)	Full-scale	Two full-scale bridges were monitored: the **Z24** concrete box-girder bridge (Switzerland) and the **KW51** steel arch railway bridge (Belgium). Long-term SHM was performed using unsupervised meta-learning to detect damage while managing environmental effects and missing data.
Daneshvar et al. [321]	2023	Accelerometers	Operational loads	▪ Modal frequencies ▪ Acceleration, Modal frequencies	▪ Medium-scale ▪ Large-scale	▪ A 58 m concrete box-girder bridge monitored long-term before demolition. ▪ A 260 m concrete cable-stayed bridge; short-term monitored after repairs and damage.
Ghiasi et al. [322]	2025	Accelerometers (carbody and bogie), GPS, cameras, lasers, and inertial sensors	Train in motion (drive-by loading)	Vertical and lateral accelerations of car body and bogie; track geometry measurements	Full-scale railway tracks	Sensors mounted on the IRIS 320 high-speed train to monitor geometric defects on 4 railway lines; acceleration data recorded at head, mid, and tail positions. TGMS was used for geometry.
Bull et al. [323]	2019	▪ Dynamic sensors (e.g., accelerometers), temperature sensors ▪ Acoustic emission sensors	▪ Ambient/ environmental loading (e.g., temperature changes) ▪ Cutting operation (metal turning process)	▪ Natural frequencies, temperature ▪ Acoustic emission signals	▪ Full-scale (real bridge) ▪ Laboratory-scale	▪ A full-scale concrete bridge in Switzerland was used for long-term SHM; damage was artificially introduced. ▪ Acoustic data from a tool-wear experiment in a turning process; tool condition assessed using 3D microscope images.
Soleimani-Babakamali et al. [324]	2025	Vibration sensors	Operational vibrations (torque in RM; natural/ environmental in structures)	Time-series vibration signals (converted to FFT features)	Laboratory-scale structures (YF and QUGS), rotating machine testbeds	Transfer learning between domains using vibration-based damage detection. Contrastive learning and domain adaptation map rotating machine fault features to structural damage cases.

on overcoming label scarcity and environmental variability with flexible, data-driven frameworks.

■ Challenges and future trends

Emerging learning strategies such as unsupervised, semi-supervised, and domain adaptation methods have shown strong potential in handling key challenges in structural health monitoring (SHM), especially under varying environmental and operational conditions. Recent studies on full-scale bridges and railway tracks demonstrate that these techniques can detect damage without relying on labeled data, using features like modal frequencies and multi-sensor inputs. However, challenges such as data variability, real-time processing demands, and the need for generalization across different structures remain.

Future research should focus on improving the scalability and efficiency of these methods, particularly in unsupervised and transfer learning settings. Developing hybrid models that combine the strengths of different learning approaches and incorporating discriminative models may enhance robustness and accuracy. Addressing label scarcity and ensuring stable performance in diverse conditions will be key to making these strategies more practical for large-scale, real-world SHM applications. Table 11

4. Summary of challenges, trends, and opportunities

Vibration-based SHM techniques offer powerful tools for detecting damage across a wide range of structures, but several critical challenges continue to hinder their practical implementation. A recurring issue across most methods whether they rely on mode shapes, natural frequencies, damping, FRFs, or statistical time series is the sensitivity of the results to environmental and operational variations, such as temperature changes or fluctuating loads. Additionally, the need for high sensor density and high-quality measurements often imposes cost and logistical constraints, especially in large-scale or complex systems like bridges or towers. Many advanced techniques, including FEM updating and signal processing methods, struggle with noisy or incomplete data, and often require prior baseline information, which is not always available in real-world deployments. Furthermore, while ML and optimization methods have significantly enhanced SHM capabilities, they introduce their own limitations, such as the need for large, labeled datasets, high computational costs, and challenges in interpretability and generalization.

To overcome these limitations, future research is expected to move toward hybrid approaches that combine data-driven techniques with physics-based modeling. This includes the integration of AI tools (e.g., deep learning, reinforcement learning) with traditional vibration analysis and FEM updating to improve both robustness and interpretability. Moreover, real-time monitoring capabilities will benefit from advances in edge computing, sensor technologies, and efficient algorithms capable of operating under resource-constrained conditions. Bayesian inference and domain adaptation methods also show promise in addressing uncertainty and variability without relying on labeled data. Ultimately, a key direction for future work is the development of scalable, adaptive, and explainable SHM frameworks that are resilient to real-world complexities. Interdisciplinary collaboration linking civil engineering, data science, and materials engineering will be essential for translating theoretical advances into field-ready solutions.

5. Conclusions

This study reviewed the latest advancements in vibration-based structural health monitoring by evaluating various damage detection methods and approaches. The techniques discussed—including modal parameter-based methods, frequency response functions, signal processing, finite element model updating, optimization, statistical time series methods, machine learning, and Bayesian methods—reveal several key themes and challenges.

A notable trend across the reviewed methods is the integration of machine learning, novel optimization methods, and hybrid approaches. These advancements collectively enhance the accuracy and efficiency of damage detection systems. However, common challenges persist, such as noise sensitivity, environmental influences, and computational complexities. For example, modal parameter-based methods struggle with noise and model discrepancies, while frequency response functions and signal processing methods face issues related to measurement accuracy and handling random excitations.

The reviewed methods have significantly improved SHM capabilities by offering enhanced damage detection accuracy, non-destructive monitoring options, and broader applicability across various structures and materials. Techniques like finite element model updating and optimization have provided more accurate structural health assessments and efficient damage detection. Machine learning methods have further revolutionized the field by improving reliability and enabling advanced data analysis techniques.

Future research should focus on addressing these challenges to advance SHM technologies. For modal parameter-based methods, integrating advanced damping models and machine learning could help mitigate noise sensitivity and improve environmental compensation. Frequency response function methods could benefit from advanced algorithms and better damage detection in noisy environments. Signal processing methods should explore combining multiple techniques and improving noise management. In finite element model updating, incorporating AI and hybrid approaches could enhance real-time applications and scalability. Optimization methods could be refined to focus on noise reduction and real-time processing with advanced neural networks. Statistical time series methods and machine learning approaches should continue to enhance robustness and accuracy, particularly by integrating with physics-based models and exploring new methods for unlabeled data and decision transparency.

Overall, the integration of robust optimization algorithms, advanced neural network architectures, and hybrid techniques is expected to drive significant improvements in SHM. Continued research in these areas will be crucial for overcoming current limitations and advancing the reliability and effectiveness of SHM systems.

CRediT authorship contribution statement

Saeed Khodadoost: Visualization, Methodology, Formal analysis, Writing – original draft, Validation, Investigation, Conceptualization. **Behnaz Nouhi:** Writing – original draft, Formal analysis, Investigation. **Siamak Talatahari:** Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis. **Pooya Sareh:** Writing – review & editing, Visualization, Supervision, Investigation, Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

No data was used for the research described in the article.

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