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REVIEW

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Recent progress and future trends on damage identification methods for bridge structures

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Summary

Damage identification forms a key objective in structural health monitoring. Several state-of-the-art review papers regarding progress in this field up to 2011 have been published. This paper summarizes the recent progress between 2011 and 2017 in the area of damage identification methods for bridge structures. This paper is organized based on the classification of bridge infrastructure in terms of fundamental structural systems, namely, beam bridges, truss bridges, arch bridges, cable-stayed bridges, and suspension bridges. The overview includes theoretical developments, enhanced simulation attempts, laboratory-scale implementations, full-scale validation, and the summary for each type of bridges. Based on the offered review, some challenges, suggestions, and future trends in damage identification are proposed. The work can be served as a basis for both academics and practitioners, who seek to implement damage identification methods in next-generation structural health monitoring systems.

KEYWORDS

arch bridge, beam bridge, cable-stayed bridge, damage identification, suspension bridge, truss bridge

1 | INTRODUCTION

Bridges are generally inspected on a regular basis for maintenance purposes. These inspections are typically conducted visually, with the integrity of the bridge at component and system-level assigned a grade by an expert/inspector. Although visual inspection can be useful for detecting surface damages such as cracks, concrete spalling, corrosion of steel members, and partially failed components, they can be particularly limited at detecting embedded and/or minor damage, such as early fatigue cracks, corrosion of embedded reinforcement, and delamination. In addition, the visual inspection process in known to be labor-intensive, costly, time consuming, and often unreliable due to its inherent reliance on the inspector's judgment.[1] The lack of effectivity of the inspection process, combined with the alarmingly aging state of transportation infrastructures, results in a complex decision system for allocating current limited resources to the bridge maintenance and operation problem. It follows that it is becoming increasingly difficult to meet the short- and long-term future needs of structural integrity, safety, and resiliency.

A solution is to shift the current inspection paradigm to one that exploits availability of sensor data and measurements, which may complement traditional inspections schemes; a strategy is known as structural health monitoring (SHM). Due to recent advances in transducers, data acquisition and transmission systems, signal processing techniques, etc., SHM has emerged as a promising solution to empower inspectors and infrastructure managers and operators with new capabilities. SHM addresses a broad spectrum of infrastructure-related issues, including structural damage detection, localization, and quantification, condition assessment, and remaining useful life prediction. Such information can be used for design verification, condition-based maintenance decisions, and post-disaster management.[2,3] Modern SHM systems generally consist of transducers networked through data acquisition and transmission systems that collect a rich set of measurements, which are processed to extract useful features that can be analyzed through physics- and/or data-driven techniques, thus enabling the decision-making process. As low-cost high-performance sensors, smart transducers, and smart materials are increasingly becoming commercially available, the deployment of sensors in sparse[4,5] and dense[6,7] network configurations is becoming economically viable. It is foreseen that SHM will increasingly play an important role in future management of transportation infrastructure.

SHM has been particularly studied in the context of damage detection, localization, and quantification. Existing methods may be classified into global and local techniques. Global damage identification leverages the characteristics of a structure at the system level, such as the natural frequency, mode shape, and flexibility matrix, to determine locations and severities of damage. A known drawback of global detection techniques is that they are often insensitive to the local damage. Conversely, local damage identification techniques can be used to detect and characterize the local damage, but the information is not indicative of structural behavior at the system level.[8] Although local damage identification methods are typically accurate and highly sensitive to damage, they generally require prior knowledge of potential damage locations. For example, it is not easy that a single-strain gauge would detect a new fatigue crack, but the strain gauge can be used to study the behavior of the crack once it has been identified through visual inspections or nondestructive evaluation. Early researches, prior to 2011, in the area of damage detection, localization, and quantification are summarized in several state-of-the-art review papers.[9-13]

Many researches have been conducted in the area of damage identification, but linking damage to the actual and future condition of a monitored structure requires more attention. This is partly attributed to the lack of realistic field data that can be used to develop and validate such algorithms. Although some complex damage identification strategies are already installed into some structures, their deployment on actual operating systems is still relatively young, and it is still a challenge to provide some clear examples of changes in structural condition. Structural damage that occurs during the operation of the SHM system can be an important benchmark problem, which allows verification of the damage identification methods in the literature and development of new approaches.[14]

The objective of this review paper is to survey latest research in the area of damage identification methods for bridges, with the intent to identify state-of-the-art examples that could be leveraged to stimulate research on condition assessment. Several state-of-the-art review papers in this field prior to 2011 have been published, although some new researches[15,16] have been conducted after 2017, this paper only reviews efforts between 2011 and 2017 due to the page limit. Two main classification approaches to review damage identification methods of bridges may be employed. The first pertains to a classification according to the types of adopted methods, that is, according to the theory, and thus, the researchers can see clearly that the same class of methods may be adopted across different kinds of bridges. For example, the modal-based damage identification methods have been applied to beam bridges, truss bridges, and it can also be used for stay cables in cables-stayed bridges, hangers in arch bridges, and suspension bridges. However, certain new methods are difficult to be classified into a single class, and some hybrid methods are related to more than one class. The second approach pertains to classification according to the bridge types, that is, according to the application; this classification is more useful for bridge engineers and managers, as well as for promotion on the use of these methods in standards. If a review paper is intended to be used as support for bridge engineers and/or managers, it should offer clues on what methods are applicable for a specific bridge. However in this case, some same classes of methods will inevitably be repeated in the sections describing different types of bridges. Both classification methods therefore come with advantages and disadvantages. Review papers following classification according to damage identification methods are research-oriented, whereas few of them focus on demands from the managers and practitioners. Therefore, a classification according to the application is adopted in this paper.

The organization of this review paper follows a classification of bridge infrastructure in terms of fundamental structural systems, namely, beam bridges, truss bridges, arch bridges, cable-stayed bridges, and suspension bridges. Each section includes theoretical development of damage identification strategies, numerical model-based damage identification, laboratory-scale and full-scale implementation or validation on test bed bridges, and the summary. The aim of this work is to serve as a basis for both academics and practitioners, who seek to implement such methods in next-generation monitoring and diagnostic systems.

2 | RECENT PROGRESS ON DAMAGE IDENTIFICATION METHODS FOR BEAM BRIDGES

The beam bridge is the most widely used type in short- and medium-span bridges and forms the most basic type of construction. The application of the damage identification technique in beam bridges has attracted most attention in recent years.

2.1 | Modal-based damage identification methods

Modal characteristics comprise the dominant features for structural identification and damage identification and are often extracted through the process of operational modal analysis, where the monitored structure is typically assumed to be excited by a sufficiently broadband excitation. The interested reader is referred to Reynders and Limongelli et al.[17,18] for thorough reviews on the methodologies.

2.1.1 | Natural frequency-based methods

Possibly one of most widely established benchmarks in the domain of modal-based damage identification for beam-type bridge structures has been the Z24 bridge; this bridge was one of first benchmarks to be established on an actual-scale bridge structure, monitored during variable environmental and operational conditions and subsequently damaged under controlled progressive damage scenarios of varying intensity.[19,20] The Z24 bridge, located in Switzerland, was a posttensioned two-cell box-girder bridge, made of concrete and featuring a main span of 30 m, with two side spans of 14 m. As part of the benchmark, the bridge dynamics was monitored for a period of 9 months via 16 accelerometers scattered on the bridge along different directions; in addition, five sensors were installed to monitor environmental conditions, including air temperature/humidity, raindrop, and wind speed/direction. Numerous works have been produced in the past several years, dealing with this system.

