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Review

Operational Modal Analysis on Bridges: A Comprehensive Review

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Abstract: Structural health monitoring systems have been employed throughout history to assess the structural responses of bridges to both natural and man-made hazards. Continuous monitoring of the integrity and analysis of the dynamic characteristics of bridges offers a solution to the limitations of visual inspection approaches and is of paramount importance for ensuring long-term safety. This review article provides a thorough, straightforward examination of the complete process for performing operational modal analysis on bridges, covering everything from data collection and preprocessing to the application of numerous modal identification techniques in both the time and frequency domains. It also incorporates advanced methods to address and overcome challenges encountered in previous approaches. The paper is distinguished by its thorough examination of various methodologies, highlighting their specific advantages and disadvantages, and providing concrete illustrations of their implementation in practical settings.

Keywords: operational modal analysis (OMA); bridge monitoring; structural health monitoring (SHM); damage detection; dynamic analysis; modal identification techniques; artificial intelligence (AI); machine learning

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1. Introduction

Infrastructures have undergone continuous improvement over time due to their critical functions and societal significance. Building, maintaining, monitoring, and reconstructing the structures have posed challenges to technicians [1]. Throughout history, a fundamental concern has been the pursuit of more effective safety measurements. It became increasingly crucial to identify, evaluate, and address potential risks, degradation, or collapse as the structures age and deteriorate and to thoroughly assess the financial and logistical aspects of rectifying structural deficiencies [2,3].

Continuous monitoring of bridge health, particularly in areas prone to natural disasters such as Japan [4], has led to the development of bridge management systems (BMSs), the integration of bridge monitoring within a centralized framework [5–9]. Increasing safety, reducing redundant costs, and enhancing management efficiency can be achieved through the implementation of BMSs.

Traditional bridge monitoring methods are based on physical inspections, which inherently possess limitations. They are time-consuming, laborious, and potentially unreliable [10]. Moreover, any delayed action or neglect of maintenance might lead to considerable future costs, specifically for structures with special importance [11]. To overcome these shortcomings, bridge structural health monitoring (BSHM) techniques have been employed, using both static and dynamic approaches. Dynamic monitoring has gained significant attention thanks to advancements in data acquisition technology, the increased accessibility of sensors, cost efficiency, and ease of installation. Additionally, concerns regarding data storage and sensor longevity have been mitigated by technological progress. Improvements in signal processing and data manipulation methods have also contributed. Through the use of sensing technologies, data acquisition systems, and analysis techniques, structural responses can be monitored, anomalies can be detected, and health statuses can be assessed through dynamic analysis.

Moreover, recently, due to the emergence and integration of advanced technologies, specifically machine learning (ML) methods [12], BSHM has undergone an evolution. Data collection, analysis, and visualization have been made easier, leading to a significant improvement in monitoring capabilities, accuracy, and efficiency. Bridge monitoring is expected to continue evolving, as these technologies are advanced, enabling more proactive and sustainable approaches to bridge maintenance and management.

Damage is regarded as a systematic alteration from an initial state that adversely affects the system's behavior. Bridge damage is often categorized in a vertical hierarchy that must be correctly followed to reach a precise estimation [12]. The most commonly used strategy was proposed by Rytter [13].

As illustrated in Figure 1, structural damage can be classified into five stages, each associated with a question. It begins with estimating the presence, advances to determining the location, type, and severity of the damage, and ultimately predicting the susceptible zone in the structure that is likely to be affected. These steps exhibit a significant interdependence; for instance, an erroneous procedure in determining the presence or localization of structural damage may result in imprecise quantification of damage severity, consequently leading to inaccurate prognostication [13].

To follow the hierarchy represented in Figure 1, the bridge's structural behavior should be first assessed through static or dynamic approaches. From a static point of view, the focus is on assessing the bridge's structural stability and load capacity. In this regard, to determine any potential weaknesses or anomalies, parameters such as strain, displacement, and stress distribution are measured. However, incorporating such hierarchical approaches within the context of dynamic analysis allows us not only to evaluate the structural dynamic behavior under varying loads and conditions, but also to identify and assess any potential damage that may occur during the bridge's operational lifespan.

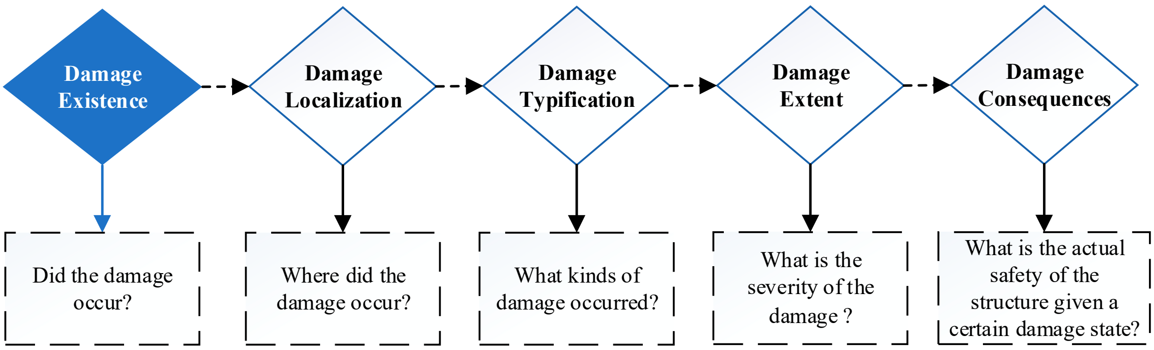

Figure 1. Damage hierarchy.

Similar to its static counterpart, dynamic analysis of structures is categorized into short- and long-term evaluations. Short-term assessment involves analyzing structural behavior during or after specific events, such as earthquakes, load testing of bridges, ambient responses to live loads, etc. On the other hand, long-term evaluation is an ongoing, periodic process that entails continuously observing and assessing the structural behavior of a bridge. This aims to identify any deviations or deterioration that may necessitate maintenance or repair, typically involving a combination of data collection, analysis, and reporting [14].

Figure 2 depicts an overview of the procedural stages required for dynamic BSHM. The initial phase involves determining the appropriate number and types of sensors for capturing relevant data. Decisions are made regarding the strategic placement of the sensors to ensure reliable and precise results. Once the sensors are in place, data collection commences, involving the continuous recording of information related to the structural behavior, including vibration, strain, temperature, and other. Subsequently, the collected data undergoes processing and transformation into a usable format. In the following step, analytical methods such as signal processing and statistical techniques are applied to comprehend the structure's dynamic behavior by determining dynamic parameters. Information management encompasses the storage, organization, and clear presentation of the analyzed data to facilitate decision-making. In the structural health examination step, the computed dynamic parameters are employed to determine the potential damage type, pinpoint its location, and assess severity. This involves comparing the current dynamic behavior with the initial state of the structure to identify any deviations. In the decision-making stage, informed decisions are made regarding the structural health, necessitating assessments of whether maintenance, repair, or further investigation is necessary. If structural deficiencies are identified, examination and repair procedures are implemented to address any detected damage, ensuring structural safety and longevity [12].

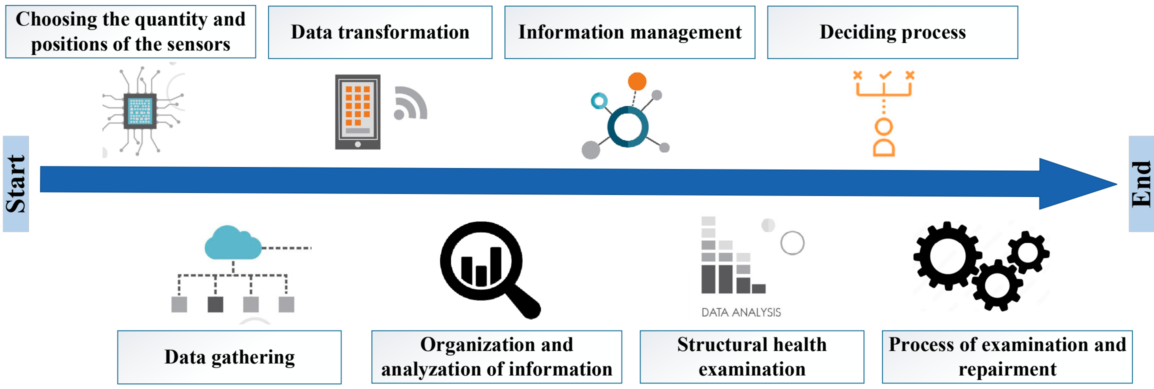

Figure 2. Overview of the structural dynamic monitoring steps [12].

Figure 3 is the schematic representation illustrating the constituent parts of the present review paper. It provides a comprehensive overview of operational modal analysis (OMA), encompassing the entire process from acquiring structural data to their utilization in BSHM applications. The paper starts by discussing the instrumentation and data acquisition system (Section 2), followed by a data preprocessing step, which involves the elimination of undesired frequencies and artifacts, as well as discussing synchronization (Section 3). Section 4 focuses on modal identification techniques in time and frequency domains, while Section 5 describes postprocessing methods, using identified modal parameters to detect any potential damage over time. Finally, Sections 6–8 explore advanced techniques aimed at improving and compensating for the limitations of previous methods, thereby advancing capabilities in bridge health assessment.

This review paper provides a comprehensive overview of the entire process involved in performing OMA on bridges. It encompasses various steps, including data acquisition and preprocessing, the application of diverse modal identification techniques in both time and frequency domains, and postprocessing. Additionally, advanced methodologies are integrated to address and overcome limitations observed in earlier approaches. The paper provides information about each methodology, emphasizing their specific merits and limitations, and offers concrete examples of their implementation in real-world scenarios. What distinguishes this paper is its extensive coverage of research in the field, making it one of the most thorough literature reviews available.

