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Review

Temperature Effect on Vibration Properties and Vibration-Based Damage Identification of Bridge Structures: A Literature Review

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Abstract: In civil engineering structures, modal changes produced by environmental conditions, especially temperature, can be equivalent to or greater than the ones produced by damage. Therefore, it is necessary to distinguish the variations in structural properties caused by environmental changes from those caused by structural damages. In this paper, we present a review of the technical literature concerning variations in the vibration properties of civil structures under varying temperature conditions and damage identification methods for bridge structures. First, the literature on the effect of temperature on vibration properties is roughly divided into experimental and theoretical studies. According to the classification of theoretical research methods, the progress in research on the probability analysis method, the artificial intelligence method, and the optimization algorithm method in this field is reviewed. Based on the different methods of experimental research employed in this field, the experimental research is reviewed according to qualitative and quantitative analyses. Then, damage identification methods for bridge structures are reviewed, considering data-based and model-based methods. Finally, different research methods are summarized.

Keywords: temperature effect; modal properties; damage identification; structural health monitoring

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1. Introduction

Structure can be damaged during service, resulting in structural failure and collapse, which may pose a major risk to human life. Therefore, the identification of structural damage in civil engineering plays an important role. In essence, structural damage refers to reductions in characteristic structural parameters. Therefore, structural damage can be evaluated based on changes in modal parameters [1–3]. Vibration-based identification techniques can be used to detect the severity and location of damage to structures. However, due to environmental factors, different data sets measured at different times may yield different monitoring results [4–10]. Numerous sets of field monitoring data and theoretical analyses show that structural modal parameters are not only related to structural properties but are also susceptible to ambient factors, especially temperature variations [11]. Changes in the structural response caused by temperature variation can cover up change in the structural response caused by structural damage. The integration and interpretation of various data types are essential for the effective use of SHM systems for structural state assessment and damage detection [12].

Some researchers have studied the mechanism of the effect of temperature variation on natural frequency. For example, Hu et al. [13] monitored a prestressed-concrete box girder bridge on the A100 Highway in Berlin and reported on the bridge's general condition and potential damage. They observed nonlinear influences of temperature on natural frequencies and used the multiple linear regression method to characterize the nonlinear relationship between temperatures and natural frequencies. Kromanis and Kripakaran [14] applied a novel calculation technique to bridge structure performance monitoring so that the temperature-induced response in the process of measurement interpretation could be quantified. They proposed a regression-based method to generate a numerical model to capture the relationship between the temperature distribution and the structural response based on the distribution measurement data collected during the reference period. The use of a laboratory truss and a concrete footbridge showed that this method could accurately predict the thermal response.

When the environment's influence on changes in dynamic structural characteristics is not properly considered, vibration-based structural damage detection methods may produce false positive or negative damage signals [15]. Therefore, eliminating the modal variability caused by temperature interference is essential in vibration-based damage detection [16]. Gu et al. [17] developed a two-step damage detection method combining novelty detection and a multi-layer neural network, which was intended to avoid false alarms in the implementation of vibration-based structural damage identification methods due to varying temperatures. This method distinguishes the natural frequency changes caused by damage from the changes caused by temperature. A simply supported beam and finite element model based on an experimental grid structure were used for numerical research to simulate different degrees of stiffness reduction under different temperature conditions, which verified the detectability and robustness of this method. Yang et al. [18] proposed a phase-shifting method based on the Fourier series expansion fitting method to mitigate the influence of the time-lag effect. They computed the phase difference between temperature and response strain data at each decomposed order, and the total phase difference can be obtained by weighted summation. The authors reported that this method could effectively reduce the time-lag effect, leading to a sound understanding of the temperature load and its effect.

The existing structural damage detection methods can be divided into data-based and model-based methods. The most commonly used data-based methods are machine learning, deep learning, support vector machine, principal component analysis, etc. The main advantage of these methods is that there is no need to build a finite element model, and the collected dynamic signals are used directly. Therefore, modeling errors can be avoided. However, a disadvantage is that a large amount of data is required, which makes data processing difficult. At the same time, the severity of damage cannot be quantified in most cases. The model-based method mainly includes the meta-heuristic optimization-based model updating method, the wavelet-based method, and the Bayesian inference-based model updating method. Those methods can more accurately determine the location and severity of damage, compared to the data-based methods. Nevertheless, their disadvantage is also obvious: these methods need to establish a benchmark finite element model, which introduces some errors.

In this paper, we review different methods of analyzing the effect of temperature on vibration properties, and provide an overview on the progress of damage identification research in bridge structures. The rest of the paper is organized as follows. In Section 2, according to the classification of theoretical research methods, the progress of research on the probability analysis method, the artificial intelligence method, and the optimization algorithm method in this field are reviewed. Furthermore, considering the different approaches to experimental research, the experimental research is reviewed according to qualitative and quantitative analyses. In Section 3, damage identification methods for bridge structures are reviewed in accordance with data-based and model-based methods. In Section 4, different research methods are summarized. In this paper, we present some representative literature on the influence of temperature on the vibration properties of bridges and damage identification in bridge structures. We aim to describe the existing problems and future development directions in these two areas of study and provide some references for future research.

2. The Effects of Ambient Temperature on the Structural Dynamic Properties

2.1. Theoretical Analysis

2.1.1. Probabilistic Methods

Due to the influence of environmental and artificial factors, the data collected in several vibration tests are not completely consistent because the measured data contain uncertainties. This may lead to incorrect damage identification results if these uncertainties are not appropriately addressed [19–24]. Therefore, some researchers have used probability-based methods to address the effect of temperature on vibration properties and to consider temperature uncertainties. Bao et al. [12] proposed a Bayesian-based damage detection technique in which structural parameters and temperature were variables of modal properties (frequencies and mode shapes). An experiment was carried out on a two-story portal frame, and the model uncertainty, measurement noise, and temperature effect were considered to verify the method's effectiveness.

Basseville et al. [25] proposed two extensions of the statistical parameter damage detection algorithm based on null space residuals associated with output-only subspace identification, which accounted for the temperature effects. The first extension was based on the use of a thermal model to derive a temperature-adjusted null space, and another involved the application of the thermal model and statistical nuisance rejection technique. Both methods were illustrated in laboratory test cases in a climate chamber. Wang et al. [16] introduced a Gaussian mixture model to cluster the temperature and frequency data into different subsets and deduced a new representative temperature for the bridge temperature field. In addition, they established a more accurate baseline correlation model. The authors reported an engineering application in a cable-stayed bridge, demonstrating the validity of eliminating the temperature-induced change in modal frequency based on long-term monitoring data.

2.1.2. Artificial Intelligence Methods

With the continuous development of artificial intelligence, this technique has been applied to various aspects of research [26–32]. In a study on the effect of temperature on vibration properties, Hsu and Loh [33] extracted the underlying environmental factors using an auto-associative neural network based on the structural system's identified or measured target features under varying environmental conditions. They reported that this technique could deal with non-increasing characteristics (stiffness) and non-decreasing characteristics (the damage index after introducing damage) without directly measuring ambient factors. Torzoni et al. [34] reported an effective damage localization strategy using vibration and temperature data to consider the influence of temperature fluctuation on the structural response. By allowing a limited number of predefined damage scenarios, temperature data were used as a condition, and deep learning technology was used as a supervised classification to deal with damage localization tasks. They tested the capability of this procedure to locate the damage through two case studies and showed a relatively high accuracy even in a rather small local stiffness properties reduction situation.