The primary challenge in adequate damage detection under such schemes is the tackling of variability owed to the influence of environmental and operational parameters. To address this issue, Reynders and Roeck[21] presented a technique using kernel principal component analysis, for eliminating environmental and operational influences on modal characteristics, that is, natural frequencies; the technique relies on the adoption of Gaussian kernel principal component analysis and is output-only, in that damage-sensitive features are extracted on the basis of response measurements alone, alleviating the need to directly measure environmental parameters. By exploiting availability of environmental measurements, Spiridonakos et al.[22] constructed a Polynomial Chaos Expansion-based approach toward establishing a robust condition indicator for damage detection, validated on the Z24 bridge. Polynomial Chaos Expansion, combined with an Independent Component Analysis algorithm, may be used to obtain (a) either a direct surrogate representation between inputs (i.e., environmental parameters) and outputs (i.e., natural frequency features)[23] or (b) in order to condition the evolution of coefficients of parametric representations (e.g., AR models) on the inputs.[24] Dervilis et al.[25]

implemented robust regression analysis, relying on least trimmed square and minimum covariance determinant estimators, for shedding light on the different origins of outliers, demonstrated on the Z24 and Tamar Bridges. On further related work, Cury et al.[26] used neural networks to simulate temperature effects on modal frequencies and shapes of a PSC box girder bridge located on the A1 motorway in France. Using additional data after bridge-retrofitting, classical statistical analysis and clustering methods are employed for assessing the shifts in the vibration signature of this bridge that may be attributed to strengthening. In this work, localization of damage or strengthening effects is not sought.

2.1.2 | Mode shape-based methods

A broadly exploited metric, relating to modal shapes, consists of using Mode Shape Curvatures (MSCs). Shokrani et al.[27] introduced a framework for detection and localization of damage under variability of environmental and operational parameters. Principal component analysis accounts for environmental variations, allowing their separation from structural damage; the method is verified on a simulated four-span bridge model, where in a first phase, natural frequencies serve as features to detect potential damage, whereas in a second phase, MSCs serve for localization. However, as indicated by Farrar and Worden,[28] MSCs suffer a number of shortcomings, including dependence on the number of modes considered, numerical differentiation issues, and a need for a dense sensor grid for ensuring accuracy, particularly for higher modes. As reported in the work by Casas and Moughty,[29] lower frequency modes provide reduced resolution for damage detection and are heavily influenced by environmental and operational conditions, whereas higher modes are harder to extract and come with larger variance, thus proving less reliable in detecting damage. In a theoretical investigation, verified on simulated case studies, Loh et al.[30] employed mode shapes along with natural frequencies as features for damage identification of a continuous two-span concrete bridge structure, using random moving vehicles as excitation; the authors discuss comparative advantages and disadvantages of three methods in terms of damage detection and localization, namely, the null-space damage index, subspace damage indices, and the MSC. Walsh et al.[31] introduced a damage detection method for Prestressed Adjacent Box-Beam Bridges, relying on variability of the first vertical mode extracted along the transverse direction of the bridge. A change in the transverse mode index is introduced, determined through modal curve fitting of frequency response functions. Beyond detection, the method proves capable of classification, as demonstrated on simulated data from a finite element (FE) model of the bridge.

2.1.3 | Flexibility matrix-based methods

Schommer et al.[32] used experimentally derived modal characteristics (frequencies, shapes, and modal masses) to calculate the so-called flexibility matrix. Although easier to extract from dynamic measurements, the flexibility matrix may not be linked to damage quantification and localization in a manner that is as straightforward as the stiffness. Similar approaches are further explored in the works of Nobahari and Seyedpoor[33] and Weng et al.[34]

2.1.4 | Operational deflection shape-based damage identification methods

As a proxy to mode shapes, Sampaio et al.[35] proposed a damage index in terms of variations in the operational deformed shapes, which is derived from frequency response functions. Dilena et al.[36] further implemented the interpolation damage detection method to the case of a reinforced concrete single-span bridge in Dogna, Italy. Wang et al.[37] demonstrated damage detection and localization on a simulated four-span bridge model by exploiting strain operating deflection shapes, along with an extraction method using frequency and spatial domain decomposition is proposed.

2.2 | Acceleration-based time-domain damage index waveform analysis methods

An et al.[38-40] proposed three methods and validated them by experiment and simulation of a simply supported beam as follows: The curvature difference probability method of waveform fractal dimension[38] is feasible for 20% reduction of element stiffness with 10% noise level but failed to identify 10% reduction of element stiffness with 5% noise level. The latter two methods, namely, the curvature difference probability of logarithm of mean square-based approach[39] and the mean normalized curvature difference of waveform degree of dispersion method,[40] can identify 5% reduction of element stiffness with 5% noise level and 15% reduction of element stiffness with 15% noise level. Therefore, they have higher damage sensitivity and anti-noise ability. Therefore, the proposed three methods especially the latter two methods[39,40] provide a breakthrough in reducing three limitations: (a) They do not require an FE model, which avoid the workload of establishing an FE model and model updating; (b) they are solely based on time-domain signals without the process of parameter identification, and the averaging or probability is used in the damage indices, so they have a strong anti-noise ability; (c) they have high sensitivity to small damage. These present methods are suitable for pulse excitation and recommended to be used in periodic tests; they do not require the input, and excitation magnitudes before and after damage have no influence on results; however, the limitation is that they are not suitable for real-time monitoring with ambient excitation.

2.3 | Displacement/strain-based damage identification methods

In alleviating shortcomings of methods relying on modal features, as well as the high-computation cost related to model-based methods, Tondreau and Deraemaeker[41] introduced an automated data-based unsupervised technique for damage localization, adopting in service dynamic strain measurements in place of accelerations; a feature extraction process is implemented by means of the so-called "modal filters," which bears the additional advantage of low computational cost; a clear advantage of strain measurements as opposed to the typically employed accelerations is the local and direct sensitivity of strains to damage; the method is verified on an experimental setup of a 3.78-m-long steel I-beam, featuring 20 piezoelectric patches, excited via an electrodynamic shaker, demonstrating potential for adoption within the context of damage detection in beam-type bridges. On the other hand, Sun et al.[42] investigated applicability of dynamic displacement signals extracted from beam-type bridge structures under moving vehicle loads, for damage detection; a closed-form solution of dynamic displacements is offered, decomposed into a quasi-static and a dynamic component; the second derivative of this expression, that is, the dynamic curvature is then used for localizing and quantifying damage; the method is verified on simulated data of a single-span beam-type steel bridge.

2.4 | Wavelet analysis-based damage identification methods

Yashodhya Swarna Sri Dhanapala[43] provided a state-of-the-art review on application of the continuous wavelet transform in SHM and further implemented the continuous wavelet transform algorithm for identification of a single-span bridge in Holland, Michigan. In a method that extends to utilization of MSCs, Ding and Chen[44] used wavelet multiscale analysis to localize damage through the extremes of the multiscale wavelet transform coefficients of MSCs. Hester and González[45] proposed a scheme coupling acceleration readings with a vehicle-bridge FE interaction model and a wavelet-based identification methodology. The method estimates the average wavelet energy content for equally spaced strips across the bridge. Damaged strips reveal higher wavelet energy contents than undamaged components, which serves as a means for localization. The method is verified on a simulated simply supported bridge beam model. In related work, Golmohamadi et al.[46] used statistical moments of the energy density function of measured response signals in the time–frequency domain. The method relies on comparison of the wavelet coefficients in damaged and predamaged state and is verified in simulated data from an FE model of a real structure, namely, the Rafsanjan–Bafgh railway bridge.

Salgado et al.[47] offered an assessment across Level 1 and Level 2 identification methods. Level 1 (detection) is examined via frequency shifts between undamaged and damaged specimens and the normalized modal difference for comparison of mode shapes. Level 2 (localization) investigates four alternatives of wavelet analysis methods, as well as the curvature method, the damage index, the change of stiffness, and flexibility methods. McGetrick and Kim[48] processed the signals acquired from vehicle response measurements using a continuous wavelet transform. The method is validated on a laboratory experiment of a beam-type bridge structure, where they test the influences of vehicle configuration, speed, and bridge damping on the ability of the vehicle to identify changes in the bridge response. Aguirre et al.[49] further demonstrated the potential of wavelet-based methods in damage identification of concrete structures, via testing of a reinforced concrete bridge column at the NEES Large High Performance Outdoor Shake Table.