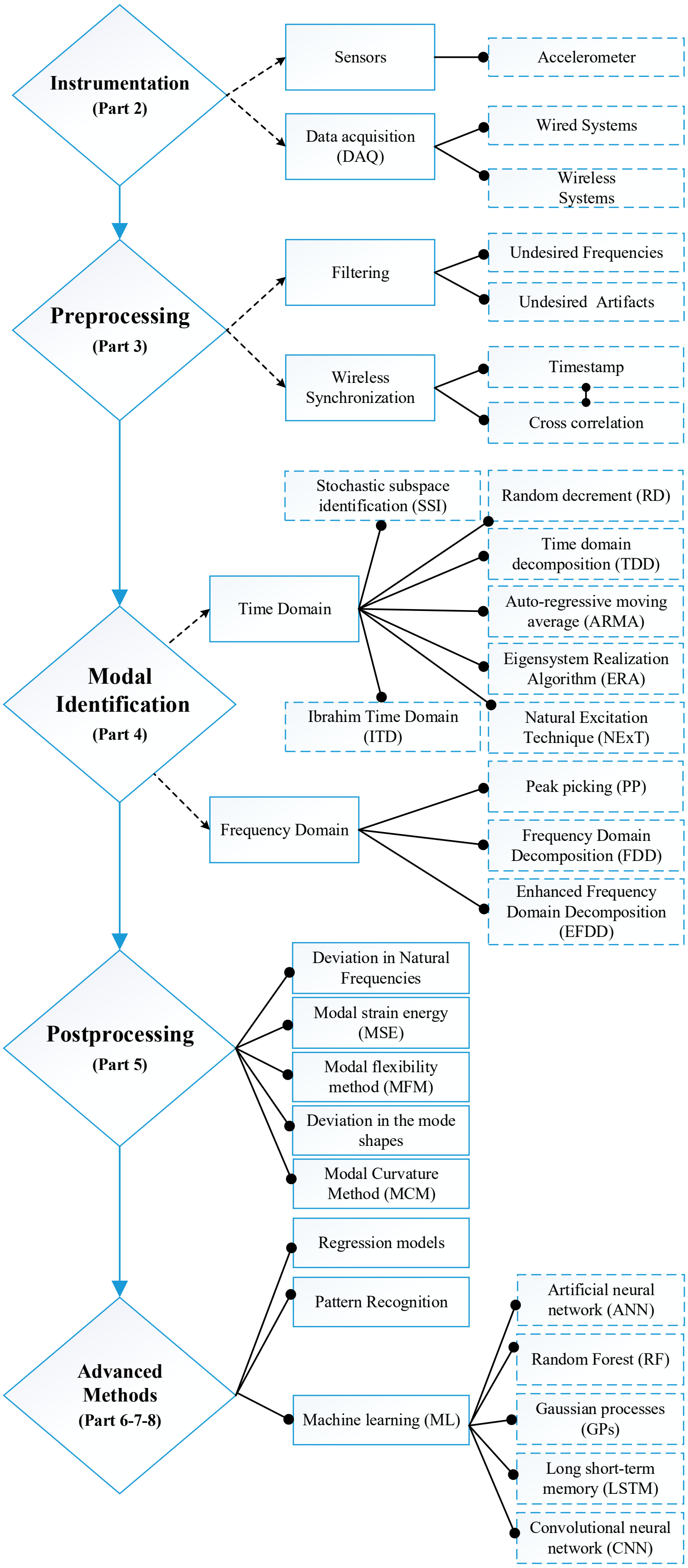

Figure 3. Overview of the sections in the paper.

Figure 4 illustrates the contributing papers that were used in the compilation of this review article based on their publication years, 1990 to 2023. The depicted growth in the publications over the recent years can be attributed to several factors, such as the advancements in data acquisition technology, which enhance the applicability and accuracy of OMA on bridges. The increased accessibility of sensors, coupled with improvements in cost efficiency and ease of installation, has further fueled this. Moreover, technological progress has addressed concerns related to data storage and sensor longevity, contributing to a more robust and sustainable OMA framework. Additionally, the evolution of signal processing methods has significantly correlated to the positive trends observed in the graph.

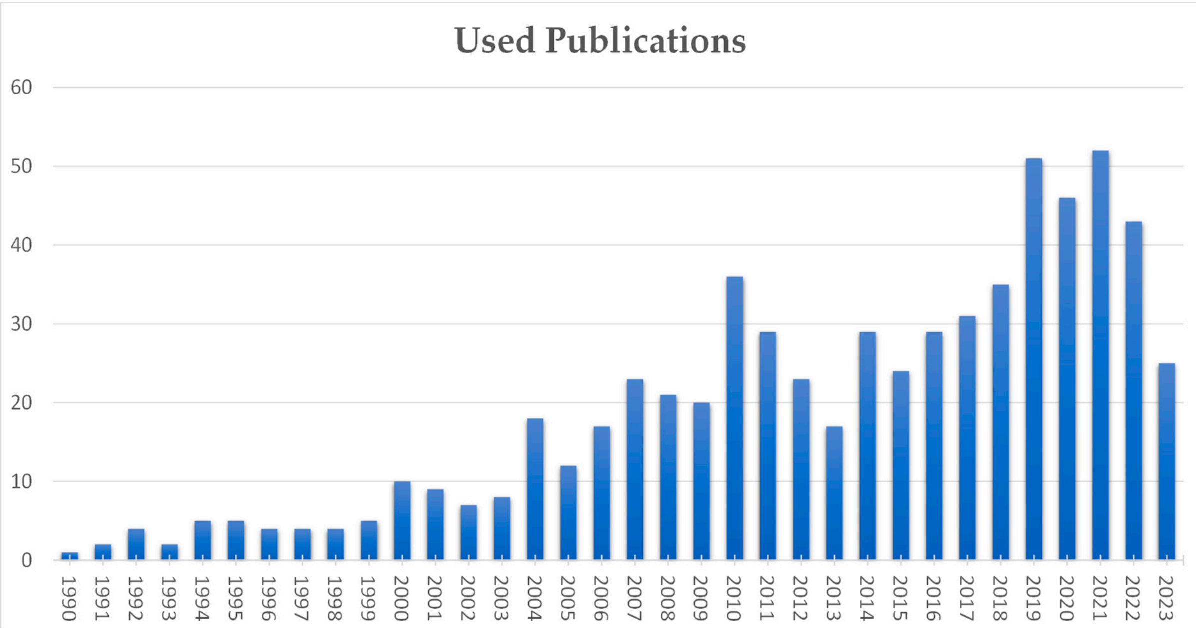

Figure 4. Contribution of the papers in this study.

2. Instrumentation

To evaluate the dynamic behavior of structures, instrumentation plays a vital role in gathering data. It comprises a network of sensors that capture data through a data acquisition component [15]. They can be collected by strategically positioning sensors along the bridge, including strain gauges (SGs) [16], displacement [17], velocity transducers [18], and accelerometers [19]. On the other hand, understanding the impact of environmental changes on bridge behavior necessitates the adoption of environmental sensors such as temperature [20], humidity [21], etc.

The primary step in planning dynamic measurements involves selecting the precise location and direction of the sensors and determining the total number of measurements. This choice can rely on experience or be based on computational simulations, utilizing finite element models (FEMs). Alternatively, it may be based on predictions of the dynamic response derived from simple beam, plate, or shell theories. Regardless of the measurement type, each transducer should possess sufficient sensitivity to detect the expected operating signals. In cases where transducers must be placed in noisy areas with poorly understood sources of vibration, or when the test is expensive or impractical to repeat, it may be necessary to use redundant adjacent transducers with different sensitivities. This precaution ensures the achievement of the desired test data even if some transducers fail. Additionally, an important consideration is to maintain a sufficiently large channel count to provide a suitable background for robust identification processes [14].

Sensing systems are divided into two categories: wired and wireless. In terms of data transition, wired sensors employ physical cables [22], while wireless sensors rely on radio frequencies or Bluetooth [23]. Although wireless sensing systems offer numerous advantages over their wired counterparts, including easy installation, flexibility for relocation, remote monitoring, and cost efficiency, they also encounter a distinct set of challenges. Wireless sensors utilize batteries as their power source. The limited energy supply from batteries poses a constraint for wireless transmissions. Moreover, wireless data transmission exhibits lower reliability compared to wired systems, resulting in relatively lower data transfer rates for wireless systems. Moreover, in wireless systems, synchronizing the data recorded by various channels is more intricate compared to cable-based systems that employ a central system clock housed at the data server [24]. To overcome transmission delays and propagation [25], various techniques, such as time-stamp estimation and correlation functions, are employed, which will be discussed later in this paper.

2.1. Accelerometers

An accelerometer is used to measure linear acceleration, from monitoring seismic activity to detecting system freefall. In OMA, the dynamic response is mainly recorded via accelerometers, which are mainly classified into these types: piezoelectric [26], piezoresistive [27], and microelectromechanical system (MEMS) accelerometers [28,29]. As a result of technological advancements in MEMS accelerometers, their application has proliferated. MEMSs are an appropriate alternative to other accelerometers due to their low power consumption, high sensitivity, affordability, and sufficient sampling frequency.

2.2. Data Acquisition (DAQ)

Before dynamic analysis techniques can be used to evaluate recorded data, the analogue signals generated by sensors must be converted into digital form using analogue-to-digital converters (ADCs). The performance of the ADC is generally determined by the number of bits available in its internal processor [14]. The market offers a variety of data acquisition systems, each distinguished by their own attributes, configurations, and pricing levels. Selecting appropriate DAQ systems becomes complex when factors beyond budget constraints come into play.