Zheng et al. [35] proposed a new method to reduce the influence of temperature variation on the dynamic modal characteristics of bridges. They used a probabilistic-based machine learning method (the Gaussian process model) to learn the correlation between the modal characteristics of the monitored bridge and the corresponding temperature variations based on field sensor measurements. Then, the authors simulated a numerical example to prove the effectiveness of this method in mitigating temperature variations or other ambient impacts in vibration-based structural health monitoring. Zhou et al. [15] used the back-propagation neural network (BPNN) technique to establish the correlation between damage-sensitive modal characteristics and temperature. With the correlation model, the measured modal characteristics under different temperature conditions were normalized to the same reference temperature state to eliminate the effect of temperature. Then, the normalized modal characteristics were applied to structural damage identification.

2.1.3. Optimal Algorithm Methods

Many researchers have studied optimization algorithm methods since they are simple and can be calculated quickly. Huang et al. [36] investigated a non-destructive global damage identification method based on a genetic algorithm (GA), which was used to identify the severity and location of damage to a structure under the influence of temperature variation and noise. The method's effectiveness was verified in several scenarios of damage to three-span continuous beams and two-span steel trusses, and it showed good robustness under random noise levels.

Meruane and Heylen [37] studied a damage detection method that was able to deal with temperature variations. In their study, the objective function correlated mode shapes and natural frequencies, and a parallel genetic algorithm handled the inverse problem. Since the elastic modulus of materials is temperature-dependent and the algorithm updated the temperature and damage parameters together, the temperature effects and real damage events could be distinguished. The authors then simulated the I-40 bridge and a three-span bridge to verify the method.

2.1.4. Other Methods

In addition to the above three methods used to study the effect of temperature on vibration properties, some scholars have adopted different methods to study this issue. For instance, Gillich et al. [38] employed adjustment coefficients to eliminate the effect of temperature, which were individually developed for each mode of vibration. Then, the authors proposed a damage assessment method based on multi-modal analysis, which allowed the assessment of beam axial force damage caused by temperature variation. Under the condition of variable temperature, numerical simulation and experimental tests were carried out on the beams with fixed ends to verify the practical applicability of the method for adjusting the coefficient.

Manoach et al. [39] presented a numerical and experimental study of the vibration of a damaged laminated beam under dynamic loads and temperature variations. Based on the analysis of Poincaré maps of the damaged and healthy plate, the early proposed non-heating plate damage detection criterion was modified, and the damage detection of beams under high temperature was tested. The importance of considering the actual temperature in damage detection was shown. Xia et al. [40] investigated the variations in structural vibration characteristics versus the structure's non-uniform temperature field. A thermodynamic model was used to estimate the temperatures of different structure components at different times. This study provided a novel way to quantify the influence of ambient effects on structural vibration features.

Zhu et al. [41] presented a feature extraction method to uncover the effects of temperature on bridge responses, which combined mode decomposition, data reduction, and blind separation. They also evaluated the effect of the extraction of the temperature-induced response on damage detectability using moving principal component analysis (MPCA). A truss bridge model was numerically analyzed to evaluate the thermal feature extraction method. The numerical results showed that this method was able to realize the separation of the temperature response.

2.2. Experimental Research

2.2.1. Quantitative Analysis

In the literature on the investigation of the effect of temperature on vibration properties, some scholars have focused on building theoretical models employing measured experimental data to quantify the impact of temperature on vibration properties. Based on a six-month monitoring experiment program, Cury et al. [42] established a model of the influence of temperature on the modal frequency of a PSC box girder bridge on the A1 highway in France. Then, they introduced a neural network to establish a regression model for quantifying the influence of temperature on modal parameters (frequencies and vibration modes). He et al. [43] studied a PC beam bridge in Oklahoma, developed an efficient temperature loading model to predict the temperature-induced response of the bridge, and formulated the criterion of the temperature loading effect in condition assessments based on reliability. They proposed a probabilistic model based on a uniform distribution of the temperature field and temperature gradient. This model was able to help engineers to predict the thermal behavior of PC bridges in Oklahoma, USA. They [44] also estimated the movement and stress under temperature loading with a three-dimensional (3D) finite element model and compared it with the monitoring counterparts.

Montassar et al. [45] studied the thermal effects of the inclined elastic stay cables' static and dynamic mechanical properties in cable-stayed structures. They proposed a nonlinear analytical method to calculate the variation in tension in stay cables under the influence of uniform temperature variations. They also investigated the influence of temperature variations on the free undamped vibration of stay cables. The validity and effectiveness of this method were verified by comparing the model results with measured data from the stay cables of the Rades-La Goulette cable-stayed bridge in Tunisia. Li et al. [46] focused on the boundary conditions' effects on the dynamic behavior of a suspension bridge. They proposed an analytical model to perform a sensitivity analysis of a bridge's modal parameters related to the stiffness of the expansion joints located at both ends of the bridge. They concluded that the boundary conditions significantly affected the low-order modal parameters of the suspension bridge. Moaveni and Behmanesh [47] studied the influence of ambient temperature variation on updating the finite element model of the Dowling Hall Footbridge. The footbridge had a continuous monitoring system that recorded the vibration and temperature of the bridge once an hour or when a large vibration was triggered. The authors then estimated a static polynomial model to "remove" the temperature effects from the identified natural frequencies. The proposed approach successfully minimized the effects of changing ambient temperature on the FE model updating of the Dowling Hall Footbridge.

Xia et al. [48] investigated the temperature distribution and the related response of a long-span suspension bridge—the 2132 m Tsing Ma Bridge—through numerical analysis and field monitoring. Under appropriate assumptions, fine finite element models of the bridge deck, section frame, and bridge tower were established to facilitate thermal analysis. They found that the combination of numerical analysis and field monitoring data provided a thorough understanding of the temperature behavior of long-span bridges. Zhou et al. [49] monitored the Ting Kau Bridge in Hong Kong for 770 h and constructed an appropriate neural network input to simulate the modal changes caused by temperature. The principal components of the average temperature, effective temperature, and temperature were constructed as inputs of the neural network to model the correlation between modal frequency and ambient temperature. They found that the temperature profile characterized by effective temperature was insufficient to establish a good correlation model between modal frequency and temperature.

Zhu et al. [50] investigated the relationships between temperature-induced stress and standard temperature variations by monitoring a 108 m-long steel truss bridge for two years. They provided a simple formula to model the relationship between temperature-induced strain and the temperature distribution. The accuracy of the proposed formula was verified using field monitoring data for box-shaped and H-shaped components. Their research can provide a simple and relatively general solution for temperature-induced strain prediction for steel truss bridges. They [51] also initially used the elastic beam theory to explore the relationship between temperature variation and temperature-induced responses.

2.2.2. Qualitative Analysis

In addition to the quantitative analysis of the effect of temperature on vibration properties, some scholars have paid more attention to the quantitative analysis of this issue. For example, using long-term monitoring data, Ding and Li [52] addressed the temperature variation problem of the measured modal frequency of the steel box girder of a suspension bridge. They studied the daily and seasonal correlations of the frequency and temperature in detail. They concluded that temperature was the key source of modal variability, and there was an overall decrease in modal frequency with temperature for all identified modes. In addition, the vibration mode's daily average modal frequency had an obvious seasonal correlation with the daily average temperature.