2.5 | Principal component analysis-based damage identification methods

Beyond the previously mentioned principal component analysis-based methods,[21,27] Laory et al.[50] introduced a model-free data-interpretation method, which couples moving principal component analysis with four regression alternatives, namely, the robust regression analysis, the multiple linear analysis, the support vector regression, and the random forest method, for the purpose of damage identification under availability of continuous monitoring data. The method is implemented on a number of case studies including the Ricciolo viaduct, a bridge over the Swiss motorway A2, where data during construction serve as data of "anomalous behavior." The results indicate superiority of combined methods in robustness and speed of identification. Nguyen et al.[51] implemented a principal component analysis-based damage identification technique for feature extraction, coupled with the concept of subspace angle for detection of irregularities, demonstrated on the Champangshiehl bridge, a two-span concrete box girder bridge located in Luxembourg.

2.6 | FE model updating-based damage identification methods

A further well-known benchmark, other than the Z24 bridge, for damage identification on beam-type bridges is the former I-40 Bridge over Rio Grande in New Mexico, tested by Farrar et al.,[52] who further examined the use of modal parameters as indicators of damage. Meruane and Heylen[53] used the results of forced vibration tests on the undamaged and damaged I-40 bridge, conducted via a hydraulic shaker, to detect damage in spite of temperature variations. They formulate an objective function correlating mode shapes and natural frequencies and use a parallel genetic algorithm to handle the inverse problem. A numerical model of the structure is set up, comprising shell elements, which assumes a temperature-dependent elasticity modulus and is further able to localize damage. Zhang et al.[54] proposed an FE model updating method based on multiresolution analysis. The concepts of the predefined stiffness information and updating stiffness information are introduced, with the resolution of the former defined by the FE mesh density and the lower resolution of latter defined by the experiment. The method is capable of identifying multiple irregular cracks and is verified on experimental data from a three-span continuous prestressed concrete bridge. In their treatise, Saidou Sanda et al.[55] attempted to detect damage in bridges using traffic-induced ambient vibrations by updating detailed 3D FE models. The Rivière-aux-Mulets Bridge located northwest of Montreal is utilized for validation. An enhanced methodology is proposed limiting the unknowns-to-equations ratio in the inverse problem setting and prevents the algorithm from imposing unrealistic assumptions on the optimization parameters. Schommer et al.[56] proposed a model-updating procedure for identifying damage in in-situ tests, where a beam element, part of a real prestressed concrete bridge is tested under static and dynamic loads, and artificial damage is invoked by cutting of the prestressed tendons. Wu et al.[57] fused static with dynamic strains, obtained from fiber optical sensors of the Fiber Bragg Grating type. An FE model is then appropriately updated on the basis of the static Fiber Bragg Grating strains and the first-order modal macrostrain parameter (frequency). The method is verified based on simulations and experiments. Betti[58] proposed a combined FE model updating and statistical pattern recognition approach to damage detection, localization, and estimation. Relying on extracted modal characteristics, a method to incorporate operational variabilities in temperature, traffic, wind, etc. is introduced. Mirzaee et al.[59] adopted the concept of response sensitivity in time domain, to formulate the so-called "adjoint variable method." The method relies on FE model updating sensitivity and acts on the numerical mode of the bridge-vehicle system. Acceleration measurements from sparse locations along the bridge are utilized to infer the flexural rigidity of different elements, which is, in turn, used for damage detection and localization.

2.7 | Bayesian theory-based damage identification methods

Papadimitriou and Papadioti[60] introduced a component mode synthesis technique in a Bayesian FE model-updating framework, for solving the forward analysis problem in a reduced space of generalized coordinates; the technique is demonstrated for damage identification applications on the Metsovo highway bridge (Greece) using simulated measurements. Figueiredo et al.[61] proposed a Bayesian approach for bridge damage detection based on the Markov chain Monte Carlo method with unknown sources of variability; the algorithm can detect structural damage using daily response data, even in the case of abnormal events such as the temperature variation; the proposed method was applied to damage detection of the Z-24 bridge, and results show the proposed method has good robustness for damage detection. Ma et al.[62] proposed a new framework for predicting the remaining strength of bridges based on a Bayesian network and in situ load testing; the Bayesian network is developed to predict structural strength degradation under the influence of stiffness degradation, corrosion damage, load-deflection response, and other factors; theoretical and experimental results of an existing reinforced concrete bridge show that the proposed method can improve the prediction accuracy. Kim et al.[63] investigated a Bayesian method for vibration-based long-term bridge monitoring, taking into account the change of environmental and operational factors; the long-term monitoring data from a plate-Gerber bridge collected over more than one year is used to verify the feasibility; the study demonstrates that the Bayesian regression with consideration of environmental and operational changes is more accurate. Alavi et al.[64] proposed a damage detection method based on probabilistic neural network and Bayesian decision theory, and the effectiveness is verified experimentally on bridge joint slabs under complex conditions. A thorough overview of the Bayesian model-updating framework for damage assessment is presented in the work of Simoen et al.[65]

2.8 | Deep learning-based damage identification methods

Zauri and Catbas[66] proposed an integrated system based on the combination of video images and conventional sensor network data for evaluating the bridge safety; the effectiveness of the method is verified experimentally on the UCF four-span bridge model. Guo et al.[67] proposed a sparse coding-based deep learning method to monitor the status of the FE model of a three-span beam bridge; a spare coding is employed to extract damage features, which are utilized to train a neural network classifier to predict the status of the model; numerical results show that the accuracy of the method is better than some existing methods under the same level of noise. Yeum and Dyke[68] proposed a vision-based automated crack detection method for bridge; object detection and grouping techniques are utilized to extract images of possible damage regions; its performance is successfully validated using images collected by a handheld camera from a large-scale rusted steel beam with cracks. Zauri et al.[69] proposed a monitoring system based on the combination of video images and conventional sensor network data to identify the possible damage on a movable steel beam bridge in Florida, USA; images and senor data are utilized to extract a series of unit influence lines, and the statistical outlier-detection algorithm is combined to detect and localize common scenarios on the real-world bridge successfully. Valenca et al.[70] proposed an automated crack detection method for concrete bridges based on image processing and laser scanning; terrestrial laser scanning technology is utilized to capture the geometric information of the bridge, which is used to correct images collected from the bridge; the method is validated by the experiment on a concrete viaduct at IC2 road, in Rio Maior, Portugal. Lin et al.[71] proposed a deep convolutional neural network-based deep learning method to achieve damage detection of a simply supported beam in simulation; a deep one-dimensional convolution neural network is employed to achieve damage detection; numerical results show that the method achieves an accuracy of 94.57% in single damage cases without noise and 86.99% with 50% noise level; the method also shows good performance in multiple damage cases. Liang et al.[72] proposed a digital image measurement-based damage detection method; the method is verified theoretically, experimentally, and in the real bridge; from theoretical analysis, it is found that the second derivative of the deflection influence line of a three-span damaged continuous beam model is not continuous around the damaged locations, and damage localization can be conducted; from laboratory testing, wavelet coefficients of the Mexican wavelet analysis are employed to capture and analyze mid-span deflection with a sudden change in the damaged location; from the field application, the method is applied to Pingtan strait bridge, and results show that there is no obvious damage for the bridge.

2.9 | Sparsity information and sparse recovery theory-based damage identification methods

Bayissa et al.[73] performed damage localization with test data from the I-40 Bridge using sparse modal information, limited measurement data, and random excitation; compared with the resonance frequency-based method, the proposed broadband frequency-based method has higher damage sensitivity and better robustness. O'Connor et al.[4] proposed a compressed sensing strategy for energy efficiency in wireless sensors for monitoring a multigirder steel-concrete deck composite bridge; acceleration responses are obtained by embedding compressive sensing into five wireless sensors, which are reconstructed using a new iterative recovery algorithm termed acrostic compressive sampling matching pursuit; results show that when the compressive sensing framework is used to sample at least 20% of the original signals, modal assurance criterion values of the first four modes of the bridge structure are greater than 0.90. Ma et al.[74] presented a systematic framework to quantify the probabilistic prediction of corrosion damage in reinforced concrete bridges when hybrid uncertainty exist; the idea is to compute the probability distribution function of the variable described by sparse data using a likelihood-based method, to obtain the probability distribution function of the variable described by expert-based information using an entropy-based transformation method; the effectiveness of the proposed method is verified by a numerical example of predicting corrosion damage of the existing reinforced concrete bridge. Jang and Dahai[75] proposed a practical damage identification strategy for full-scale bridge based on the stochastic damage locating vector (SDLV) method[76]; statistical modal analysis is carried out based on acceleration and temperature test data measured over 5 years on a curved box-girder bridge in Connecticut, USA; results show that the SDLV method can identify the potential damage locations with a sparse array of sensors.