3. Preprocessing of the Data

To improve data quality, raw data must undergo preprocessing to eliminate noise and artifacts before extracting dynamic characteristics. Filtering techniques, such as low-pass, high-pass, bandpass, or decimation, are employed to eliminate undesired frequencies, thereby increasing the signal-to-noise ratio by enhancing the frequency range of interest. Additionally, a detrending filter is used to remove or reduce the impact of low-frequency trends or drifts in the data. Furthermore, external interference and errors in measurement may cause artifacts in data acquisition. In this regard, techniques such as signal interpolation, outlier detection, and data smoothing are employed [24].

On the other hand, while dealing with multiple sensors, to achieve accurate dynamic characteristics, specifically mode shapes [30], precise data alignment and synchronization are necessary. When dealing with wireless and wired sensing systems, several factors should be considered. The recorded data from wired sensors can be directly managed and synchronized due to their physically cabled connection to a centralized DAQ system, providing precise timing. In contrast, achieving synchronization for data recorded by multiple sensors is intricate in wireless connections, due to their inherent nature. Consequently, time-stamp estimation and cross-correlation functions are utilized to evaluate propagation and adjust the transmission delays [31,32]. Nevertheless, it is important to highlight that when utilizing the timing synchronization function (TSF), which depends on a dedicated timer managed by the network access point (i.e., the router) for time-stamp estimation, a slight timing error of one millisecond may arise during the data alignment process. This minor misalignment is unlikely to result in significant complications in the modal identification results.

4. Dynamic Analysis of the Bridge

To evaluate the long-term structural behavior of the bridge, dynamic characteristics, including natural frequencies, mode shapes, and damping ratios, are monitored over time. This procedure involves the application of modal identification methods, as explained in Section 4.1.

4.1. Modal Identification Methods

Experimental modal analysis (EMA) and operational modal analysis (OMA) are two widely employed approaches for modal identification. The application of EMA [33–35] includes applying controlled input excitations with predetermined force magnitudes at specified frequencies, which yields the advantage of mitigating undesired sources of noise in the recorded structural responses. Moreover, applied loading can be adjusted to align with the specific testing criteria. With regard to bridges, vibration excitation can be achieved through eccentric rotating mass vibrators or an impulsive shaker [35]. On the other hand, OMA [36–44], also known as output-only modal analysis, ambient modal identification, or in-operation modal analysis, relies on vibration data collected while the structure is under its operational state. OMA becomes practical when the structure's size prohibits artificial excitation or when the system cannot undergo a complete interruption in operation. OMA relies only on response data since the excitation sources are not known. One of the advantages of OMA over prior methods is its independence from input excitation. This makes it valuable when the structure is subjected to random excitation from the ambient environment, such as occurs with bridges. Furthermore, OMA can be used for real-time monitoring of a structure while it is in use. In addition, bridges, towers, and high-rise buildings that pose accessibility or cost challenges can be monitored with OMA [14].

There are other non-destructive tests (NDTs) in addition to visual inspection that have been used for bridge inspection, such as ultrasonic testing (UT), radiographic testing (RT), magnetic particle testing (MPT), eddy current testing (ECT), etc. [45,46]. OMA offers several advantages over other NDT methods, including its ability to provide a comprehensive assessment by identifying both the overall dynamic characteristics of the entire structure and specific localized issues. Its non-intrusive and non-destructive nature is crucial for preventing damage or disturbance to the bridge's natural vibration modes. Moreover, its real-time data acquisition capabilities enable the detection of structural damage at an early stage, before it becomes visible or causes significant problems. OMA is also cost-effective and enhances safety in the inspection process.

In modal identification, a significant challenge lies in the demand for computational power and efficiency. This is more obvious when processing hundreds of output data points at the same time. OMA emerged as an important topic in the late 1980s, especially along with the evolution of computational technologies [47]. Considerable progress in OMA has been made since the early 1990s [24].

Two main techniques are used for modal analysis in OMA: the frequency domain and the time domain. In the time domain, the emphasis is on observing the structural reaction over a period of time, revealing short-term behaviors and temporal phenomena. On the other hand, in the frequency domain, time-domain data is translated into frequency components using techniques such as Fourier transform, which allows natural frequencies, mode shapes, and damping ratios to be identified [24].

4.2. Frequency Domain Analysis

The frequency domain offers a wider range of applications compared to time-domain techniques, primarily due to the inherent stability of structural characteristics in this domain [14]. While in the time domain, the focus is on free responses that manifest throughout the entire considered time duration; in the frequency domain, each mode exhibits prominence within a limited frequency band, leading to the presence of a "natural modal decomposition". This decomposition emerges from the consideration of distinct frequency bands where individual modes exert dominance [24].

There are three main modal identification methods in the frequency domain for BSHM: peak picking (PP), frequency domain decomposition (FDD), and enhanced frequency domain decomposition (EFDD).

4.2.1. Peak Picking (PP)

PP stands as the first OMA technique that enabled the evaluation of structural behavior using frequency spectra [48–53]. In this method, the identification process of natural frequencies is based on detecting the peaks within the power spectrum plot. This method is practical when structural modes are well separated and damping is minimal. While the employment of the method is straightforward, it may yield misleading results when closely spaced modes occur [54]. However, during the modal analysis considering real and complex structures such as a bridge, closely spaced modes are invariably present [55]. To address this limitation, a frequency domain technique known as frequency domain decomposition (FDD) was introduced, which will be described here later. The PP method was adopted as a modal identification technique for assessing the dynamic characteristics of the Z24 Bridge, a reinforced concrete bridge in Switzerland, by Peeter et al. [55]. They evaluated the effectiveness of PP in comparison with other modal analysis techniques used by participating laboratories. Guo et al. [56] used this method to analyze the dynamic responses of the Xihoumen Bridge in China under various wind conditions, such as typhoons and regular winds, and they also compared the PP results with time-domain methods. Furthermore, Zong et al. [49] employed PP in the dynamic analysis of concrete-filled steel tubular (CFST) half-through arch bridges to determine the natural frequencies, while Feng et al. [57] utilized PP for the modal extraction of two instrumented highway bridges. The application of the PP technique is emphasized in the aforementioned research [58–68].

4.2.2. Frequency Domain Decomposition (FDD)

FDD was introduced as an extension of PP based on singular value decomposition (SVD) to make the power spectral density (PSD) matrix out of the response spectra matrix. This method was enhanced by Brinker et al. [69] in 2000, which led to the current FDD method. FDD is a widely accepted method capable of handling closely spaced modes, nonlinear systems, and nonstationary signals [14]. It is considered nonparametric since it does not require previously known mathematical models to identify the modal parameters. In this method, while natural frequencies are the singular values obtained from the PSD matrix, mode shapes are estimated using singular vectors [24]. The main drawbacks of using the FDD method are the accuracy of the natural frequencies, which are limited by the resolution of the FFT, and its inability to accurately calculate the damping ratio of the structure. Malekjafarian et al. [70] and Elhattab et al. [71] used FDD to identify the mode shapes of a bridge from vehicle-induced dynamic response signals. To investigate the truck effects on the natural frequencies and mode shapes of a post-tensioned concrete box girder bridge, Akköse et al. [72] employed FDD. Brincker et al. [73] applied FDD as modal identification, utilizing a spectral density matrix transformed into single-degree-of-freedom (SDOF) systems, validated by the Great Belt Bridge, Denmark. Another study by Wu et al. combined FDD with strain mode identification to address damage assessment challenges in reinforced concrete beams [74]. Research by Alamdari et al. [75] employed FDD for detecting progressive damage by reducing the dimensionality space. OBrien [76] adapted short-time FDD for damage detection from slow-moving vehicles and compared simulated structures with known parameters. In a comparative study, FDD analysis of the ambient vibration data of the Vasco da Gama Bridge in Portugal was conducted and compared with the results of PP and SSI by Cunha et al. [77]. Choe et al. [78] assessed a wireless sensor network-based SHM system's accuracy through FDD. Weng et al. [79] employed FDD and SSI for modal frequency extraction from cable–deck interactions. Using an automated FDD algorithm, another paper developed an OMA tool for easily integrating default estimates of modal parameters into commercial software packages [80]. FDD was also compared with a ground-based interferometric radar approach for bridge assessment through natural frequency estimation from displacement measurements by Michel et al. [81]. Moreover, these papers discussed the implementation of the FDD method [82–86].

4.2.3. Enhanced Frequency Domain Decomposition (EFDD)

As mentioned, through the application of the FDD method, natural frequencies and mode shapes can be accurately identified, even in cases where modes are closely spaced. However, its significant drawback is the inability to provide estimations for damping ratios. To overcome this limitation, an improved version of FDD, named enhanced frequency domain decomposition (EFDD) [87], was introduced. EFDD proved more precise capabilities in the estimation of mode shapes, damping ratios, and natural frequencies compared to conventional FDD. EFDD identifies the PSD function close to the resonance peaks [88,89] and converts it to the time domain using inverse discrete Fourier transform (IDFT). This involves estimating the natural frequencies by counting zero crossings over time and determining damping ratios through logarithmic decrements from the normalized autocorrelation function [89]. Kasimzade et al. [41] explored the modal parameters of a steel model bridge using the EFDD method, and the effectiveness of the method was proven in determining these parameters accurately for BSHM. Jacobsen et al. [89] also employed EFDD to handle harmonic effects during modal extraction, resulting in more robust estimates of structural characteristics. Furthermore, in another study, EFDD was used for stone masonry arch bridge modal identification in Turkey's northeastern region by Gonen et al. [90], with a comparative analysis of the strengths and limitations of different techniques. Moreover, AltuniŞik et al. [91] compared EFDD and SSI, noting close agreement between their results. The referenced papers also mentioned EFDD as the modal identification method used [92–96].