Mao et al. [53] measured the dynamic characteristics (including acceleration, strain responses, and modal frequencies) of the Sutong Cable-Stayed Bridge for one year. They also analyzed the variability of structural modal frequency caused by ambient temperature. The results showed that temperature was the crucial environmental factor for vertical and torsional modal frequencies. Mosavi et al. [54] investigated the influence of temperature variations on the modal properties of a two-span steel-concrete composite bridge in North Carolina. Field tests included measuring the bridge's vibration response, temperature, and deflection throughout a summer day. They found that temperature variation could induce modal variability in a daily cycle. Teng et al. [55] carried out the long-term monitoring of an arch bridge. They used correlation analysis, numerical simulation, and the neural network technique to report the influence of temperature on structural frequency. They observed that due to the influence of temperature, the frequency of the beam mode was affected by boundary conditions and the elastic modulus, and the change in the elastic modulus only affected the frequency of the arch models.

Xia et al. [56] monitored a long-span suspension bridge for one year and studied the influence of thermal variations on structural performance under operating conditions. The authors statistically analyzed the long-term temperature and structural response data, including displacement, strain, and suspender frequency. The statistical analysis results showed that the longitudinal temperature distribution along the main beam was nonuniform. They [57] also proposed a structural damage identification method using the temperature-induced response. They derived the structural transfer function by taking the input and output data of temperature load changes and temperature-induced strain. Yun et al. [58] studied the Guangzhou New TV Tower (GNTVT) and they reported the varying patterns of the operational modal parameters under the effects of different environmental factors. The authors found that temperature only affected the modulus of elasticity and the geometric stiffness of the structure.

2.2.3. Temperature Test Method

The instrumentation and steps applied for measuring the effect of temperature on bridge structures are as follows. Firstly, thermal resistance is installed on the surface and inside the bridge structure, and a multi-point wireless temperature automatic test system is used to measure the temperature of the bridge pier and beam. Then, before and after the vibration tests, the thermal radiation value of the structure surface is measured by means of a thermal radiometer, and an infrared imager captures temperature field images of the structure during the test. Finally, the temperature-time history of the bridge structure, three typical temperature distribution modes of a beam (vertical positive temperature difference, vertical negative temperature difference, and transverse temperature distribution), and two directional temperature distribution modes of the pier are obtained.

3. Damage Detection Methods for Bridge Structures

In the previous section, from the perspectives of theoretical analysis and experimental validation, we have summarized the existing studies that focus on the influence of ambient temperature on natural frequency and mode shape. In this section, a series of damage identification methods for bridge structures are reviewed and discussed in detail.

3.1. Model-Based Methods

Model-based methods are a category of structural damage detection (SDD) methods that require the assistance of the finite element model of the corresponding structure. The main idea is first to determine the benchmark finite element model based on an undamaged structure, and then the analytical vibration data are extracted to conduct a comparison with the measured data from the damaged structure so that the damage can be detected directly. Therefore, the model-based method strongly depends on the corresponding finite element model, it also can achieve the damage identification of level III, namely, the quantification of damage severity.

3.1.1. Meta-Heuristic Optimization-Based Model Updating Method

Structural model updating is a method that was originally designed to correct the physical and/or geometric parameters of an established FEM to obtain the benchmark FEM of the actual structure. By minimizing the discrepancy between analytical and measured features, iterative analysis is conducted until the benchmark FEM can reflect the consistency of the real one. Following this idea, we can exploit this method to identify structural damage.

Following the theory of structural dynamics, we have a structural dynamic equation that can be shown as follows:

$$[M]\ddot{x} + [C]\dot{x} + [K]x = \{f\} \tag{1}$$

where $[M]$, $[C]$, and $[K]$ stand for the mass, damping, and stiffness matrix of a structure, respectively; $\{f\}$ refers to the external force excitation; and $\ddot{x}$, $\dot{x}$, and x represent structural acceleration, velocity, and the displacement vector, respectively. Let $\{f\} = 0$, ignoring the damping, and the above equation can be transformed into an undamped free vibration differential equation, which can be expressed as follows:

$$([K] - \lambda_i[M])\{\varphi_i\} = 0 \tag{2}$$

where λ_i and φ_i denote i-th eigenvalue and eigenvector. When considering the theory of finite element analysis, assuming that the damage only causes a change in the structural stiffness, the SDD model can be formulated as follows [59]:

$$[k]_e^d = (1 - \theta_e)[k]_e^u \tag{3}$$

$$[K]_e^d = [S]^T[k]_e^d[S] \tag{4}$$

$$[K]_d = \sum_{e=1}^{nele}[K]_e^d \tag{5}$$

where $[k]_e^d$ and $[k]_e^u$ stand for the e-th damaged and intact structural element stiffness matrix in the local coordinate, respectively; θ_e is the damage coefficient of the e-th structural element; $[S]$ represents coordination transformation matrix; and $[K]_e^d$ and $[K]_d$ are the e-th element stiffness matrix in the global coordination and the global stiffness matrix of a structure, respectively. Based on the above statement, we can conduct SDD by narrowing the gap of dynamic characteristics between the intact structure (benchmark FEM) and the damaged structure (actual structure). So that the issue can be mathematized as an optimization problem with constraints, it can be represented as follows:

$$\underset{\Theta=\{\theta_1,\theta_2,\cdots,\theta_{nele}\}}{\operatorname{argmin}} \{Obj(\Theta)\}, s.t 0 \le \theta_e < 1, e = 1, 2, ..., nele \tag{6}$$

where $Obj(\Theta)$ denotes the objective function of damage identification, which can be minimized through an optimization algorithm, and then the output Θ stands for the site and extent of structural damage.

Regarding the description of the FEM-updating damage detection method, two issues should be pointed out: (1) an optimization algorithm with high convergence efficiency and good global search ability is needed to solve it; and (2) the objective function should be constructed based on some indicators with good damage sensitivity and noise robustness. The common optimization tools adopted in FEM-updating SDI SDD methods are shown in Table 1.

Table 1. The optimization tools adopted in FEM-updating SDD methods.

Item	Methodology	Advantage and/or Trait
Optimization Tools	Genetic Algorithm [59]	The first one used in SDD
	Particle Swarm Optimization [60]	Elite orientation for position updating
	Cuckoo Search [61,62]	Random elimination mechanism
	Jaya Optimization [63,64]	Parameter-free
	Moth-flame Optimization [65,66] Whale Optimization [67–69]	Logarithmic spiral function for position updating
	Sunflower Optimization [70]	Inverse square law radiation and random pollination
	Echolocation Search Algorithm [71]	Dislocalization technique to avoid local optima
	Tug-of-war optimization [72]	Originally proposed for SDI
	Gray Wolf optimization [73]	Gray wolf hierarchy for the selection of the best agent
	Experience-based Learning (EBL) algorithm [74]	Two modes to balance the exploration and exploitation
Improved Optimization Tools	PSO-CS [75]	Better global search performance
	(PSO)-Simplex Algorithm [76,77]	Improvement in the local search
	Enhanced MFO [78]	Both global and local search abilities are enhanced
	Hybrid Jaya and Tree Seeds Algorithm [79]	Avoiding local minimal
	Improved Jaya algorithm [80]	Clustering strategy to enhance the global optimization capability