2.10 | Damage identification methods with consideration of temperature variations

Kulprapha and Warnitchai[77] established an SHM system for a multispan prestressed concrete continuous girder bridge to detect flexural damage based on thermal loads and responses; an analytical model is developed for the prediction of the intact bridge's thermal responses using the monitored temperatures and then the baseline is determined for damage quantification and damage distribution pattern; five different distributed flexural damage states are simulated on a scaled experimental bridge's girder that comprises different types and numbers of cracks and spallings. Meruane and Heylen[78] extended a damage identification method to consider the effect of the varying temperature; the damage index is established by a previous optimization algorithm; several numerical damage cases (30% stiffness reduction of the central region in middle span under varying temperatures) at a three-span beam bridge and several experimental damage cases (four levels of simulated fatigue cracks under ambient temperature variations) at the middle span of a plate girder in a real-girder bridge were conducted. Kromanis and Kripakaran[79] proposed a support vector regression-based anomaly detection method under temperature variation; the proposed method successfully detects single-damage close to the middle section of the first span in a typical reinforced concrete girder numerical model. An et al.[80] studied the applicability of two damage identification methods to real bridge structures under varying temperature and traffic loading conditions; both of the two reference-free methods (i.e., the transfer impedance method and the dual-PZT method) can detect the artificial crack induced in the field test of a decommissioned real box girder bridge (i.e., the Ramp-G Bridge in Korea), and the dual-PZT method can give correct damage identification results under the temperature variation by altering the threshold of the damage index. Lakshmi and Rao[81] proposed a damage localization method based on the autoregressive moving average with exogenous inputs model and the Cepstral distance; damage cases are simulated under varying temperature conditions contaminated with measurement noise; the dependence of the elasticity modulus on varying temperature is handled by a normalization procedure using the autoregressive coefficients, and the effectiveness is confirmed on a numerical beam model.

2.11 | Summary for beam bridges

Methods relying on modal characteristics still comprise the majority of proposed damage identification schemes, because they offer the benefit of direct physical interpretation. While frequencies may only serve for a Level 1[82] investigation (detection), as they form a global feature, mode shapes are further linked to the spatial deformation of the system and may thus be used for the purpose of localization (Level 2). Because mode shapes exhibit rather low sensitivity to damage and could necessitate use of a rather large number of sensors, further modal quantities have been exploited in a damage detection context, including modal flexibilities, modal curvatures, and modal strain energies, as well as more extended properties, such as operational mode shapes. When it is desirable to proceed to Level 3 of the damage assessment procedure, that is, damage quantification, FE model updating offers a viable means for doing so, most commonly through estimation of elemental stiffness parameters. Conversely, purely data-driven methods, which lack an underlying physical model, are not suited for quantification but may certainly offer a faster means for detection and possibly localization. On the other hand, hybrid approaches[83] may exploit the advantages of both the model-based and data-driven path. Finally, it should be noted that the issue of detection and localization should be combined with optimal sensor placement methodologies[84-86] or ensuring and enhancing detectability.

3 | RECENT PROGRESS ON DAMAGE IDENTIFICATION METHODS FOR TRUSS BRIDGES

The truss bridge is commonly used in the bridges with longer spans. Many damage identification methods for truss structures have been presented in the past 7 years, with some relating to actual-scale (field) case studies.[87-90] Compared with the validation of damage identification methods based on numerical models and laboratorial models, the application in real bridges can better validate the performance of the methods, and tests on real bridges make considerable contribution for the development of SHM for bridge engineering.

3.1 | Modal parameters-based damage identification methods

Shih et al.[91] proposed a multicriterion-based damage identification method for truss bridges to detect single and multiple damage cases; the proposed method merges the modal flexibility, modal strain energy, and changes in natural frequencies for damage identification, which can overcome the drawbacks in damage identification using a single index; damage is simulated by flexural stiffness reduction of 50% on the deck and axial stiffness reduction of 50% on the truss member, and numerical results show that the proposed method is effective. Jang et al.[92] developed a decentralized receptance-based damage localization method for truss structures using the stochastic dynamic damage locating vector method; damage is simulated by a 40% stiffness reduction in longitudinal and diagonal truss members; first, the decentralized stochastic dynamic damage locating vector method is verified through an experiment conducted on a laboratory scale truss bridge using a wired sensor system to emulate the wireless smart sensors; then, the method is applied on the Imote2 WSS platform to develop a comprehensive damage identification application for wireless smart sensors networks, that is, the decentralized damage identification; finally, the effectiveness of the decentralized damage identification application is demonstrated; the robustness of the proposed method is validated through two damage indices, namely, the maximum stress index and the average stress index.

During 2012–2014, researchers[93,94] applied the modal filtration method to the damage localization in the joint of truss structures, with the verification through numerical simulation and laboratory experiment; the localization is not very accurate but can still approximately localize damage. In recent years, the SDLV method has been studied extensively[76,95] and shown to be a very useful tool for damage localization of truss structures; it is a real-time damage localization method, and it can determine the location of damaged truss members without measuring the input excitation. An et al.[95] investigated three main aspects through simulation and experiment to provide guidance for the SDLV method: The influence of formulation of the C matrix on the accuracy of damage identification results is studied, and the conclusion is that the selection rule of C matrix is closely related to the percentage of the measured nodes; three sensor layout strategies for truss structures with limited sensors are proposed and verified; the accuracy of damage localization increases with the increase of damage severity, and the sensitivities of the SDLV method to different kinds of truss elements are different: 70%, 50%, and 25% stiffness reduction can be identified successfully in the vertical, the longitudinal, and the diagonal truss element, respectively. An et al.[96] proposes a real-time damage localization method for truss structures using the rank-revealing QR decomposition (RRQR) of the difference of flexibility matrix and the damage locating vector (DLV) method,[97] that is, the RRQR-DLV method; the proposed method has been validated by simulation and experiment; numerical results indicate that it has a higher sensitivity to damage: A 10%, 20%, and 35% stiffness reduction of the diagonal, longitudinal, and vertical truss elements can be detected successfully.

Chang and Kim[98] conducted a field experiment on an actual simply supported steel truss bridge based on modal-parameter identification; a damage identification approach relying on feature extraction and discrimination was validated to be effective if the damage-sensitive feature was suitably selected; multiple modal assurance criteria values and coordinate modal assurance criteria values were feasible features if sufficient modes were considered. Shadan et al.[99] proposed a damage identification method using natural frequencies and frequency response functions data; the method was examined numerically through a reference example truss, and results show that the location and severity of damage were identified precisely in all cases. Nguyen et al.[100] developed a new vibration parameter, that is, ratio of geometric modal strain energy to eigenvalue, and a new damage identification method was proposed based on the parameter; the proposed method can identify the location and size of damage, and the performance and practicality of the method are verified through a numerical truss bridge. Seyedpoor and Montazer[101] proposed a damage identification method for truss structures based on the flexibility-based damage probability index and differential evolution algorithm; the problem of damage identification is transformed into an optimization problem and then the algorithm is employed to identify the actual location and severity of the damage; high efficiency of the two-stage method for the truss structure is verified through numerical results of multiple damage cases. Kanta and Samit[102] proposed a new approach to detect and quantify damage in railway truss bridges; damage localization is conducted using an approach based on mode shape and its derivative, and the sensitivity-based Bayesian damage identification algorithm is applied to evaluate the damage extent; the method was validated through the simulation and laboratory experiment; however, the reliability of the approach suffers when data are contaminated by high level of noise. Kim et al.[103] analyzed the influence of damage on changes in modal parameters of a real truss bridge; the sensitivity and precision of different modal parameters under different damage cases are evaluated on field test data.