4.3. Time Domain Analysis

Due to the limitations in the frequency resolution of spectral estimates and leakage errors in the frequency domain identification approaches, time-domain methods were subsequently developed. In the time domain, the identification problem is considered full rank. The fact that all modes are present at any given time can also be considered a drawback, as it can make the estimation process more complex. The advantage of time domain identification is that it is easier to acquire bias-free data. This is because the free decays used are not as sensitive to noise as they are in the frequency domain. Moreover, time domain methods provide better results when a large frequency range or multiple number of modes exist in the data [14,97].

The most widely used time domain methods in OMA are random decrement (RD), Ibrahim time domain (ITD), the eigensystem realization algorithm (ERA), the autoregressive moving average (ARMA), time domain decomposition (TDD), stochastic subspace identification (SSI), and the natural excitation technique (NExT).

4.3.1. Random Decrement (RD)

RD is an output-only method in the time domain introduced by Cole in 1968 [98], which focuses on the averaging method [99,100]. In this method, real-time interpretation is achieved by translating the data time history into a sum of autocorrelation functions through generalized harmonic analysis of a single-degree-of-freedom system. RD's methodology is demonstrated by a high-speed digital computer to analyze the structural dynamic response. Within the domain of RD, considerations are given to the effects of finite time, the filtering of several degrees of freedom, the approach to stability boundaries, nonlinear systems, and structural failure. RD provides an accurate result for damping ratios, natural frequencies, mean square values, and half-power points of the input [98]. The application of RD for concrete bridge girder damage location identification using fiber Bragg grating (FBG) sensors is illustrated in [101]. Furthermore, RD was employed by Kordestani et al. [102] for BSHM, particularly under the influence of a moving load, which was validated by experimental examples. Using the Nanjing Yangtze River Bridge in China for method verification, He et al. [103] used the RD-based empirical mode decomposition (EMD) technique for modal identification in vibrational data. Wu et al. [104] introduced a mode separation technique, followed by the development of a multiple random decrement method to isolate free vibration responses while excluding excitation effects. The proposed methodology was applied to ambient velocity measurements from the cables of the Chi-Lu Bridge in Taiwan. In another study, Kaloop et al. [105] utilized RD to estimate the impulse response of the tower's displacement of a bridge using data from a global positioning system (GPS). These papers also contributed to the utilization of the RD method [106–109].

4.3.2. Ibrahim Time Domain (ITD)

As one of the first methods for modal identification in multiple-output systems, the ITD method was developed by Ibrahim in 1973 [110–112] for implementation in OMA, where free decays are obtained from random responses. ITD estimates the structural modal parameters such as the natural frequencies, damping ratios, and mode shapes from the time function data via the construction and solving of an eigenvalue problem. The time functions can be either free decays from the structure, impulse response functions, or pseudo free decays [113]. To investigate highly coupled systems with severe modal interference, ITD can identify modes with relatively small contributions to the response [114]. Siringoringo et al. [115] compared ITD with other time domain methods for analyzing a suspension bridge's ambient vibration. Huang [114] utilized ITD to identify vibration frequencies, mode shapes, and damping ratios of a concrete box girder bridge, noting the strong correlation between free and ambient vibration tests. The ITD method formed the basis for extracting dynamic characteristics from a laboratory cable-stayed bridge model, enhancing its feasibility and practicality, in a study by Liu et al. [116]. Asmussen et al. [117] and Fujino et al. [118] combined ITD with the RD technique for modal parameter extraction on the Queensborough Bridge in Canada and the Hakucho Bridge in Japan, respectively, effectively estimating eigenfrequencies, damping ratios, and mode shapes from ambient data. Cable-stayed bridge identification was further explored by Wu et al. [119], who introduced a mode separation technique utilizing ITD for parameter identification. The application of ITD can also be followed in these papers [120–122].

4.3.3. Eigensystem Realization Algorithm (ERA)

ERA was initially proposed by NASA's Langley Research Center in 1984, and it generates a system realization using the time domain response, (multi) input and (multi) output data. It uses a minimal realization [123], which means that it has the smallest possible number of states while still representing the input–output relationship of the actual system. This makes the model more efficient and easier to analyze [115]. It was first implemented with impulse excitation and then later with ambient vibration data using NExT. ERA is considered one of the most accurate identification methods for output-only measurement and has been applied to several types of civil engineering structures under operational conditions [123,124]. In the study by Qin et al. [125], ERA was applied as the modal identification of the Tsing Ma Bridge in Hong Kong, using ambient testing data. To enhance accuracy, techniques such as Chebyshev digital filtering and RD functions were also employed to reduce noise and transform ambient responses into free vibrations. The improved ERA incorporated cross-correlation functions, eigenvalue decomposition, and a Hankel matrix for modal identification, successfully identifying 79 modes with complex modes due to uneven damping. Furthermore, ERA combined with the modal similarity index (MSI) and mode energy level (MEL) criteria ensured reliable mode identification in a paper by Zhang et al. [126]. In addition, the introduction of the modal response contribution index (MRCI) for ERA by Qu et al. [127] addressed challenges posed by noise and spurious modes, enhancing accuracy. Moreover, ERA was utilized for damage identification in a full-scale steel stringer bridge, compared with complex mode indicator function (CMIF) results [128]. Other research also employed ERA for modal identification [105,129,130].

4.3.4. Autoregressive Moving Average (ARMA)

ARMA is another modal identification technique in the time domain that has the capability to predict future values in a time series by utilizing both past values and prediction errors. According to [131], mathematician Walker introduced the ARMA model in 1931. It is a developed model of a linear time-invariant system under white noise excitation, which has an assumption of a stationary measured response. In this model, the coefficient matrix is derived from a multivariate time series. If the objective is to determine the dynamic characteristics of the system, this matrix is transformed into a state transition matrix within a stochastic state space model. This transformation serves as the foundation for extracting modal parameters. Additionally, in scenarios with multiple input excitations, the vector ARMA or ARMAV model is implemented [132]. The paper by Chen et al. [133] used ARMA in modelling the spatial correlation of traffic excitation in bridge structures. The model was able to capture the frequency-dependent nature of the excitation spectrum density matrix, which resulted in more accurate estimates of the structural properties. Moreover, Erdoğan et al. [134] employed ARMA to model the stochastic components of the time series of the bridge's movements, capturing the random fluctuations in the data and identifying the different frequencies that were present. In another case study, to estimate the vibration modes of the Golden Gate Bridge in the US, ARMA was utilized by Pakzad et al. [135] to fit a time series to a linear combination of past values and a white noise excitation. Fang et al. [136] used this identification method to estimate and predict deflection data of the typical monitoring site of the Masangxi Bridge in China. ARMA was applied to a concrete-filled steel tube (CFST) arch bridge located in China by Lu et al. [137]. They investigated the effects of variations in the strength and diameter of the strands on the reliability assessment of the suspenders. These papers also contributed to the application of the ARMA method [138–141].

4.3.5. Time Domain Decomposition (TDD)

TDD is based on an approach with a single degree of freedom in the time domain. This method initially extracts the mode shapes and then identifies the corresponding natural frequencies. The approach assumes that the solution to the governing equations of motion can be separated into functions of time only and space only, which leads to a more efficient and simpler technique. Although TDD needs frequency information for natural frequency extraction and filter design, the most computationally expensive part of the method is processing time domain data [142]. Kim et al. [143] proposed a new technique for extracting modal parameters of a railway bridge using TDD. The technique was tested on a two-span steel composite girder bridge, which is a typical Korean high-speed railway bridge system. In another paper, TDD was employed as part of the methodology by Daniotti et al. [144] for the damping estimation of traffic-induced vibrations on a long-span suspension bridge. Furthermore, Salokhe et al. [145] applied TDD to the dynamic response data of a girder bridge to extract modal frequencies. This information was then utilized, along with visualization and noise reduction techniques, for damage detection, particularly with the assistance of SVD. Park et al. [146] used TDD for mode shape extraction from ambient vibration measurements of a cable-stayed bridge. Moreover, Huang et al. [147] used a simulated finite element model of the Lavic Road Overcrossing Bridge in California, US, demonstrating how TDD and the methodology can effectively update the structural properties while accounting for measurement uncertainties.

4.3.6. Stochastic Subspace Identification (SSI)

SSI is another time-domain modal identification method of OMA, developed by Van Overschee and De Moor in 1991 [148], which enables derivation of a state-space model for complex dynamic systems under stochastic excitation directly from measured data [149,150]. In contrast to other techniques such as ARMAV, it has less computational complexity. It is categorized into two algorithms: data-driven SSI (SSI-DATA) and covariance-driven SSI (SSI-COV). Both are capable of estimating system modal parameters; however, SSI-COV excels in providing more accurate estimations of damping ratios compared to SSI-DATA [151]. Nan Jin et al. [152] used the short-time SSI (ST-SSI) framework for estimating bridge frequencies from passing vehicles' dynamic responses. Yang et al. [153] also utilized SSI to analyze bridge frequencies with rough road surfaces and multiple vehicles, modifying observability matrices to isolate the bridge characteristics. Boonyapinyo et al. [154] highlighted the superior SSI-DATA method for flutter derivative estimation, particularly in certain bridge configurations. In [155], Brownjohn et al. analyzed the ambient vibration data from the Humber Bridge in the United Kingdom using SSI, comparing results with other methods and a previous test from 1985. Furthermore, Li et al. [156] simulated bridge excitation and validated modal parameters through numerical and experimental means using SSI. Zhou et al. [157] employed SSI in wind tunnel testing, showing improved modal parameter identification for the Oujiang Bridge in China. Loh et al. [158] used SSI-COV to analyze a real-world arch bridge, employing a stabilization diagram for accurate modal parameters. Wu et al. [159] addressed mode identifiability complexities in cable-stayed bridges under traffic and wind excitation, setting amplitude thresholds. Moreover, Tran et al. [160] applied Combined Deterministic SSI alongside other methods for large-scale bridge identification. The SSI technique finds widespread use in assessing bridge performance through modal analysis [79,161–172].