Huang et al. [59] introduced a genetic algorithm and an objective function constructed based on frequencies and mode shapes with different weight coefficients to address the issue of damage identification considering varying temperature effects. A three-span continuous beam and a two-span steel grid under temperature variation conditions were exploited to validate the method's feasibility. Tang et al. [60] adopted a technique called "damage signal match" to locate the possible damage site, then particle swarm optimization was used to determine the real damage severity. Huang et al. [61] studied the damage identification problem in a steel-concrete composite bridge under varying temperature conditions, and a cuckoo search was employed to tackle this problem. Du et al. [63,64] evaluated the efficiency of the Jaya algorithm in solving optimization-based damage identification problems based on some numerical examples. Huang et al. [65] first used a support vector machine to predict nonlinear ambient temperature variations, then moth-flame optimization was used to identify the damage. The authors in [67] combined whale optimization with a modal flexibility index to propose a novel damage identification method, which could reduce the impact of the surrounding elements on the damaged elements. Gomes et al. [70] used sunflower optimization to detect the damage in composite laminated plates, and the results showed that it was more accurate than the genetic algorithm. Nobahari et al. [71] proposed the echolocation search algorithm to solve the multiple parameters damage location and quantification, and the results indicated good reliability. Kaveh and Zolghadr [72] first developed a novel optimization tool named tug-of-war optimization. The algorithm was used to identify cases of highly damaged and slightly damaged elements. Hosseinzadeh et al. [73] proved that gray wolf optimization has a great global optimization ability, and can be used to solve highly ill-posed problems in damage detection. Zheng et al. [74] utilized simulation and experimental examples to verify the feasibility of an experience-based learning algorithm for damage detection.

Furthermore, due to the original limitations of the use of one optimization method, researchers have proposed some measurements to improve and/or enhance the sole optimization approach or have tried to mix multiple algorithms to obtain a hybrid one with better performance. In this regard, Huang et al. [75] combined the elimination mechanism of a cuckoo search with the original PSO to propose a PSO-CS hybrid algorithm, and performed damage identification considering the ambient temperature. Chen and Yu [77] combined the Nelder–Mead method with PSO to solve the optimization problem in the Bayesian multi-multi-sample objective function of SDD. Huang et al. [78] used multiple methods to enhance moth-flame optimization, and both global and local search abilities were improved. Ding et al. [79,80], using the Jaya algorithm, introduced the tree seeds algorithm and a clustering technique to enhance the global optimization ability and avoid the local optimal.

On the other hand, the existing papers have also focused on the investigation of the objective function of damage detection. Common objective functions include the natural/eigenfrequency change ratio (FCR), mode shapes (MS) and the modal assurance criterion (MAC), modal flexibility, multiple damage location assurance criterion (MDLAC), and modal strain energy (MSE), etc., as listed in Table 2. In the early stage of research, only a sole indicator was used to construct the objective function; however, the use of only one indicator cannot provide accurate damage identification results, so scholars began to adopt a combination of multiple indicators to enhance their models' performance in damage detection.

Table 2. The objective functions used in FEM-updating SDD methods.

Description	Objective function	Source
FCR	$obj(\theta) = \sqrt{\frac{1}{n\mathrm{mod}} \sum_{i=1}^{n\mathrm{mod}} \left(1 - \frac{\omega_i^e}{\omega(\theta)_i^a}\right)^2}$	Gome et al. [70]
FCR + MAC	$obj(\theta) = C_1 \cdot \sum_{j=1}^{n\mathrm{mod}} \left(\frac{\omega_{aj} - \omega_{ej}}{\omega_{ej}}\right)^2 + C_2 \cdot \sum_{j=1}^{n\mathrm{mod}} \left(\frac{1 - \sqrt{MAC_j}}{MAC_j}\right)^2$	Huang et al. [36]
FCR + MAC + MSE	$obj(\theta) = C_1 \cdot \sum_{j=1}^{n\mathrm{mod}} \left(\frac{\omega_{aj} - \omega_{ej}}{\omega_{ej}}\right)^2 + C_2 \cdot \sum_{j=1}^{n\mathrm{mod}} \left(\frac{1 - \sqrt{MAC_j}}{MAC_j}\right)^2$ $+ C_3 \cdot \sum_{j=1}^{n\mathrm{mod}} \left(\frac{MSE_{aj}^i}{MSE_{ej}^i} - 1\right)^2$	Huang et al. [75]
FCR + MAC + regularization term	$obj(\theta) = \sum_{j=1}^{n\mathrm{mod}} \left(\frac{\lvert\omega_{aj} - \omega_{ej}\rvert}{\omega_{ej}}\right)^2 + \sum_{j=1}^{n\mathrm{mod}} (1 - MAC_j) + \lambda \lVert 1 - \theta \rVert_{0.5}$	Ding et al. [79]
FCR + MAC + regularization term based on Bayesian method	$obj(\theta) = \sum_{j=1}^{n\mathrm{mod}} \frac{\lvert\omega_{aj} - \omega_{ej}\rvert^2}{2\sigma_i^2} + \sum_{j=1}^{n\mathrm{mod}} (1 - MAC_j) + \lambda \lVert \theta \rVert_1$	Ding et al. [80]
FCR + MS + regularization term	$obj(\boldsymbol{\theta}) = \frac{1}{n\mathrm{mod}} \sum_{i=1}^{n\mathrm{mod}} \left[\frac{f_i^a(\boldsymbol{\theta}) - f_i^e}{f_i^e}\right]^2 + \frac{1}{n\mathrm{mod} \times np} \sum_{i=1}^{n\mathrm{mod}} \sum_{j=1}^{np} \left[\phi_{ij}^a(\boldsymbol{\theta}) - \phi_{ij}^e\right]^2$ $+ \frac{\beta}{n} \lVert \boldsymbol{\theta} \rVert_1$	Huang et al. [59]
FCR + MS is based on the Bayesian method	$obj(\theta) = -\frac{1}{2} \sum_{i=1}^{nm} \left[\frac{(f_i - f_i(\theta))^2}{2\varepsilon_{f_i}^2} + \frac{(\boldsymbol{\varphi}_i - \boldsymbol{\varphi}_i(\theta))^T (\boldsymbol{\varphi}_i - \boldsymbol{\varphi}(\theta))}{2\delta_{\varphi_i}^2}\right]$	Chen and Yu [77]
MFSEAC + Modal Flexibility	$obj(\theta) = C_1 \cdot \sum_{j=1}^{nm} \left(\frac{1 - \sqrt{MFSEAC_j}}{MFSEAC_j}\right)^2 + C_2 \cdot \sum_{j=1}^{nm} (G_j^A - G_j^E)^2$	Huang et al. [78]
MDLAC	$obj(\theta) = 1 - MDLAC(\theta), MDLAC(\theta) = \frac{\lvert \Delta F^T \times \delta F(\theta) \rvert^2}{(\Delta F^T \times \Delta F)(\delta F^T(\theta) \times \delta F(\theta))}$	Huang et al. [81]
MDLAC + modal flexibility	$obj(\theta) = (1 - MDLAC(\theta)) + \frac{1}{n\mathrm{mod}} \sum_{j}^{nc} \left(\frac{\lVert F_j^{\exp} - F_j^{ana}(\theta) \rVert_{Fro}}{\lVert F_j^{\exp} \rVert_{Fro}}\right)^2$	Du et al. [63]
MDLAC + modal strain energy	$obj(\theta) = (1 - MDLAC(\theta)) + \frac{\sum_{e=1}^{nele} MSEBI^e}{nele}$	Huang et al. [65]

Due to the ease of obtaining of natural frequencies and mode shapes, it is convenient and efficient for engineers and researchers to assess structural damage based on these data; however, due to the limited number of sensors, and their limited sensitivity, it is difficult to measure high-order modal parameters and complete mode shapes. Therefore, for a large structure, the whole health condition can be evaluated based on FCR and MAC, but the damage localization may not be very accurate. To solve this issue, modal flexibility can be used, because in the equation of modal flexibility, the higher the order of the modal parameters, the less they contribute to the computation. Meanwhile, MSE is obtained based on the mode shapes and structural element stiffness matrix. It is very sensitive to the local damage of a structure, thus, MSE can be utilized to locate elements of damage and reduce the search range in damage detection. Considering the drawbacks of the MSE approach, the modal frequency strain energy assurance criterion (MFSEAC) was proposed, incorporating the component of natural frequency, which can balance the local and global damage indication performance.