3.2 | Wavelet analysis based-damage identification methods

Several works based on the wavelet analysis about damage identification of truss structures have been published. Garcia-Perez et al.[104] proposed a damage identification methodology for identifying and locating single and multiple combined damage in a truss structure, which merges a single wavelet packet and the empirical mode decomposition method with artificial neural networks; damage is simulated by reducing the truss member's diameter with a 53% stiffness reduction, loosened bolt at one end of a truss member or internal corrosion with a 54% stiffness reduction; several kinds of damage and their combinations, simulated in a scaled truss structure model, are identified and localized efficiently and reliably; results show the potential of the proposed methodology in automated and online damage identification procedure. A wavelet transform technique-based damage detection and quantification method for mixed-mode cracks in large span truss structures is proposed in 2014[105,106]; the proposed wavelet transform-based method can detect small mixed-mode cracks in large truss structures using modal parameters under noise interference, and the amplitude of wavelet coefficients is selected as the index for damage quantification in truss structures; the crack location is identified successfully with the normalized error (i.e., the damage location error) less than 4% when the damage cases are simulated in triangular truss, Warren truss and Howe truss structures; the accuracy of damage detection is significantly affected by crack location: The damage near the connection joints is hard to be detected, whereas the proposed method is effective when the crack location is beyond the joints by about 15% of the member length. Li and Hao[107] applied recently developed relative displacement sensors to monitor the joint conditions in a laboratory model of a steel truss bridge; the damage of loosen bolt in the joint connection of the model was identified by analyzing the relative displacement data using continuous wavelet transform; the effectiveness and performance of using relative displacement sensors to assess the joint connection condition of the truss bridge were verified by the laboratory experiment. Knitter-Piatkowska et al.[108] presented a damage identification method for the truss structure based on discrete wavelet transformation; the numerical investigations were conducted, and the damage was modelled by reducing the local stiffness of one or two lower chord bars; results show that the scope for effective observation of defects from one measurement point is equal to about 25% of the lower chord.

3.3 | Intelligent algorithm-based damage identification methods

Srinivas et al.[109] proposed a multistage method for damage detection and quantification in truss structures using the combination of modal strain energy and evolutionary optimization technique; with a rough detection in the first step utilizing the modal strain energy method and a refined localization and quantification in the second step utilizing the genetic algorithm-based optimization approach, the efficiency of the proposed multistage method is enhanced obviously compared with the conventional optimization approach based on evolutionary algorithms. Wang et al.[110] introduced a multilayer genetic algorithm (ML-GA) for damage identification of complex steel truss bridges; compared with the traditional genetic algorithm, the ML-GA has higher computing efficiency and better convergence performance; the effectiveness and efficiency of the ML-GA method are verified through the analytical and experimental studies in both single and multiple damage cases; the truss element 5 has a 25% and 50% stiffness reduction, and the truss element 61 has a 50% stiffness reduction; the proposed method can identify these damage cases, and a convincing result with less errors is obtained with the increase in damage severity of element 5. Viola and Bocchini[111] proposed a damage detection and quantification method for truss structures based on static load tests; residual stiffness of the truss element is determined for damage localization and quantification; besides, the genetic algorithm is proposed to detect damage due to the lack of measurement data; the proposed method can detect global and local damage of the member in both 2 dimensional (2D) and 3D truss structures. Kim et al.[112] proposed an optimization method for damage detection and quantification of truss structures, including two stages: to identify the possible damaged members with an anti-optimization technique and determine the damage severity with a micro genetic algorithm; the diagonal element and vertical element are damaged by reducing its stiffness to 70% and 50% of the initial value, respectively; the proposed method is successfully used to identify the damage simulated in the numerical model of the truss structure with high computational efficiency. Kim et al.[113] developed a method for locating and quantifying the damage in truss structures based on a combination of the force method and the micro genetic algorithm; the process can be summarized as the formulation of general equilibrium equations and kinematic relations, presentence of compatibility equations in terms of forces using the singular value decomposition technique, and the solution of optimization problem using the micro genetic algorithm; the effectiveness and the efficiency of the proposed method are validated by the numerical solutions based on the 2D and 3D truss models; the longitudinal element, diagonal element, and vertical element are damaged by reducing its stiffness to 60%, 40%, and 30% of the initial value, respectively; the proposed method can identify these damage cases successfully; moreover, obvious superiority of the force method is found in computation efficiency compared with the displacement method. Khoshnoudian and Talaei[114] proposed a new damage index using frequency response function data, a data reduction technique called the 2D principal component analysis (2D-PCA) method and pattern recognition techniques such as the artificial neural networks and look-up-table method, and its effectiveness has been vilified in simulation by a truss bridge with single and multiple damage scenarios; the proposed algorithm has strong robustness against with up to 20% noise level. Khoshnoudian et al.[115] proposed a damage identification method using frequency response function data, 2D-PCA, artificial neural networks, and imperialist competitive algorithm; the artificial neural networks are used to form a smooth function of the sum of absolute errors, which are calculated between the unknown damage index and the selected indices, and the imperialist competitive algorithm is employed to minimize the function to identify the damage location and severity; the method was validated using a truss bridge structure in simulation, and it works with noise level up to 20%.

3.4 | FE model updating-based damage quantification methods

Damage quantification is one of the final stages of damage identification, and it is very important for structural safety assessment and maintenance[116]; An and Ou[116] presented a model-updating method for damage quantification based on four cost functions: (a) correlation coefficient of free vibration accelerations; (b) correlation coefficient of local mode shapes; (c) free vibration accelerations assurance criterion; and (d) local modal assurance criterion; both experimental and numerical simulation results based on a steel-truss bridge Benchmark model indicate that the proposed method is feasible and effective. Lee et al.[117] proposed a multistep damage detection and quantification method for open cracks in truss structures; first, the damaged elements are detected by a statistical reference-free damage localization method in Lee and Yun[118]; then, the damage quantification index, that is, the open crack depth, is identified by tuning the FE model based on experimental modal properties; the feasibility and efficiency of the proposed method are validated through the laboratory experiment under single and multiple damage scenarios.

3.5 | Bayesian theory-based damage identification methods

Zheng et al.[119] developed an improved computational framework based on efficient Bayesian inference for damage detection of truss structures; based on the frequency domain measurement data from complex truss structures, the probabilistic inference framework is improved by revising transitional Markov chain Monte Carlo algorithm; numerical results of truss structures show that the proposed framework can identify damage not only on truss components but also on truss joints within acceptable accuracy. Behmanesh and Moaveni[120] proposed a Bayesian FE model updating-based probabilistic damage identification method for a truss bridge, that is, the Dowling Hall footbridge on the campus of Tufts University; modal parameters extracted from the measured acceleration responses of the bridge are used to update the FE model; results show that the proposed method can accurately estimate the location and extent of damage; furthermore, the level of confidence on damage identification results can also be provided. Kanta and Samit[102] presented a damage localization and quantification method based on Bayesian framework for railway truss bridges; mode shapes and their derivatives are used to locate the damage, and then in the updating of Bayesian model, the prediction error variance approach based on parameter sensitivity is used to extract the maximum information in modal data to quantify the damage; the method is numerically demonstrated on a truss bridge. Mustafa et al.[121] presented a damage identification method for the truss bridge using updated model parameters; first, a reliable baseline model of a large truss bridge is established, and the accurate sectional properties of the bridge components are obtained; then, once the sectional properties change, the damage can be detected using a probabilistic damage identification approach called Bayesian probabilistic methodology; the method is not only capable of identifying the damaged member but also the damage quantification. Pedroza Torres et al.[122] proposed a hybrid methodology method based on the results of a comparative study between self-organizing maps and Bayesian networks in order to reduce computational cost and improve performance in fault condition detection of structures; the proposed method can detect damage efficiently based on numerical results of a truss. Mustafa and Matsumoto[123] presented a Bayesian model-updating method for detecting local damage by introducing a new objective function and a realistic parameterization of the mass and stiffness matrices; the FE model of a real steel truss bridge can be updated effectively using four identified stiffness parameters from the measured vibration data; numerical and experimental results of a real truss bridge show that the method could only detect local damage when the global modal parameters changed significantly.