4.3.7. Natural Excitation Technique (NExT)

The NExT method is one of the OMA methods that was initially employed by James et al. [173]. This technique was first used for EMA and then for OMA. NExT uses cross-spectra of ambient vibration responses to generate impulse response functions (IRFs). Similarly to other OMA methods, this also requires the structural response caused by environmental excitation at multiple locations of the structure. Subsequently, using the data time histories, the correlation function is calculated, which is an important tool for studying systems subjected to ambient excitation [115]. The NExT method can be considered an OMA technique when combined with a time-domain multi-input multioutput (MIMO) algorithm, such as the ERA, the extended Ibrahim time-domain (EITD) method, and the polyreference complex exponential (PRCE) techniques [47]. Farrar and James provided an in-depth derivation of the NExT concept in [174]. Yang et al. addressed the challenge of multiple-channel asynchronous responses in BSHM [175] by enhancing NExT by minimizing phase slopes and maximizing linear dependencies of modal components, effectively aligning multiple-channel responses and achieving precise mode shapes. Another study by Kim et al. [176] employed NExT to identify bridge damping ratios from nonstationary ambient vibration data. By stationarizing the process, the mean and standard deviation of this dynamic parameter for the first vertical mode decrease, proposing a technique that reduces uncertainties in damping identification. Additionally, the NExT method has been utilized in other papers [177–180].

5. Damage Detection Using Modal Parameters

The objective of this phase is to determine whether damage is actually present in a structure. The algorithms used in this step are of two types: a model-driven approach and a data-driven approach. While the first includes an iterative process of numerical model updating, the other method directly compares the derived dynamic characteristics. To quantify and detect damage, damage-sensitive features (DSFs) are quantifiable parameters derived from sensor data. DSFs depend on alterations in dynamic responses such as shifting natural frequencies, mode shapes, strain levels, damping properties, and modifying energy dissipation [181,182]. They are based on dynamic features such as natural frequencies, mode shapes, modal beam curvatures, modal flexibilities, and modal strain energy.

5.1. Changes to the Natural Frequencies

As one of the common methods, analyzing the temporal evolution of natural frequencies in structures, such as bridges, is a tool for damage detection, which results from changes in stiffness and mass. The extent of these alterations depends on the location, severity, and types of damage, as well as the sensitivity of the instrumentation used for data collection. Early work by Adams et al. [183] in the late 1970s introduced the concept of identifying damage through shifts in natural frequencies, later expanded by Crawly & Adams and Salawu in 1979 [184,185]. In another study, the investigation of alterations in natural frequencies was undertaken to anticipate prestressing losses in both concrete post-tensioned girder bridges and steel post-tensioned bridges. In particular, employing the fundamental frequency is not suggested for concrete girder bridges experiencing minor cracking and for steel girder bridges with tendon deviators spanning their lengths. Conversely, the use of the fundamental frequency is endorsed for evaluating their flexural stiffness [186,187]. Messina et al. proposed the damage location assurance criterion (DLAC) and the multiple damage location assurance criterion (MDLAC) while considering the alteration in the natural frequencies [188], which were used to locate predefined damage locations using 10 to 12 modes. Nevertheless, in this case, spurious locations could also arise. As another approach, the single damage indicator (SDI), developed by Kim et al. [189], detects cracks and quantifies their severity by assessing frequency changes. Complex structures pose challenges in localizing damage using modal frequencies [190,191], although regular geometries can employ this method effectively, requiring damaged and undamaged states and an appropriate number of frequencies [192,193]. From another perspective, minor damage has a limited effect on larger structures' natural frequencies, making this method less efficient [191]. Additionally, natural frequencies can change in the same way if damage occurs at two symmetrical locations in the same structure [193]. Comparable alterations can emerge from mass changes or environmental factors. To address environmental effects on natural frequencies, techniques such as principal component analysis (PCA) [194], Kalman filters [195], and the Mahalanobis squared distance [196] are employed to mitigate the influence of environmental factors on measured frequencies.

5.2. Changes to the Mode Shapes

Compared to natural frequencies, mode shapes are less influenced by environmental factors, and provide spatial insights for damage localization purposes [13]. Various techniques have emerged over time, including the modal assurance criterion (MAC), developed by Allemang and Brown [197] in 1982, which utilizes eigenvector orthogonality to identify alterations in mode shapes [198,199]. Later, Kim et al. [200] developed the coordinate modal assurance criterion (COMAC), using modal node displacement for damage detection and localization. Salawu and Williams [201] evaluated the application of MAC and COMAC, and reported their effectiveness, although spurious damage indications were also observed. However, COMAC often results in errors in the deterioration detection of beam structures, which was observed by Salgado et al. [202], with scaling and polarity errors. Putting aside this limitation, the application of COMAC remains diverse in engineering fields, which leads to its integration with other approaches in addition to civil engineering fields [203,204]. The efficiency of COMAC is based on the correct identification of relevant modes contributing to correlation. With regard to this concern, Hunt et al. [205], in 1992, proposed the enhanced coordinate modal assurance criterion (ECOMAC). ECOMAC improves upon COMAC with the computation of the mean deviations of modal amplitudes of each node to enhance the accuracy and reliability of damage detection [182,206].

5.3. Modal Curvature Method (MCM)

In 1991, the MCM was proposed by Pandey et al. [207] with the aim of exploring the second derivative of modal curvatures for deeper mode shape monitoring using the curvature–flexural stiffness correlation. Through the increase in the values of modal curvature, this method detects the reduction in stiffness by comparing damaged and undamaged states. Ho and Ewins [208] developed the MCM by improving abnormal curvature change differentiation. Despite the advantages of using this method, it faces some limitations. Numerous sensors and modes are demanded for a precise higher mode definition [209], and curvature estimation from vibration data will contain errors by a central difference approximation, which will also be exacerbated via high-frequency noise [210]. Although increasing the number of samples results in noise mitigation, truncation errors may also occur [211]. Furthermore, the comparison of the MCM with strain measurements reveals inherent errors [212], discouraging sole reliance on the MCM for damage identification. The integration of the MCM with other DSF parameters such as frequencies can enhance the accuracy of damage detection and localization, as proved by Capecchi et al. [213], who combined MCM with sparse sensor layouts for improved damage sensitivity in an arch bridge. Later, mode shape curvature squared (MSCS) was suggested by Wahab and De Roeck [214], exploring practical applications of modal curvature and the curvature damage factor (CDF), leveraging the Z24 bridge analysis involving simulated and real data [182,206].

5.4. Modal Strain Energy (MSE)

MSE, integral to various modal-based DSFs, is exemplified by the damage index method (DIM) [215]. The energy stored while a structure undergoes deformation is called the modal strain energy. The DIM approach is based on Bernoulli–Euler beam theory to detect the damage by monitoring the reductions in modal strain, which represent the diminished energy storage capacity. Moreover, MSE facilitated a quantitative assessment of the damage extent, i.e., enabling a crack size estimation. An investigation by Kim et al. [216] containing an FE beam model showed the superiority of MSE over frequency-based damage indicators. Additionally, the research by Yam et al. [217] proved similarities in displacement modes and strain modes. One of the shortcomings of MSE is that while strain modes are highly sensitive to local-scale structural changes, higher modes are less effective at detecting damage. Additionally, similarly to the challenges of implementing MCM, the DIM's reliance on modal curvatures presents the same limitations, including the need for central difference approximation. Notably, the DIM involves the acquisition of continuous strain values through curve fitting between sensor locations, a procedure that may inadvertently obscure local damage [182,209].

5.5. Modal Flexibility Method (MFM)

The MFM was first proposed in 1994 by Pandey and Biswas [218] and subsequently applied to bridge structures by Toksoy and Aktan [219]. It is based on the inverse relationship between stiffness and flexibility matrices, offering a brief representation of structural behavior with fewer modes in comparison to the stiffness matrices. This feature increases the damage sensitivity of the method, especially in easily extractable lower modes, as demonstrated by Wang et al. [220]. By integrating the modal curvature method with the MFM, Zhang and Aktan [221] extended the method's damage sensitivity. Furthermore, using an experimental test, Lu et al. [222] evaluated the implementation of modal flexibility with the flexibility curvature of a beam. Although it increased the sensitivity to local damage, challenges in pinpointing flexibility peaks under multiple damage scenarios arise [182].

5.6. DSFs Application

Several studies have focused on assessing a bridge's structural health to estimate the severity and location of damage using different DSFs. Talebinejad et al. [223] applied the ECOMAC, DIM, MCM, and MFM on a cable-stayed bridge, subjected to varying noise and excitation levels. It was demonstrated that the contamination of noises hindered damage sensitivity, allowing only significant damage events to be detected. Ndambi et al. [224] evaluated reinforced concrete beams, testing frequencies, using the MFM, MAC, COMAC, and DIM in a laboratory setting. Both the COMAC and DIM methods excelled in localizing the damage but struggled to accurately quantify incremental damage progression. In another study, to estimate the mode shapes, using the MCM and MFM, Cruz and Salgado [225] used a composite bridge simulation model with vibration data. All applied DSFs were successful in detecting and localizing the damage under no noise contamination. However, under the contamination of noise, the performance of the mentioned DSFs decreased noticeably. With regard to the real data, in higher modes of the structure, clear changes were observed, but not for the lower modes, even in the presence of severe damage. According to Cruz and Salgado, among all utilized DSFs, the MCM and MFM showed the highest levels of detection and localization capabilities. Moreover, Fan and Qiao [226] demonstrated the prior findings in their paper by assessing the frequencies, mode shapes, MCM, and DIM. They confirmed that in higher modes, the applied DSFs, particularly modal curvature-based parameters, are more sensitive to damage than lower modes. They also found that the performance of all damage features decreased when noise was added. It can be concluded from the mentioned investigations that the application of DSFs presents varying performance and is susceptible to noise, posing limitations in real-world applications due to assumptions of a linear stationary structural vibration response, a concern for nonstationary vehicle-induced excitations on damaged bridges. Putting aside these limitations, DSFs can still be useful for the assessment of structures with regular geometry, especially when used in conjunction with other methods [182].