Moreover, introducing a regularization term to the objective function is a good way to enhance the noise-robustness; however, it must be noted that the regularization parameter plays an important role in the balance between damage indication discrepancies and the damage coefficient vector. Thus, researchers should pay close attention to the selection of this parameter.

3.1.2. Wavelet-Based Method

A wavelet transform is a classical method to decompose a signal based on the level-by-level principle. The main operation is to form the original signal through linear combinations of wavelet base functions. Thus, an extension of the wavelet transform, called wavelet packet transform (WPT), can be employed to obtain the features in signals with stationary and non-stationary characteristics. Regarding the merits of WPT, researchers have tried to utilize it to detect structural damage based on collected acceleration data.

Based on the theory of WPT, the original signal can be decomposed to the j level of decomposition, which can be denoted as follows [82]:

$$f(t) = \sum_{i=1}^{2^j} f_j^i(t) \tag{7}$$

Then, $f_j^i(t)$, as a wavelet packet component, can be formed using a linear combination of wavelet packet functions, namely,

$$f_j^i(t) = \sum_{k=-\infty}^{\infty} c_{j,k}^i(t)\varphi_{j,k}^i(t) \tag{8}$$

where $c_{j,k}^i(t)$ refers to the wavelet packet coefficients, which can be calculated as follows:

$$c_{j,k}^i(t) = \int_{-\infty}^{\infty} f(t)\varphi_{j,k}^i(t)dt \tag{9}$$

where $\varphi_{j,k}^i(t)$ is the wavelet function, and it is also orthogonal, namely,

$$\varphi_{j,k}^p(t)\varphi_{j,k}^q(t) = 0, if\ p \neq q \tag{10}$$

After this, we can adopt the wavelet packet energy index to localize the structural damage site. It can be expressed as follows:

$$E_{f_j} = \int_{-\infty}^{\infty} f^2(t)dt = \sum_{p=1}^{2^j}\sum_{q=1}^{2^j}\int_{-\infty}^{\infty} f_j^p(t)f_j^q(t)dt \tag{11}$$

We take Equations (8)–(11), and, regarding the orthogonal, the above equation can be transformed as follows:

$$E_{f_j} = \sum_{i=1}^{2^j} E_{f_j^i} \tag{12}$$

where $E_{f_j^i} = \int_{-\infty}^{\infty} f_j^i(t)^2 dt$. Therefore, considering p main component energies, we can define the damage index as follows:

$$D = \sum_{i=1}^{p}\left|\left(E_{f_j^i}\right)_d - \left(E_{f_j^i}\right)_u\right| \tag{13}$$

where subscript d and u stand for damaged and undamaged, respectively.

On the basis of the wavelet transform approach, scholars have conducted numerous works. Hester and González [83] considered the fact that the deflection signal is difficult to record and the road profile of practical bridge, and proposed a novel damage detection method combining an acceleration signal with a wavelet tool. The proposed method showed good sensitivity to damage. Li et al. [84] combined the damage identification issue under moving vehicular loads with the wavelet domain dynamic response reconstruction technique, this method was validated by an experimental bridge. Yu et al. [85] addressed continuous wavelet transformation to deal with the deflection of the beam, so that the location of damage could be determined, and then the Lipschitz exponent was used to measure the severity of structural damage. The authors of that study also investigated the different damage cases, sensor locations, and external load velocities and magnitudes. Chu et al. [86] studied the damage detection of beam bridges using the characteristic curvature and adopted the wavelet threshold method to reduce the noise interference and ensure the accuracy of the damage assessment. Aiming at the identification of bridge mode shapes in the field of structural health monitoring (SHM), Jian et al. [87] proposed a wavelet analysis method to directly obtain mode shapes based on the dynamic responses of a tractor trailer vehicle model, and a wavelet denoising algorithm was utilized to enhance the accuracy. Machorro-Lopez et al. [88] presented a novel wavelet-based method, called the wavelet energy accumulation method, to assess the damage of vehicular bridges. First, a continuous wavelet transform was used to localize the site, then the wavelet energy was used to quantify the extent, and finally, the Rio Papaloapan Bridge was adopted to validate the method's feasibility. Mousavi et al. [89] reported a combination of an empirical wavelet transform and an artificial neural network to detect the presence of structural damage. The wavelet transform was used to extract features and the artificial neural network was used to identify the damage location and intensity. Qu et al. [90] undertook an adaptive wavelet analysis to process their collected signals, which showed good efficiency in separating each component. The damage detection issues displayed by the numerical example and a cable-stayed bridge in a shaking table test were adopted to verify the method. Sha et al. [91] aimed at the damage detection of laminated composite beams. The measured mode shapes were processed with the Teager energy operator, together with a wavelet transform, to obtain a sensitive and noise-robust damage indicator. Finally, the experimental validation proved that this method provided a good way of detecting damage in a high-noise environment.

To summarize, the existing studies indicate that wavelet transform methods have been mainly applied to feature extraction [92], dynamical signal denoising [93], and modal identification [94–96] in the field of SHM. Meanwhile, this method can provide a stable and better result. Furthermore, it they have also been widely adopted in the field of acoustic emission damage detection [97]. Regarding their applicability, researchers can thus investigate more applications of the wavelet transform technique in the field of SHM.

3.1.3. Bayesian Inference-Based Model Updating Method

Bridge structures are always influenced by a series of environmental factors, such as traffic flows, earthquakes, temperature variations, weather changes, and solar radiation. The complex service environment introduces many interferences to the field of SHM, further leading to the high level of uncertainty in damage identification. Due to these pervasive uncertainties, Bayesian inference can provide a useful way to obtain a probabilistic damage result.