3.6 | Time domain signal processing-based damage identification methods

An et al.[124] proposed the curvature difference method of strain waveform fractal dimension for damage detection of truss structures using free vibration strain response signals, and both experimental and numerical results indicate that it is effective to detect the damage in boundary conditions and the truss member with high anti-noise ability; moreover, it can classify the damage types, that is, damage in joints and damage in measured zones of members. Kim et al.[125] conducted a field experiment on a real continuous steel Gerber-truss bridge to detect the damage modeled by artificial damage under the traffic-induced vibrations; the modal parameters were examined to attempt to indicate the damage, and Nair's damage indicator,[126] which is a time series-based damage index, is better than the modal parameters to indicate the damage, because its statistical pattern is high sensitive to damage. Yu and Zhu[127] proposed an integrated method combining the damage-sensitive feature extraction, the higher statistical moments of structural responses, and the fuzzy c-means clustering algorithm with a time series analysis-based damage prognosis method for structural damage prognosis of a truss bridge model; damage cases were set up by loosening connection bolts; experimental results based on a six-bay truss bridge model indicate that the method can detect damage successfully. Blachowski et al.[128] proposed an efficient method for damage localization of truss structures, that is, the axial strain accelerations approach; the proposed method is a model-free method, which avoids a FE model development and updating; it does not require identifying modal parameters or solving global optimization problems, and it has higher sensitivity to damage; experimental validation using laboratory-scale models of two types of frequently used trusses shows its efficiency and robustness.

3.7 | Damage identification methods with consideration of temperature variations

Moser and Moaveni[129] computed the confidence interval of the natural frequency, which is a function of the varying temperature, using the field monitoring data collected from the Dowling Hall Footbridge (a two-span continuous steel truss bridge in Tufts University, USA); natural frequencies located outside of the established confidence intervals at corresponding temperatures indicate the potential damage. Laory et al.[130] evaluated damage detectability and detection time of two model-free damage detection methods, that is, the moving principal component analysis method and the robust regression analysis method, considering the temperature effect; the evaluation is conducted in a numerical analysis based on a railway truss bridge in Germany, and three numerical damage cases were simulated in the form of stiffness losses at the top and bottom chords of the truss bridge model; results show that the two methods are complementary and have different seasonal variation sensitivities. Zhu and Rizzo[131] presented a damage detection method for truss welded joints based on guided ultrasonic waves; cracks of various sizes near the weld toe of a joint in an experimental truss are simulated under varying environmental effects; it is found that the combination of damage features can increase the damage sensitivity and decrease environmental effects including the varying temperature and the boundary condition.

3.8 | Sparsity information and sparse recovery theory-based damage identification methods

Bao et al.[132] presented a structural damage identification method by combining the substructure-based sensitivity and the sparse regularization; exact solutions for the sparse vector of damage extent can be obtained using compressive sensing theory; with measurement noise, the proposed method can identify multidamage on a 20-bay truss structure including damage locations and extents using a small number of sensors. Link et al.[133] proposed a damage identification method based on frequency response functions and orthogonal matching pursuit; the system of equations is usually overdetermined, and orthogonal matching pursuit, which is a method of sparse recovery, is used to solve the equations for the percent damage; simulations on a truss structure show that the proposed method can identify multiple damage cases accurately. Zhang and Xu[134] presented a damage identification method of sparse regularization based on the sensitivity-based model updating to solve the ill-posedness problem; comparative simulation studies on a planar truss were conducted using Tikhonov regularization and sparse regularization, and results show that the method of sparse regularization is superior.

3.9 | Other damage identification methods

Nuno[87] applied the frequency response function curvature method in a real-steel truss bridge for damage identification; different damage scenarios with different levels of severity are identified based on field test data; however, the presented method can detect the damage only with a certain sensor layout, which decreases the feasibility of the presented method. Kim et al.[88-90] investigated the practicability of a damage detection method for truss structures using statistical patterns of different damage features with the Mahalanobis-Taguchi System; the damage is made artificially: A diagonal truss member in a nine-span continuous Gerber-truss bridge is severed[88,90]; half or full cut in a vertical member of a simply supported steel Warren truss bridge[89]; through the application of different damage sensitive features to the real truss bridges subjected to several artificial damage cases and considering the effect of different vibration types and sensor set types, the efficiency of the investigated parameters in damage detection are evaluated. Ostermann et al.[135] illustrated the application of autoregressive moving average processes in the detection of structural changes; an off-duty steel truss railway bridge was served to demonstrate the performance of the proposed method. Goi and Kim[136] proposed a damage indicator using a set of multivariate autoregressive models obtained from ambient vibrations of bridges; field tests were conducted on a real-steel truss bridge, and its truss members were severed artificially; three damage cases, that is, half and full cut in vertical member at the mid-span and full cut in vertical member at 5/8th-span were detected successfully using the proposed method.

Bao et al.[137] used D-S evidence theory to combine damage identification results from different individual data sets, which reduces the uncertainty of model error and measurement noise; diagonal and vertical truss members are removed to simulate damage in the experiment, and results obtained by combining the damage basic probability assignment functions are better than the individual result obtained by each test data separately. Lee et al.[138] proposed a damage identification method for truss structures using axial stress and strain energy data; by calculating the changes in structural stiffness, stress and strain energy before and after damage, the static equilibrium equation can be derived in the damaged structure, and then multiple damage in the truss structure can be detected using the field monitoring data corrupted by ambient noise; the efficiency is improved through the partition of the damage-expected substructure and measurement of the displacements at the boundary of the partitioned subsystem. Siebel and Mayer[139] proposed a damage identification method for the truss structures based on transmissibility functions without the need of excitation force measurement and numerical model: In a numerical and an experimental model of a 40-bar space truss, the proposed method has given accurate results of single damage cases in the low-frequency range using the longitudinal vibration data; however, damage cases in which the truss member's diameter is reduced cannot be detected due to the proposed method's sensitivity to measurement uncertainty, whereas only severe damage cases in which the member is removed can be detected successfully; measurement uncertainty has an important influence on the proposed damage index.

Sen and Bhattacharya[140] proposed an online health monitoring scheme that was utilized to synchronously estimate the system parameters along with the response states of a reduced-order system based on dual extended Kalman filtering technique; location-based structural properties are introduced as the system parameter so that the damage localization beyond sensor resolution can be conducted successfully; numerical results based on a truss bridge show that the proposed algorithm can locate damage beyond sensor resolution successfully. Fan et al.[141] proposed a new method to identify damage based on the time domain impedance response; a damage index based on singular value decomposition was defined by using the time frequency autoregressive moving average model; the high sensitivity and robustness of the proposed method for detecting the bolt damage in the gusset plates were verified based on an experimental model of a space steel truss bridge. Lin[142] developed a crack localization method based on rotational frequency response functions obtained from measured translational frequency response function data; a crack location matrix was constructed using the estimated rotational frequency response functions to localize cracks, and a new numerical inverse frequency response function sensitivity method was proposed to identify crack parameters such as crack depths; results based on a numerical cantilever truss structure show that the location and depth of the crack can be identified successfully even in the presence of 5% noise level. Boumechra[143] introduced a damage identification method for truss structure based on the inverse analysis of the static response caused by moving loads; numerical results of a truss show that the method can detect stiffness changes or reductions successfully. Tran[144] proposed a structural damage identification method with big data using parallel computing based on multiprocessor system on chip; the performance for the local damage detection has been verified by a numerical example of a plane steel truss structure.

3.10 | Summary for truss bridges

Generally, sensitivity to damage for vertical truss members is lower compared with that for longitudinal (the direction along the traffic direction) and diagonal truss members. However, the vertical truss members are not as critical to structural safety as the longitudinal and diagonal members. Therefore, it is enough for structural safety to monitor important members only. Strategies for optimal sensor placement on truss structures should be more investigated in the future in order to save the SHM system cost. Generally for damage identification, periodic test methods have higher sensitivity to damage compared with real-time damage identification methods. Therefore, it is recommended that the two kinds of methods should be merged: Periodic test methods are used to check the possible small damage, and the real-time damage identification methods are used to identify the possible big damage during the interval of the periodic test.