5.7. Shortcomings of the Preceding Methods and the Solution

The challenge in assessing the structural health of bridges is to distinguish between normal and abnormal changes in their dynamic properties over time. Abnormal changes result from deviations in material properties, such as loss of stiffness, which is indicative of damage. In contrast, normal variations in the data are primarily caused by environmental and operational factors. It is important to recognize that these factors can affect the accuracy of the results when using the DSFs mentioned and should not cause false alarms in the monitoring system. External conditions such as changes in temperature and humidity or traffic loads can determine variations in stiffness, which in turn affect the dynamic characteristics of the bridge. Temperature fluctuations cause daily frequency shifts of approximately 5% and seasonal shifts of 10% [227–229]. As mentioned, the frequency alterations derived from fluctuations in temperature pose a challenge in distinguishing them from structural damage [230,231]. The study by Farrar et al. [232] revealed that this can mask the actual damage in gradually deteriorated bridge girders. Although a decrease in the natural frequencies, caused by the reduction in the stiffness, is expected while damage occurs, the observed results were different. Instead, in the initial damage scenarios, caused by the laboratory temperature, the frequencies initially increased before decreasing. Moisture impact can even make it worse, having revealed nonlinear modal frequency distributions for the Z-24 Bridge during freezing temperatures due to frozen moisture in the structure, according to studies by Peeters and De Roeck [227]. With operational conditions contributing over 5% of fluctuations [233], operational variability, more than environmental factors, impacts daily frequency fluctuations [234]. In 2001, Kim et al. [235] found that the natural frequency variations induced by traffic are negligible for medium- to long-span bridges, while they significantly affect shorter-span bridges, as reported in 2012 [236]. As an additional factor that affects the welded connections during their operation, fatigue-induced stress cycles can be considered. Orthotropic steel decks, with complex geometry and subjected to stochastic traffic loads, exhibit complex stress fields. Alcover et al. [237] determined a linear relationship between stress cycles for orthotropic steel deck joints and traffic volume, specifically rib-to-deck welded joints. Song and Ding [238] also worked on the correlations between stress amplitudes and ambient temperatures due to material property changes caused by temperature variations.

In conclusion, the effects of environmental and operational factors on the application of DSFs for structural damage detection are challenging and inevitable. To increase the accuracy and reliability of the previously mentioned damage detection process, the dominant effects of these variables should be mitigated as much as possible. In this regard, Sohn [239] and Xia et al. [240] explored the application of data normalization techniques to address these limitations. It should be noted that these techniques consider scenarios with both environmental or operational data (implementing regression models) and without (employing pattern recognition methods). The goal is to mitigate the effect of external factors, normalize the data, and improve the reliability and precision of damage estimation and detection processes [182].

6. Regression Models

In real-world applications, developing complex models to reduce the impact of external factors on the data is often impractical. Therefore, instead of delving deep into the physics of the problem, it is advisable to rely on it as a black-box model. These models have their parameters fine-tuned using extensive datasets, allowing the establishment of relationships between potential influencing factors and dynamic characteristics, which can be accomplished with the implementation of regression analysis. This statistical technique is employed to establish a connection between dependent and independent (predictor) variables to gain insight into how each predictor (model inputs) influences the dependent variable (model output). For instance, when creating regression models to understand the influence of temperature on natural frequencies, it is crucial to construct one for each frequency. This comprehensive approach involves considering a wide range of variations, including data from both summer and winter periods [241]. This was demonstrated by Peeters et al. [242], who employed linear regression analysis, particularly the ARX model (autoregressive (AR) model with exogenous input) to remove the temperature effect of the identified vibration frequencies from a bridge in Leuven, Belgium. Due to their capabilities in modelling the shift changes in frequency due to below-zero temperatures, multilinear regression models can be employed as a suitable option. A regression error value of approximately 5% is generally used to reduce the effect of erroneous data [243]. In another study conducted by Sohn et al. [244], the recorded data from the Alamosa Canyon Bridge in the US was used to construct a model which characterized the alterations in eigenfrequencies caused by fluctuating temperatures. The model was then utilized to establish confidence intervals for the frequencies corresponding to a new temperature profile. However, in complex data scenarios, advanced regression techniques, including polynomial, ridge, lasso, elastic net, Bayesian, support vector regression (SVR), decision tree, random forest (RF), and gradient boosting regression, are used, which enable the analysis of the complex environmental and operational factors, exemplified by the polynomial regression method used by Ding and Li [245] when mapping the modal frequency variability in long-span suspension bridges. Moreover, Hassan et al. [246] employed multiple regression for bridge health prediction, while Mangalathu et al. [247] employed lasso regression to identify seismic demand models for bridges. A Bayesian vibration-based approach was proposed by Kim et al. [248] for long-term BSHM, and a study by Laory et al. [249] developed regression trees, neural networks, and support vector regression models for analyzing the Tamar Suspension Bridge in the UK.

7. Pattern Recognition (PR)

Farrar et al. [232], in 1994, defined PR as a method to highlight the changes in the frequency response functions measured using cracked (damaged) and uncracked (undamaged) bridges. PR in BSHM involves applying methods such as statistical (SPR) [250], machine learning, time–frequency analysis, and data mining [251,252]. Differentiating between patterned or structural changes in the intact and damaged state under operational and environmental variations is the primary objective of the SPR paradigm. Its process can be outlined as consisting of four stages: assessing operational performance, collecting data, extracting and generating features, and using statistical models for feature classification. Establishing rigid boundaries between these stages can be challenging. It is crucial to recognize that several important processes come into play within the data acquisition, feature extraction, and statistical modelling aspects of the SPR, including data normalization, data cleansing, data fusion, and data compression [253]. The first one involves separating sensor reading variations induced by real damage from those caused by varying operational and environmental conditions, effectively addressing data contamination with external factors. Data cleansing is the practice of selectively choosing data for inclusion or exclusion from the feature selection process. Data fusion, however, combines information from multiple sensors to increase damage detection accuracy. Finally, the last one focuses on reducing the data dimensions or the features extracted from the data. The goal is to facilitate the efficiency of the storage, and improve the statistical quantification of parameters [251]. Figueiredo et al. [251] emphasized implementing SPR and ML to enhance the performance and safety of bridges. Furthermore, while using statistical pattern recognition, Hu et al. [254] conducted vibration-based SHM on a prestressed concrete box girder bridge. In another paper, Haritos et al. [255] investigated the application of statistical pattern recognition and system identification for BSHM, suggesting a combined approach for comprehensive damage assessment. Datteo et al. [256] focused on employing statistical pattern recognition and PCA to reduce the complexity in the analysis of vibration data, exemplified through the G. Meazza stadium in Milan, Italy. Cheung et al. [257] also used pattern recognition in field tests while noting localization challenges and the importance of signal conditioning.

8. Machine Learning (ML)

BSHM systems employ ML to compare two states. It works with constructing a model to extract specific characteristics from the desired dataset with the training and testing stages. As an ideal condition, the used database should be the representation of the complete array of structural excitations. Furthermore, employing signal processing methods such as noise filtering and data normalization can directly contribute to the generation of a highly calibrated dataset. ML finds it application for BSHM in damage detection of sensor-detected data [258].

Figure 5 illustrates the workflow needed to develop an ML model for SHM. The process begins with an excitation step, where the structure undergoes any type of stimuli. Subsequently, data acquisition captures relevant information from the structure's response. The acquired data then undergoes normalization to standardize its scale and facilitate consistent analysis. Following normalization, data cleaning eliminates any noise or outliers. The process then involves data compression through dimensionality reduction techniques to streamline information while retaining its crucial features. Feature extraction identifies and highlights essential characteristics in the data, contributing to the subsequent stage of data fusion, where multiple data sources are integrated for a comprehensive understanding. The final stage, pattern recognition, employs ML algorithms to detect and interpret patterns in the fused data, ultimately enabling effective structural health monitoring [259].