Based on the Bayesian formula, the posterior probability distribution of a parameter can be calculated as follows [98]:

$$P(\theta|D,\widetilde{M}) = \frac{P(\theta\middle|\widetilde{M})P(D\middle|\theta,\widetilde{M})}{P(D\middle|\widetilde{M})} \tag{14}$$

in which $\widetilde{M}$ refers to the damage identification model; D denotes the experimental modal parameters; θ represents the damage coefficient; $P(D|\theta,\widetilde{M})$ and $P(\theta|\widetilde{M})$ indicate the likelihood function and the prior probability density function (PDF), respectively; and $P(D|\widetilde{M})$ is an unrelated constant for the use of normalization. Due to the pervasive uncertainties, such as measurement and modeling errors, we usually assume that uncertainties all obey a Gaussian distribution; thus, we can obtain equations as follows:

$$\varepsilon_f = f_i - f_i(\theta) \sim N(0, \mathrm{cov}_{f_i}^{-1}) \tag{15}$$

$$\varepsilon_\varphi = \boldsymbol{\varphi}_i - \boldsymbol{\varphi}_i(\theta) \sim N(0, \mathrm{cov}_{\varphi_i}^{-1}) \tag{16}$$

in which and $\boldsymbol{\varphi}_i(\theta)$ stand for the i-th analytical natural frequency and mode shape corresponding to the damage coefficient θ, respectively; f_i and φ_i denote the i-th measured natural frequency and mode shape; and $\mathrm{cov}_{f_i}^{-1}$ and $\mathrm{cov}_{\varphi_i}^{-1}$ indicate the covariances, which can measure the uncertainty of the natural frequency and mode shape, respectively. Combining Equation (15) with (16), and considering each modal test as independent, so that the measured modal parameters are also independent, we can finally observe the likelihood function of the damage coefficient θ is as follows:

$$P(f|\theta) = \prod_{i=1}^{nm} P(f_i|\theta) = \left(\prod_{i=1}^{nm} \frac{\mathrm{cov}_{f_i}}{2\pi}\right)^{\frac{1}{2}} \exp\left(-\frac{1}{2}\sum_{i=1}^{nm} \frac{(f_i - f_i(\theta))^2}{\mathrm{cov}_{f_i}}\right) \tag{17}$$

$$P(\boldsymbol{\varphi}|\theta) = \prod_{i=1}^{nm} P(\boldsymbol{\varphi}_i|\theta) = \left(\prod_{i=1}^{nm} \frac{\mathrm{cov}_{\varphi_i}}{2\pi}\right)^{\frac{1}{2}} \exp\left(-\frac{1}{2}\sum_{i=1}^{nm} \frac{(\boldsymbol{\varphi}_i - \boldsymbol{\varphi}_i(\theta))^T(\boldsymbol{\varphi}_i - \boldsymbol{\varphi}(\theta))}{\mathrm{cov}_{\varphi_i}}\right) \tag{18}$$

in which nm refers to the considered modal orders. Then, taking the above two equations to the Bayesian formula, we can obtain the posterior probability density function of the damage coefficient θ as follows:

$$\begin{aligned} P(\theta\Big|D, \widetilde{M}) &= c^{-1} P(f\Big|\theta) P(\boldsymbol{\varphi}\Big|\theta) \\ &= c^{-1}\left(\prod_{i=1}^{nm} \frac{\mathrm{cov}_{f_i}}{2\pi}\right)^{\frac{1}{2}} \left(\prod_{i=1}^{nm} \frac{\mathrm{cov}_{\varphi_i}}{2\pi}\right)^{\frac{1}{2}} \cdot \\ &\exp\left\{-\frac{1}{2}\sum_{i=1}^{nm}\left[\frac{(f_i - f_i(\theta))^2}{\mathrm{cov}_{f_i}} + \frac{(\boldsymbol{\varphi}_i - \boldsymbol{\varphi}_i(\theta))^T(\boldsymbol{\varphi}_i - \boldsymbol{\varphi}(\theta))}{\mathrm{cov}_{\varphi_i}}\right]\right\} \end{aligned} \tag{19}$$

in which c is a constant number. Furthermore, we can adopt the Monte Carlo Markov chain (MCMC) method to solve this equation and then obtain a probabilistic damage identification result.

Regarding the Bayesian method's ability to measure uncertainty, it has been widely used in the field of damage identification. Mustafa et al. [99] adopted the Bayesian damage detection method to consider variations in material and geometric properties and measurement errors; a real-life rail-cum-roadway long steel truss bridge was utilized to verify its feasibility. Based on the Bayesian method, Figueiredo et al. [100] tackled the challenge of assessing the negative effects of operational and environmental variations on structural responses, finding some limitations of damage detection could be overcome, and the proposed approach showed great applicability for actual bridges. Ebrahimian et al. [101] proposed a batch Bayesian estimation approach to solve the task of nonlinear model updating. Furthermore, to identify the structural damage, a realistic structural FE model of a bridge pier and a moment resisting steel frame were adopted to perform the verification, and the results showed excellent performance for SHM. Behmanesh et al. [102] reported on the use of a hierarchical Bayesian modeling method to carry out probabilistic FEM updating. The proposed approach was validated through the use of a numerical shear building, and modeling errors and incomplete measurements were considered. Yang and Lam [103] improved upon the traditional MCMC method, proposing an efficient adaptive sequential Monte Carlo (ASMC) method, and introduced the ASMC method, achieving high efficiency and accurate damage detection, with case studies indicating that the obtained posterior

PDF had good precision. Yin et al. [104] researched periodically supported structures from the perspective of the Bayesian probabilistic method. A periodically supported flanged pipeline numerical example and an experimental multi-span aluminum beam model were adopted for verification. The results illustrated the feasibility of the proposed method. Kuok and Yuen [105] monitored Canton Tower using a Bayesian framework. The Bayesian spectral density approach was employed to obtain the modal information based on the collected acceleration data, then Bayesian model updating was carried out to correct the results. Astroza et al. [106] aimed to address the issue of complex nonlinear FEM updating, exploiting a batch-recursive variant method to cut down on the computational cost and enhance efficiency. Two experimental examples with strong nonlinearities, i.e., a 2-D steel frame building and a 3-D isolated bridge, were used to validate the method, with results showing that the proposed method could be used to calibrate large and complex hysteretic FE models. Luo et al. [107] focused on the improvement of the MCMC sampling method and obtaining damage identification accuracy, proposing a novel and effective sampling method called the MH-PSO hybrid MCMC sampling method. The damage identification poster PDF objective function was also constructed based on the autoregressive model, and the related work was able to enhance the damage identification accuracy greatly.

Therefore, considering the pervasive uncertainties, there is no doubt that approaches to the probabilistic damage detection problem can rely on the Bayesian framework, as it provides a probabilistic rather than a specific result for damage detection, which is more realistic. In addition, interval mathematics can also be useful, but this approach yields a solution with an approximate interval rather than a probabilistic one [108,109].

3.2. Data-Based Methods

Compared with model-based methods, data-based methods have some advantages, as they are FEM-free, with good feature extraction capability, automatic and precise pattern recognition, and excellent nonlinear fitting performance. This type of method has become a very popular approach in the field of SHM, and they have been widely applied and extended, accompanied by developments in computational power and highly sensitive sensors.

3.2.1. Machine Learning Methods

The basic idea of SDD using machine learning (ML) can be summarized as classifying the different patterns of the input and using a label to represent a pattern. The input includes but is not limited to the modal parameters, acceleration signals, strain and stress, or/and other data features obtained from various preprocessing tools. Moreover, the label can be defined according to the damage case, failure site, damage severity, etc. In this regard, support vector machines (SVMs) and artificial neural networks (ANNs) are the classical ML methods in the field of SHM.

(1) Support Vector Machines (SVMs) [65]

An SVM can be explained as a classifier with a generalized linear classification capability, which also belongs to the category of supervised learning. An SVM maps the input data into a high-dimensional space, and then the maximum margin hyperplane is used to classify the different patterns or regression, as illustrated in Figure 1. The corresponding loss function is the hinge loss with a regularization term; it also has the merit of being parameter-free.