4 | RECENT PROGRESS ON DAMAGE IDENTIFICATION METHODS FOR ARCH BRIDGES

The section is devoted to damage identification methods of arch bridges, distinguishing between two types of arch bridges, namely, deck arch or tied-arch bridges. Nevertheless, both structural systems may contain beams, hangers, and trusses, and it follows that most of the methods presented in previous sections apply here as well. However, some aspects specific to the mechanical behavior of arches should be carefully considered. To make this overview practical and comprehensive, the methods presented in this section are sorted with respect to the specific structural properties of the considered bridges, and then with respect to the methods' individual features.

4.1 | Damage identification methods for steel arch bridges

4.1.1 | Historic arch bridges

Researchers have investigated the San Michele bridge located close to Paderno, Italy, a combined road and railway bridge consisting of a single span parabolic arch, an upper trussed box girder, and many piers. The arch spans 150 m and is made of wrought iron. Gentile and Saisi[145] described ambient vibration testing conducted on the bridge to assess its condition; during the testing, 26 accelerometers have been used to identify 17 natural frequencies and corresponding modes. Cabboi et al.[146] considered automation of the modal identification and tracking procedures; they used two modal validation criteria to reject spurious poles and filtering the stabilization diagram using mean phase deviation and modal phase collinearity. Although the change in the modal damping ratio can also be used as the damage index, the accuracy of the method remains uncertain. Yamaguchi et al.[147] and Dammika et al.[148] investigated the analytical modal damping evaluation, and an energy-based damping model was used to estimate damping parameters of a steel arch bridge; equivalent loss factors of structural components and modal damping ratios of the arch bridge were then evaluated based on these damping parameters.

4.1.2 | Modern single-span bridges

Li et al.[149] investigated the monitoring of arch bridge suspenders using optical fiber Bragg grating sensors; they introduced the concept of smart suspender, which was successfully implemented on Ebian Bridge in China; they also proposed fatigue damage dynamic evaluation method utilizing the Weibull probability density function and Goodman conversion formula based on the test data. Guo et al.[150] proposed a damage identification method using wavelet packet transform, and a wavelet packet energy index combined with Shannon entropy was used to localize the damage; a numerical model of Guotai steel arch bridge was established to simulate damage, and the method is demonstrated using the simulation. Huang and Nagarajaiah[151] proposed a method termed wavelet modified second-order blind identification, which has been experimentally verified on a scaled model of an arch bridge across U.S. highway 59.

4.1.3 | Modern multispan bridges

Lin et al.[152] applied the static and dynamic virtual distortion methods to damage identification of hangers in the FE model of Boguan Bridge, China; numerical results show that the proposed methods can identify the damage location and severity. Recently, the Nanjing Dashengguan Yangtze river bridge,[153] which is the first six-track high-speed railway arch bridge in the world with the design speed of 300 km/hr, became a popular benchmark problem; a continuous steel truss arch forms the superstructure of the bridge; the main bridge counts six spans, and it was the high-speed railway bridge with the highest loading capacity in the world. Detection of degraded bearings using monitoring of the longitudinal expansion of the main girder was presented by Wang et al.[154] Resonance between the hanger and main girder was a topic of the detailed study by Zhao et al.[155] The impact factor calculation method based on strains has been investigated by Song et al.[156] An et al.[153] studied the vibration characteristics and fast warning of the rigid hanger for high-speed railway arch bridges using long-term monitoring data; they analyzed the influence of environmental factors on the hanger's transverse vibration characteristics and proposed a method for establishing the reference service condition database and then conducting fast warning of hanger anomalies. Ye et al.[157] also described the SHM system installed on Jiubao Bridge; they applied the wavelet multiresolution method to separate the temperature effect from the raw strain data; they concluded that measured strain time histories contain both low-frequency and high-frequency signals, and the wavelet multiresolution algorithm is able to decompose the strain and isolate the live load-induced stresses.

4.2 | Damage identification methods for concrete arch bridges

A study dealt with a tied arch bridge composed of reinforced concrete arch ribs and prestressed concrete tie beams; the bridge was built in 1993 at Hangzhou, China; Duan et al.[158] analyzed strain-temperature correlation to distinguish changes in bridge's behavior, and the changes of interest are those caused by environmental parameters such as temperature or humidity. Another concrete arch bridge equipped with an SHM system is the Infante D. Henrique Bridge, a long span concrete arch bridge located in the Porto city. For this bridge, Magalhaes and Cunha[159] compared three of the most popular system identification techniques, namely, frequency domain decomposition, covariance driven stochastic subspace identification, and poly-least squares complex frequency domain. An extension of the method to the case where damage assessment is done automatically based on results of operational modal analysis was conducted by Magalhaes et al.[160]; they applied a principal component analysis-based approach, coupled with static and dynamic regression models, for normalizing modal frequency evolution over acting environmental and operational parameters and detecting damage in simulated scenarios. Comanducci et al.[161] conducted the vibration-based damage detection using multivariate statistical techniques, and they used the concept of local principal component analysis, which allows one to overcome the assumption of linear correlation between output variables. Ren et al.[162] and Lin et al.[163] established a damage-sensitive but environment-insensitive damage index through the covariance-driven identification based on the stochastic subspace together with the statistical pattern recognition technology; the damage index is insensitive to the temperature variation; numerical results show it can detect 20% stiffness reduction at a position near three-fouth span of the first span of a continuous beam; moreover, the method proves capable of detecting 17% prestressed force loss in a laboratory prestressed reinforced concrete beam, as well as the damage supposed by the renewal stage change in a real box-type reinforced concrete arch bridge under varying temperature.

4.3 | Damage identification methods for masonry arch bridges

Many historic arch bridges were made of masonry, making damage identification an even more complex task. Damage detection of interest for this type of arch bridge is often related to scour, because of the erosion of the soil beneath the central pier of the bridge. A study on this problem was conducted by Ruocci et al.[164]; they researched scour-sensitive features in three different domains (i.e., time, spectral, and modal ones); a masonry arch bridge model built in the laboratory and a mechanical device have been used to simulate the settlements of the pier. Serra et al.[165] used the coda wave interferometry to detect the modification change of elastic properties of a masonry bridge due to scour.

4.4 | Summary for arch bridges

From the above methods applied to arch bridges, it can be observed that there are generally three types of methods that are commonly applied, namely, modal-based methods, time-domain methods, and data-driven methods. For historic arch bridges, the noninvasive installation of sensors is very important. Moreover, model-free damage identification methods or 3D laser scanner-based FE modeling techniques should be developed, because possibly the drawings of historic bridges are not conserved well enough to establish its structural FE model. Modern steel and concrete arch bridges are often equipped with short- and long-gauge fiber Bragg grating sensors. Besides of strain and acceleration sensors, temperature sensors are critical in arch bridges, because measured states of interest are more prone to temperature changes than in the case of the other types of bridges. Finally, for the masonry arch bridge, promising damage identification techniques seem to be laser scanning-based methods and image processing-based methods.

5 | RECENT PROGRESS ON DAMAGE IDENTIFICATION METHODS FOR CABLE-STAYED BRIDGES

As imposing structural damages to actual cable-stayed bridges is difficult in field testing, most researchers have focused on numerical studies, fundamental studies for possible pre-preparation stage of damage identification, and damage identification of stay cables. Several fundamental studies for possible pre-preparation stage of damage identification are conducted on a cable-stayed bridge, that is, Ting Kau bridge in Hong Kong. Li and Ni[166] presented an investigation of the modal identifiability of this bridge using an adapted proper orthogonal decomposition technique, and they concluded that vibration modes can be identified well only when the energy participation factor is greater than a threshold value. Kuok and Yuen[167] carried out an investigation of modal identification and modal identifiability with the Bayesian probabilistic framework, based on the field measurements from the same SHM benchmark bridge; the output-only modal identification is conducted using the Bayesian spectral density method, and the significance of different modes in modal identification is evaluated by the Bayesian model class selection method; the effectiveness and potential of Bayesian framework on bridge health monitoring is validated on the benchmark study of the Ting Kau cable-stayed bridge. Parka et al.[168] examined vibration responses of Ting Kau bridge under excitation conditions to estimate wind and traffic-induced variations of its dynamic characteristics; the relationship between the wind velocity and modal parameters are analyzed, and typhoon-induced effects on dynamic characteristics are estimated. Studies of damage identification for cable-stayed bridges, and damage identification of stay cables, are summarized as follows. Earlier development before 2011 can be found in the review article on SHM of cable-stayed bridges by Li and Ou.[169]

5.1 | FE model-based damage identification methods

In most modern industrialized countries, long-span cable-stayed bridges have higher priority in the maintenance plan due to its social and economic impact. Thus, it is difficult to prepare a full-scale cable-stayed bridge as a test bed, to which actual structural damage can be imposed. Indeed, most damage identification studies for the cable-stayed bridges have been numerically conducted, although field validation is limited.