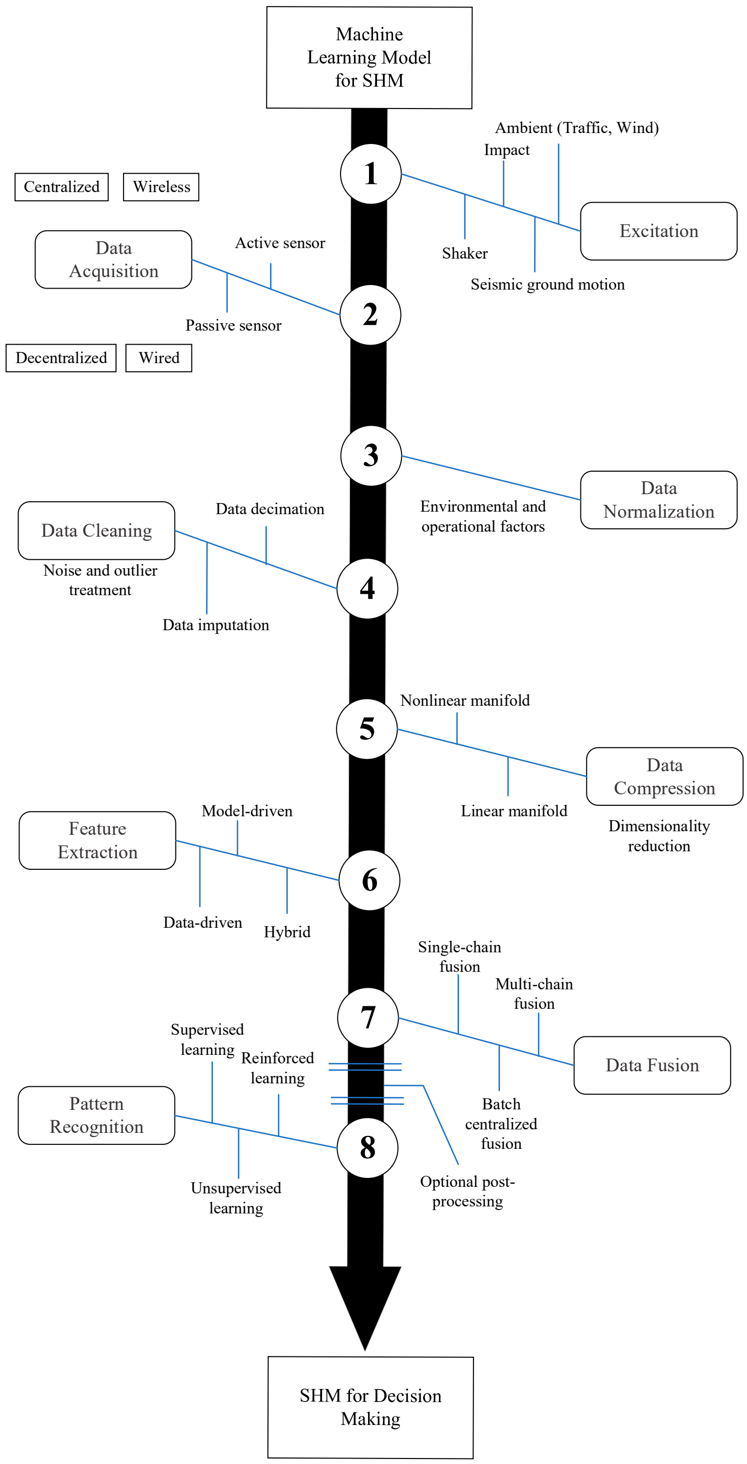

Figure 5. Overview of essential and optional steps in data-driven SHM systems with ML enhancements [259,260].

Through the implementation for the case studies, ML approaches have demonstrated their capability in addressing the following issues with regard to BSHM [261]:

- They can effectively describe physically complex correlations;
- Automatic detection and compensation of sensor faults are achievable;
- Trained models can be transferred to other structures/problems with similar boundary conditions;
- The separation of factors affecting specific structural behaviors is facilitated;

- Future structural behavior can be estimated based on previously predicted values.

The most commonly used ML techniques used in BSHM are artificial neural networks (ANNs), support vector machines (SVMs), random forests (RFs), Gaussian processes (GPs), convolutional neural networks (CNNs), and long short-term memory (LSTM) neural networks.

8.1. Artificial Neural Network (ANN)

An ANN is a computational network inspired by biological systems that uses basic concepts of the human brain. These networks can be trained for pattern identification and information classification that are similar to human cognitive processes [12,262,263]. In ANNs, information is transmitted between the neurons, which play the communication roles between layers, determined by their structure and synaptic weights. Input layers are user-defined, considering elements such as geometries, mechanical/structural properties, and physical parameters. On the other hand, hidden layers emerge as a consequence of computations based on the input layers, finally culminating in the generation of output layers as the final results [264–266]. For BSHM for prediction and anomaly detection, Kwon et al. [267] combined ANNs with the building information modelling (BIM) method, which effectively identified element anomalies for maintenance when applied to a field cable-stayed bridge in Korea. In another study, Huang et al. [268] analyzed effective factors, investigating ANNs' effectiveness in predicting bridge deck deterioration. Furthermore, to tackle the challenges of incomplete and imprecise data, Mehrjoo et al. [269] discussed the numerical analyses of an ANN-based method for the intensity estimation of damage in truss bridge joints. Favarelli et al. [270], and Weinsteinet al. [271], Nguyen et al. [272], and Jayasundara [273], employed ANN-based anomaly detection with bridge vibrational data, and Xu et al. [274] developed an ANN-based two-step algorithm for vibration-based damage identification (VBDI) applied on the Crowchild Bridge located in Alberta, Canada. Eftekhar et al. [275] integrated ANNs with proper orthogonal decomposition (POD) and subspace-based damage indicators, respectively. Nguyen et al. [276] leveraged ANNs with residual FRFs and PCA for SHM of a concrete arch beam replica. Tran [277] also provided a thesis focused on the damage detection accuracy of ANN-based methods.

8.2. Support Vector Machines (SVMs)

SVMs, first developed by Cortes and Vapnik [278] in 1995, are a supervised ML method that is used in regression and classification, operating within a high-dimensional space to divide the data into two distinct groups. Using iterative training, this method is used to enhance the performance by fine-tuning the separation between the data points and the hyperplane. SVMs excel in dealing with challenges caused by nonlinear and high-dimensional datasets, even with the limited sampling size. BSHM employs SVMs to distinguish between normal and abnormal conditions based on annotated data. Through this capability, structural irregularities can be identified early [12]. Pan et al. [279] and Alamdari et al. [280] adopted SVMs to distinguish between damaged and undamaged cases and detect anomalies in dynamic response data. Additionally, Pan et al. [281] used SVMs in combination with enhanced feature extraction techniques such as the wavelet transform, the Hilbert–Huang transform (HHT), and the Teager–Huang transform (THT) for detecting damage in cable-stayed bridges. Navamuel et al. [282] used SVMs in an SHM alert system to differentiate between undamaged and damaged scenarios based on modal properties and temperature variations. Kim et al. [283] utilized SVMs for automated detection, recovery, and isolation of faulty data in OMA using wireless sensor networks (WSNs) for cable-stayed bridge damping estimation. Gui et al. [284] proposed optimization algorithm-based SVMs for large-scale structural damage detection, resulting in an improved damage detection method compared to traditional methods, particularly the one optimized using a genetic algorithm. These papers also contributed to the utilization of SVMs in their research [285–288].

8.3. Random Forest (RF)

Breiman, in 1996 [289], proposed a nonparametric and tree-based ensemble method as a random forest using multiple decision tree models. To generate each ensemble member, the RF uses the bagging technique, a method for data collection from multiple training datasets. Bagging randomly chooses samples from the decision tree space in a consistent manner. This method is vastly used for both classification and regression purposes and is among the most frequently utilized ML algorithms [12,290–292]. As a result of its inherent ability to handle enormous datasets while delivering resilient predictions, this algorithm gained considerable attention within the domain of BSHM. In their study, Arnold et al. [293] investigated the application of the RF as an approach for detecting events and classifying time series in bridge monitoring. Lei et al. [294] used RF algorithms to evaluate vibration-based seismic damage for regional bridges. The model demonstrated the prediction performance with over 90% accuracy, identifying critical parameters for seismic design and disaster prevention. Furthermore, these papers also contributed to the utilization of the RF in bridge monitoring [295–297].

8.4. Gaussian Processes (GPs)

As explained by Rasmussen and Williams [298], GPs represent a generalized Gaussian probability distribution. The application of this method aims at data regression and prediction. It has a stochastic process and is classified into a mean and a covariance function, often applied for the definition of a priori distribution in Bayesian inference [299]. Indeed, a stochastic process can be defined as the probability distribution of a set of random variables that are in sync with the input data provided as a group of random variables [300]. Chalouhi et al. [301] used a GP-based ML framework for damage detection by modelling deck accelerations. Moreover, a simplified treed Gaussian process (TGP) was applied by Zhang et al. [302] to address the nonstationary behavior in BSHM using motorcycle accident and Z24 bridge SHM data. Da Silva et al. [303] employed Gaussian process regression (GPR) applied on a bridge under varying temperatures. Furthermore, O'Connor et al. [304] developed a cyber-enabled wireless SHM system using GPR for highway bridges. Moreover, GPs were utilized by Moravej et al. [305] for the calibration of the Bayesian model and updating.

8.5. Convolutional Neural Network (CNN)

The CNN is a widely used deep learning method known for its advantages, including shared weights, local connections, and subsampling, and is a promising approach for data anomaly detection that enables the extraction of valid characteristics from data automatically. Its structure consists of an input layer, a convolutional layer, a pooling layer, and a fully connected layer. The second layer's function is the feature extraction from the input database via a user-defined filter matrix. On the other hand, the pooling layer reduces the spatial data dimensions, and the fully connected layers perform classification tasks. The CNN's performance depends on the balanced training samples. While facing the anomaly patterns in a complex system, the tuning process might be time-consuming and laborious [12,306,307]. Nguyen et al. [308] used a CNN to detect and localize structural damage based on changes in modal curvature, exemplified through the Bo Nghi bridge in Vietnam, as a case study. In another study by Zhang et al. in [306], a CNN was applied to analyze the acceleration data recorded from a bridge, in combination with the feature extraction capabilities of statistical features for anomaly detection and classification. Shajihan et al. [309] employed CNNs to classify SHM data faults from sensors using three-channel input data, achieving accuracy and recall on an unseen dataset. Moreover, Duan et al. [310] applied CNNs for damage identification in hanger cables of a tied-arch bridge. Zou et al. [311] proposed a CNN model by incorporating temporal features from the gated recurrent unit (GRU) model, demonstrating significant improvement in structural damage identification compared to other models. Yessoufou et al. [312] used a one-class convolutional neural network (OC-CNN) model capable of detecting bridge damage across various vehicle weights and speeds. Chamangard et al. [313] utilized compact one-dimensional (1D) CNNs with transfer learning to detect damage accurately, even with limited training data, achieving high accuracy when sufficient data were available. Li et al. [314] combined a CNN with short- and long-term memory neural networks to detect bolt-nut losses in steel bridges. Khodabandehlou et al. [315] used a CNN to predict the predefined damage states (including extent and location) with accuracy using vibration response data from a reinforced concrete highway bridge model. Pamuncak et al. [316] applied a CNN to estimate the structural response in real-world data from the Suramadu bridge monitoring system in Indonesia. The study by Lee et al. [317] also employed a CNN to achieve 87.3% accuracy in real-time damage localization for bridges. Furthermore, Teng et al. [318] proposed a method where a diverse population of bridge structures is created, and a CNN is used to extract damage features.