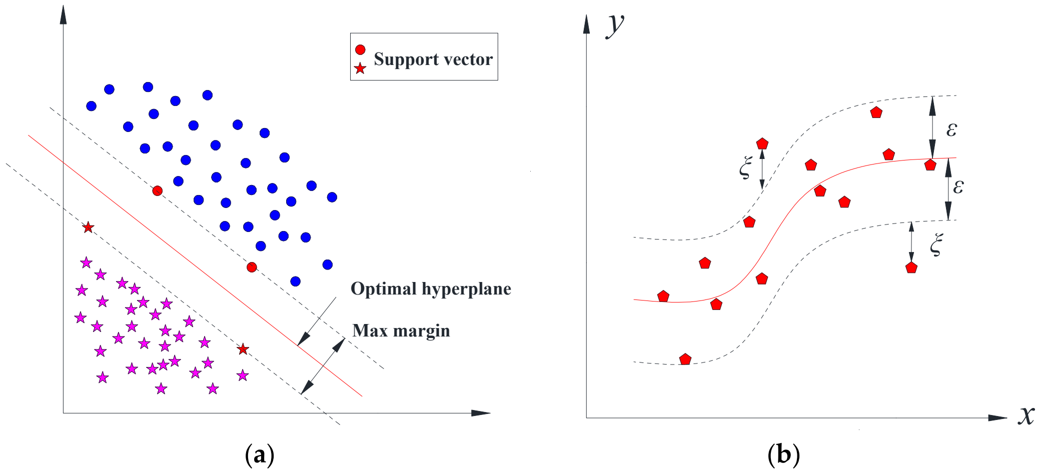

Figure 1. Support vector machine: (**a**) optimal hyperplane for classification and (**b**) SVM for regression [65].

For n sets of input data $(x_i, y_i)(x_i \in X \subseteq R^n, y_i \in Y \subseteq R)$, they can be labeled as belonging to two categories, A and B. When $x_i \in A$, then $y_i = 1$, and otherwise $y_i = 0$. Then these data points are mapped to a high-dimensional space, so that there is a hyperplane that can perfectly classify them, and the related mathematical equation can be described as follows:

$$f(x) = \begin{cases} wx_i + b \geq 1 y_i = 1 \\ wx_i + b \leq 1 y_i = 0 \end{cases}, i = 1, 2, \cdots, n \tag{20}$$

in which w and b stand for the weight and bias, respectively. Thus, we can measure the distance from the input data x_i to the hyperplane as follows:

$$\varepsilon_i = y_i(wx_i + b) = |wx_i + b| \tag{21}$$

Based on the above equation, we can determine the hyperplane via optimization, namely,

$$\min \frac{1}{2}\|w\|^2, s.t. y_i(wx_i + b) \geq 1, i = 1, 2, \cdots, n \tag{22}$$

The Lagrange multiplier method can be adopted to solve Equation (22).

As they are small and easy to use, SVMs have been used for SDD in some studies. Zhou et al. [110] adopted Dempster–Shafer (DS) evidence theory to improve upon the original SVM to enhance its performance in SDD, based on a benchmark structure. The result showed that the proposed approach could achieve a more stable SDD. Yu et al. [111] proposed a novel SVM SDD framework to solve the SDD problems of wood utility poles. An SVM multi-classifier was adopted, and it was optimized using a GA for better accuracy. The experimental example indicated that the proposed method could make full use of the collected sensor signals. Ghiasi et al. [112] incorporated a novel combinational kernel function to SVM. The authors also exploited the social harmony search algorithm to find the best parameters for the improved SVM. The results showed that these improvement could enhance SDD accuracy. Wang and Cha [113] reported a novel SDD method that combined a deep auto-encoder and an SVM. The deep auto-encoder was used to extract damage-sensitive indicators from the raw acceleration data, and the SVM was utilized to classify the damage situation. This method was able to achieve a stable and robust SDD, and its performance was very good. Seyedpoor and Nopour [114] aimed to achieve the SDD of the moment frame connections. First, the authors employed SVM to locate the damaged location of the connection based on the collected modal characteristics, and then the differential evolution algorithm was linked to prior damage location knowledge to quantify the extent of the damage of the connection. The damage location and quantification results were good. Diao et al. [115] used a combination of the Hilbert–Huang transform and SVM for SDD. The damage features were constructed using the Hilbert–Huang transform from the measured vibration signals, whereas SVM classification was used for localizing the damage location, and regression was used for quantifying the damage severity. Lei et al. [116] studied the use of an SVM and statistical analysis for SDD. A total of three damage indicators were obtained. Then, with the help of an SVM, some damage features' fusion schedules were proposed to detect damage cases.

(2) Artificial Neural Network (ANN) [117]

The classical neural network is the back-propagation neural network (BPNN), which has attracted much attention from researchers in the past decades. BPNN is a multi-layer feed-forward neural network. It always includes several layers, such as an input layer, a hidden layer, and an output layer. In the training stage, the input data $X = \{x_1 \quad x_2 \quad \ldots \quad x_n\}^T$ are first used to train the BPNN model with random weighting. Then, the corresponding output $\hat{Y}$ is obtained from the output layer. This process can be mathematized as follows:

$$y_k = h_2\left(\sum_{j=1}^{N_2} W_{jk}^2 h_1\left(\sum_{i=1}^{N_1} W_{ij}^1 x_i + b_i\right) + b_j\right) \quad (23)$$

in which y_i and x_i stand for the i-th element of $\hat{Y}$ and X, respectively; W_{ij}^k is the weight corresponding to the i-th neuron of k-th layer links to j-th neuron; bias is represented by b_j; N_i denotes the total number of neurons in each layer; and $h(x)$ can be defined as activation function. In BPNN, the sigmoid function is always used. With the numerous datasets that have been fed into the BPNN model, a nonlinear mapping relationship has been established, so the pattern can be identified by a well-trained BPNN model.

Betti et al. [118] conducted an experimental investigation to evaluate the performance of an ANN. Natural frequencies and mode shapes were used as the input data. Tran-Ngoc et al. [119] proposed an effective ANN for the SDD of bridge structures, optimized by means of a cuckoo search. This technique avoided the local optima of the original gradient descent method, and also improved the computational cost. Nguyen et al. [120] took transmissibility functions as the input of an ANN to solve the SDD of the Ca-Non Bridge. The well-trained ANN was able to assess the damage well. Hakim et al. [121] studied the SDD of steel girder bridges using several orders of natural frequencies, with the obtained results demonstrating that the ANN could identify structural damage with few frequency data, and it showed good potential for practical applications. Padil et al. [122] considered the deterministic output of a traditional ANN. A non-probabilistic approach called the interval mathematics method was incorporated into the basic ANN to obtain an interval result, which was able to improve the overconfident output to some extent. Shu et al. [123] investigated the statistical features of the collected dynamic responses, the obtained damage features were input into an ANN, and sensitivity analysis of the input was also carried out. Finally, a single-span, simply supported beam railway bridge was used to validate the method's feasibility. Nick et al. [124] put forward a two-stage SDD method. Firstly, the modal strain energy-based damage index was used to localize the damage site, and then the well-trained ANN was used to measure the severity of structural damage.