8.6. Long Short-Term Memory (LSTM) Networks

LSTM networks introduced a new feature over recurrent neural networks (RNNs), named "gated cells", by Hochreiter and Schmidhuberin in 1997 [319]. Three distinct gate mechanisms are incorporated within this method: the input, the output, and the forget gates, which collectively represent an additional control system for signal flow regulation into and out of the model to collect crucial features over time. Consequently, it has the ability to manage information flow via gated cells and is effective in learning complex and nonlinear relationships between factors such as environmental conditions [320–322]. By Shin et al. [323], a C-LSTM network integrated with a CNN and LSTM was applied to identify driving segments on bridges using vibration data, focusing on vibration peaks at bridge joints for damage detection. Moreover, Yue et al. [324] employed an enhanced Stack-LSTM-CNN mode in identifying the abnormal temperature-induced deflections in cable-stayed bridges. Hou et al. [325] proposed a warning framework using LSTM based on the BIM platform for the early detection of hazardous components with bridge monitoring data. Furthermore, Yang et al. [326] employed LSTM networks to model multisensory mapping relationships in SHM, addressing challenges in handling long-term and multidimensional series data. With respect to analyzing the bridge deflection, Guo et al. [327] used LSTM for predicting and comparing this parameter, and Duan et al. [328] proposed a novel approach to reconstruct bridge dynamic displacements using the strain and acceleration data source, overcoming the limitations of direct measurement techniques. Yue et al. [329] used LSTM networks to model a digital regression for temperature-induced deflection in cable-stayed bridge main girders, outperforming linear regression models. Zhao et al. [330] employed LSTM regression networks for in-service bridge monitoring, mapping temperature-induced strains, dynamic displacements, and vehicle-induced strains. In another paper, Sharma et al. [331] assessed the impact of ambient temperature on structures for anomaly detection while using LSTM networks. In the same way, Wang et al. [332] analyzed deflection and temperature data from the Chongqing Egongyan Rail Transit Suspension Bridge, China, using LSTM to detect potential damage signs. To recover the missing structural temperature data from the Nanjing Dashengguan Yangtze River Bridge in China, Liu et al. [333] applied LSTM. Zhao et al. [334] employed LSTM networks for the early detection of cracks in prestressed concrete box girder bridges using live-load strain data. Moreover, while using bidirectional LSTM (BiLSTM), Lu et al. [335] and Yang et al. [336] contributed to enhancing the BSHM.

In conclusion, our exploration of various ML models in the context of bridge structural health monitoring demonstrates a commendable level of precision. The overall low errors, including mean absolute error (MAE), root mean square error (RMSE), mean squared error (MSE), etc., across the reviewed literature, attest to the efficacy of ML approaches in enhancing the accuracy of structural health monitoring. The recommendation for the application of machine learning models in the dynamic monitoring of bridges is further underscored by the general trend of favorable outcomes observed in the surveyed papers. To enhance the reliability and usability of ML models employed in various aspects of BSHM, it is crucial to incorporate a considerable volume of data during the model construction process. Additionally, when developing an ML model for bridges, it is imperative to ensure its applicability across diverse scenarios. This is essential, as instances have been observed where the generated model is exclusively suitable for specific real structure scenarios with particular geometric or physical attributes.

It is also important to note that recent technological advancements and enhancements in various approaches, such as laser scanning (LiDAR) [337], terrestrial laser scanning (TLS) [338–346], unmanned aerial vehicles (UAVs/drones) [347–349], photogrammetry [350], and ground-penetrating radar (GPR) [341], have significantly facilitated the data capturing and establishment of a continuous data monitoring system for bridges. These developments have encouraged researchers and stakeholders to leverage 3D models of bridges and create their digital twins (DTs). These innovative approaches empower us to efficiently assess the structural health of bridges, identify potential issues, and plan maintenance or repairs with minimal disruption. LiDAR, employing laser pulses, generates a highly precise 3D point cloud that represents the bridge's geometry, making it suitable for regional-level assessments. TLS captures detailed 3D images using stationary laser scanners, creating a point cloud through laser beams emitted in horizontal and vertical planes. UAVs, equipped with LiDAR sensors or cameras, provide a flexible and cost-effective solution for monitoring bridges, accessing challenging areas for regular inspections without disrupting traffic. GPR utilizes electromagnetic waves to image and investigate structures such as bridges, and photogrammetry involves capturing bridge images from various angles to create a 3D point cloud, subsequently transformed into a mesh model for comprehensive bridge monitoring and the development of digital twins.

9. Conclusions

In recent years, OMA has increasingly supplanted EMA due to its advantages and fewer implementation restrictions, which include the independence from the input excitation (no external source required), applicability during bridge operation, suitability for monitoring complex structures, cost-effectiveness, real-time monitoring capabilities, and lack of impact on the structural integrity. This article provides a comprehensive review of operational modal analysis applied for bridge health monitoring. It covers various aspects such as instrumentation and data acquisition systems, preprocessing steps including filtering techniques, and modal identification techniques explored in both the time and frequency domains, such as SSI, RD, TDD, ARMA, ERA, NExT, ITD, PP, FDD, EFDD, postprocessing methods, including deviation in the natural frequencies and mode shapes, MSE, the MFM, and the MCM. Additionally, advanced techniques like regression models, pattern recognition, and machine learning methods such as ANN, RF, GP, LSTM, and CNN are discussed to overcome previous limitations. Each approach is showcased, outlining its specific advantages and disadvantages, and practical implementation examples are provided.

From the authors' perspective, it is crucial to recognize and follow certain essential principles to attain accurate and reliable OMA outcomes for BSHM:

- Instrumentation plays a foundational role in OMA. The selection of the sensing system must align precisely with the specific requirements, and the placement and installation of the sensors on the bridge should be performed with attention to the expected results. Achieving accurate modal identification outcomes requires the careful handling of instrumentation.
- When considering wireless networking as the data acquisition system while employing multiple sensors on the bridge, it is crucial to ensure the precise synchronization of data recorded. Even a minor discrepancy in data synchronization can lead to errors in the identified modal parameters, particularly mode shapes. In such cases, the accuracy of bridge damage detection can be compromised.
- In terms of achieving optimal reliability, efficiency, precision, and applicability in various modal identification techniques within the time or frequency domain, the SSI

method stands out as the preferred approach among researchers in the time domain, whereas EFDD excels in the frequency domain.

- The effects of environmental and operational factors on the application of DSFs for bridge damage detection are challenging and inevitable. To increase the accuracy and reliability of the damage detection process, the dominant effects of these variables should be mitigated as much as possible.
- To ensure the precision of the results, two key considerations emerge. First, it is advisable to implement multiple distinct DSF approaches simultaneously, enabling the localization and assessment of damage severity. Second, employing regression and pattern recognition techniques can mitigate the influence of environmental and operational factors on the data.
- Utilizing advanced methods such as machine learning proves precision in achieving OMA results for BSHM. However, when constructing the mathematical models for these methods, it is crucial to incorporate a diverse dataset. This ensures that the resulting model remains applicable across various bridges, accommodating variations in their geometric and material characteristics.

Looking ahead to the future, thanks to the technological advancements and increased sensor accessibility, bridge health monitoring systems will continue to progress. From an instrumentation perspective, wireless monitoring systems will gradually replace their wired counterparts due to advantages such as ease of installation, flexibility of relocation, remote monitoring, and cost-effectiveness. In addition, significant advances in signal processing techniques will improve the quality of input data and optimize data analysis for modal identification. The integration of state-of-the-art methods, especially those involving AI, has the potential to further enhance the performance of modal-based DSFs. In addition, the integration of AI with technologies such as drones, robots, etc., opens up new possibilities for engineers to bridge SHM systems. Despite significant advances in AI, there remains a scientific gap in understanding how environmental and operational variations affect the effectiveness of structural health monitoring using these innovative technologies. While previous studies have provided valuable insights, further research efforts are recommended to investigate this issue more comprehensively in the future.

In addition to the previously discussed points, the authors emphasize two crucial considerations in their perspective. First, while innovative approaches in analytical and scientific methods are proposed and validated through academic endeavors, it is imperative to ensure that the application of these techniques remains practical and falls within the operational capacity of technicians in daily practices. It is not sufficient for these advancements to merely exist in theory; they must be accessible and implementable in real-world scenarios. Secondly, there exists an ongoing necessity to train technicians comprehensively. Their understanding and proficiency in utilizing these novel methods for dynamic identification techniques in civil engineering should be cultivated. This training is essential to bridge the gap between theoretical knowledge and practical application, ensuring that technicians are not only aware of these advancements but are also adept at integrating them into their professional workflows. Consequently, enhancing a well-trained workforce becomes a critical component in the successful adoption and implementation of these cutting-edge techniques within the realm of civil engineering.

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