3.2.2. Deep Learning Method

Because the traditional ANN only has a few layers, its shallow architecture strongly limits its performance in nonlinear fitting. However, in order to deal with the more complex SDD situation, we can adopt a deep neural network, an approach which is also known as the deep learning (DL) technique shown in Figure 2. DL can be approximately determined as an advanced version of machine learning. It has been able to achieve great accuracy and efficiency in the field of SHM.

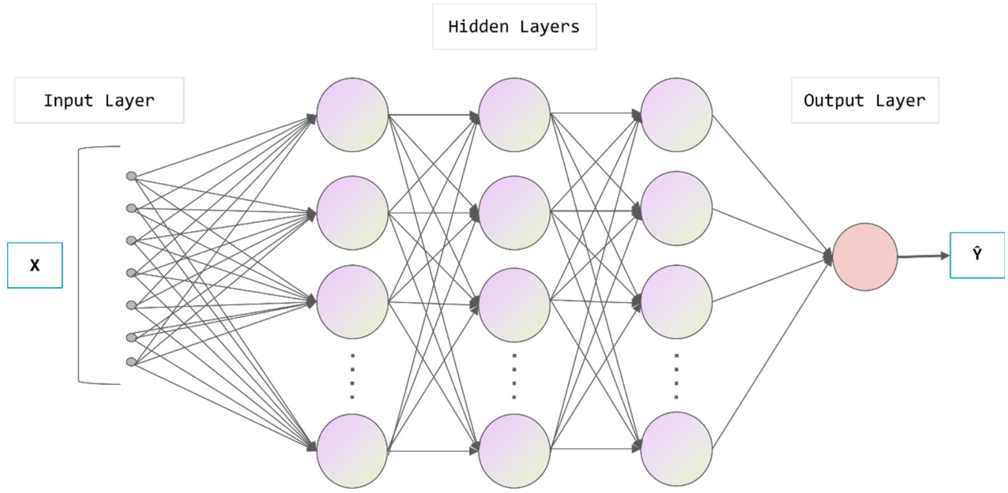

Figure 2. Deep neural network.

Based on structural response, He et al. [125] adopted a recurrence graph to extract damage features to represent different damage cases; then, a convolutional neural network (CNN) was used to identify different graphs and furthermore to output minor structural damage. Yang and Huang [126] focused on the safety of prestressed concrete girder bridges. The flexibility curvature was combined with a CNN to realize the SDD, and numerical simulations proved that the method had great feasibility. Nguyen [127] reported on the use of the gapped smoothing method and modal curvature to evaluate damage sites without the help of a health structure. Then, the damage index was fed into a CNN to achieve damage quantification for the Bo Nghi bridge. Fernandez-Navamuel [128] used FEM to enhance the input data for the training of the DL model, then a well-trained autoencoder neural network was utilized to estimate the location and extent of damage. Finally, the authors evaluated the performance of the reported method using two full-scale bridges, and the method was applied successfully. Duan et al. [129] transformed the collected acceleration signals into Fourier amplitude spectra, then combined this with the use of a CNN to detect the damage of hanger cables in a tied-arch bridge. The proposed method showed good robustness under the interference of environmental noise and wind speeds. Zhang and Lei [130] tried to remove the abnormal data from collected monitoring datasets. The authors developed a novel data anomaly detector based on a CNN to identify and discard the abnormal data, and further to ensure the subsequent work of SDD. Qiao et al. [131] aimed to ensure the safety of steel bridges by proposing an intelligent vision-based crack detector to label cracks and exposed steel bars, which was realized by redesigning the original densely connected convolutional networks though adding the expected maximum attention (EMA) module after the last pooling layer. Zhang et al. [132] used the advantages of the Internet of Things to improve SDD performance. A novel, intelligent and digital crack identification approach was developed to enhance detection efficiency in bridge safety diagnoses, as well as to reduce the risk factor. Xu et al. [133] used a dataset consisting of 350 raw images taken by a consumer-grade camera, adopting the fusion technique to modify a plain CNN to enhance the SDD accuracy. The modified CNN was used to detect surface fatigue cracks. Quqa et al. [134] studied the problem of crack identification, with the validation proving that the CNN could achieve accurate crack image detection and good noise robustness and accuracy. Zhu et al. [135] proposed a transfer learning technique to enhance a plain CNN. The high dependency on empirical knowledge of traditional crack detectors was overcome through comparative studies, and the results demonstrated that the proposed technique could obtain better accuracy. Mantawy and Mantawy [136] overcame the limitations of a small collected data set by encoding the time-series data into images. Then, a CNN was used to classify the image dataset to achieve bridge structural health monitoring. Dang et al. [137] evaluated different DL algorithms to measure their corresponding damage identification capabilities based on raw acceleration. These included the multi-layer perceptron, long short-term memory network, 1D CNN, and plain CNN approaches. The results showed that 2D CNN could achieve good performance in terms of both accuracy and complexity. Fan et al. [138] considered the data loss problem in relation to SHM data. The authors used a CNN to realize the construction of an incomplete dataset, and long-term monitoring data for the Dowling Hall Footbridge were utilized to validate the method's feasibility.

4. Conclusions

In this paper, we reviewed the progress of research on the effect of temperature on vibration properties and damage identification technology in bridge structures. Our main conclusions are as follows.

(1) The probability analysis method can take into account uncertainties such as ambient temperature, and artificial intelligence can be used to process a large amount of data. Probability and artificial intelligence methods have attracted the most attention from researchers among the three methods in the theoretical analysis of the relationship between temperature and vibration properties. In the quantitative analysis of experimental results, probability analysis methods and artificial intelligence methods have been adopted by most researchers in the processing of experimental data. For qualitative analysis in experimental studies, researchers have concluded that temperature is the critical source contributing to modal variability. There is an overall decrease in modal frequency with temperature for all the identified modes. Furthermore, temperature variations can induce modal variability on a daily cycle. Temperature is the most important environmental factor for vertical and torsional modal frequencies. Temperature only affects the modulus of elasticity and the geometric stiffness of the structure.

(2) In model-based damage identification methods, the use of optimization algorithms has been studied by many researchers since they are simple and can be calculated quickly, and a variety of damage identification objective functions have been proposed for these methods. Given that the WPT can be employed to obtain the features of signals with stationary and non-stationary characteristics, this technique has been applied in the SHM field by some researchers to detect structural damage based on collected acceleration data. The existing studies indicate that the wavelet transform has been mainly applied to feature extraction, dynamical signal denoising, and modal identification in the SHM field. Meanwhile, this method can provide stable and superior results. Furthermore, this approach is also widely adopted in acoustic emission damage detection. Due to its applicability, researchers could thus investigate more applications of the wavelet transform technique in future studies the field of SHM. Due to the pervasive uncertainties involved, there is no doubt that solutions to probabilistic damage detection problems can rely on the Bayesian framework. It provides a probabilistic rather than a specific result in damage detection, which is more realistic. In addition, interval mathematics can be useful, although this approach yields a solution with an approximate interval rather than a probabilistic one.

(3) With the development of artificial intelligence technology, the field of damage identification is becoming more closely linked with artificial intelligence technology, and a variety of damage identification technologies based on machine learning and deep learning have been developed. Compared with model-based methods, data-based methods have some superior advantages, as they are FEM-free, with good feature extraction capabilities, automatic and precise pattern recognition, and excellent nonlinear fitting performance.

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