A notable study was presented by Arangio and Bontempi,[170] who conducted damage identification of an actual cable-stayed bridge, the Tianjin Yonghe Bridge in China; the bridge was one of the earliest cable-stayed bridge constructed in mainland China and found to have two types of structural damages including (a) cracks in the bridge deck and (b) pier damage, which caused the partial loss of the vertical support. Vibration data before and after the damages was recorded by a SHM system on the bridge and had been open to public as a benchmark problem provided.[16] Damage detection was performed using the Bayesian neural network, suggesting the presence of an anomaly in the behavior of the bridge. Domaneschi et al.[171] applied an operational deformed shapes-based damage identification method to the FE model of a cable-stayed bridge; results show the method can locate the damage successfully on the basis of an accurate estimation of the operational deformed shapes.

The numerical analysis-based damage identification generally involves numerical models of physical structures such as FE model. A typical type of the numerical analysis-based is to employ damage indices calculated from structural responses before and after damage. Talebinejad et al.[172] used FE models of a cable-stayed bridge to simulate acceleration responses and evaluate four different damage identification methods of enhanced coordinate modal, assurance criterion, damage index method, mode shape curvature method, and modal flexibility index method. As these methods are not specifically developed for cable-stayed bridges, their relative merits and shortcomings in damage identification of long-span cable-stayed bridges are discussed in detail. Yin and Tang[173] proposed a damage detection method that can find multiple simultaneous damages in a cable-stayed bridge using simulated structural responses from the FE model. This study features interaction between the bridge and a moving vehicle as an enabler of damage detection. Zhou et al.[174] utilized the probabilistic neural network for damage localization in a cable-stayed bridge, that is, Ting Kau Bridge. The numerical simulation showed that the damage type and region could be identified with 85% of true detections.

Optimization schemes to identify structural damage are also reported in the literature. This approach is quite similar to the structural model updating, in that a numerical model representing the current structure is optimally determined using measured responses. Casciati and Elia[175] used bio-inspired optimization algorithms to evaluate structural damage. The FE model of De Gasperi Bridge, a cable-stayed bridge in Italy, was constructed, and imposed damage represented by stiffness reduction in structural members were successfully identified. Zhong et al.[176] proposed a multiscale FE model validation for cable-stayed bridges, which was intended to be further used for structural damage prognosis. This approach considered uncertainties of structural parameters and its propagation when subregions were combined in the multiscale FE model.

5.2 | Damage identification methods for stay cables

As the stay cable is one of the most important load carrying components in the cable-stayed bridge, research efforts have been intensively made to development of various SHM methodologies for the stay cables. The damage identification research focusing on stay cables can be divided into (a) direct detection of damage in the stay cable and (b) damage evaluation by measuring cable tension forces.

Ho et al.[177] proposed an image-based method to detect damage on the surface of the stay cables; they developed a robot system with a camera that was designed to embrace the stay cable and climb up while recording the cable surface; an image processing algorithm was developed, and experiment results show that the proposed method has potential to detect the surface damage of real stay cables. Similarly, Kim et al.[178] developed a cable climbing robot with elasto-magnetic (EM) sensors to find local damage in the cable. Scarella et al.[179] presented a method for determining stay cables, which partially or completely lost their tensile load-carrying capacities; this study interestingly utilized distributed dynamic strains of the bridge deck, measured by fiber-optic sensors. Monitoring the tension forces in the stay cables is quite important for the safety and maintenance purposes. Although a change in the cable tension force does not necessarily mean the corresponding stay cable is damaged directly, it can be thought as an indication that the structure undergoes damage or at least structural changes. The cable tension force can be measured by either direct (e.g., load cell) or indirect (e.g., vibration-based tension estimation) methods. Despite the direct method is accurate and straightforward, installing a load cell on the stay cables in service is expensive. Alternatively, indirect methods with better field applicability have been desired. Various vibration-based tension estimation approaches[180-182] had been developed many years ago, whereas their accuracies can be degraded due to environmental and cable configuration effects.

In this regard, Wang et al.[183] proposed an advanced vibration-based approach to monitor the internal force of the flexible components, and they improve the accuracy and applicability by incorporating influential factors and measuring frequencies precisely. Kim et al.[184] presented a computer vision approach for cable tension estimation using the vibration-based method; the digital image correlation was employed in the image processing for measuring unscaled displacement of the stay cable, which were, in turn, utilized to calculate the tension force; the noncontact approach can be conveniently applied to long-term monitoring of cable tensions. Sim et al.[185] developed an automated cable tension monitoring system using Imote2 smart sensors and deployed on the Jindo Bridge in Korea to demonstrate the performance in the long-term monitoring. The system was mostly automated in that sensing and data processing to estimate the cable tension force in addition to operation scheduling were all embedded in each sensor node. However, during the 1-month monitoring, any significant change in the tension force was not observed. A recent development by Yang et al.[186] considered time-varying cable tension; through an unsupervised learning of complexity pursuit, online tracking of the varying cable tension could be monitoring with minimal information of two acceleration time histories. Whereas these studies primarily used the vibration-based method, Yim et al.[187] introduced an EM stress sensor, which was designed for measuring the cable tension force; the fundamental principle of the EM sensor is that the magnetic permeability is linearly related to the stress level of a material; EM sensors were used to measure the cable tension during the construction stage of the Hwa-Myung Bridge in Korea, proving the performance in terms of the measurement accuracy. Cho et al.[188] performed a comparative study of three different cable tension measurement methods of the EM sensor, the vibration-based, and the traditional lift-off test at the cable-stayed Hwa-Myung Bridge, located in Korea. Chen et al.[189] presented damage detection of cable-stayed bridges based on variation of cable tension forces; the damage detection method was developed to eliminate the temperature effect on the relationship between the cable forces and the actual damage. An et al.[190] proposed a model-free, output-only, and fast damage diagnosis method for stay cables based on frequency change; frequency differences due to small damage of the stay cable are always submerged by the error of the parameter identification and surrounding noise; a temporary diagonal steel bar is installed with one end on the stay cable and the other end on the bridge deck, and then the stay cable is divided into a short part and a long part; as a result, the frequency changes due to small damage increases dramatically than that without the temporary diagonal steel bar; the method has been validated by simulation and experiment. Bao et al.[191] presented a method for identifying time-varying cable tension forces of bridges using adaptive sparse time-frequency analysis; results of experiments on cables show that the approach can estimate time-varying cable tension forces more accurately than the Hilbert-Huang transform method.

5.3 | Summary for cable-stayed bridges

This section discussed the recent development on damage identification of cable-stayed bridges. Because it is difficult to impose structural damage to the cable-stayed bridges in service for research purposes, most research articles on damage identification utilized numerical model. As the stay cable is an important load carrying member, damage identification of the stay cable was found to be one of the main focuses of the cable-stayed bridge research. Damage identification of cable surfaces, estimation of the cable tension force, and tension force-related damage detection were actively studied.

6 | RECENT PROGRESS ON DAMAGE IDENTIFICATION METHODS FOR SUSPENSION BRIDGES

The application of damage identification technique in suspension bridges has attracted much attention in recent years. Research progress on this structural system is summarized in what follows.

6.1 | Neural network-based damage identification methods

Zhang and Sun[192] proposed a damage detection and quantification method for self-anchored suspension bridge using the BP neural network model and genetic-simulated annealing algorithm; damage is detected using a BP neural network model, and the damage severity is assessed with the genetic-simulated annealing algorithm; the global convergence effect of the proposed approach is enhanced compared with the conventional genetic algorithm. Wang and Ni[193] proposed a damage detection and localization method for the suspension bridge; the proposed method is used for damage alarming based on the refined autoassociative neural network technique and damage localization based on the refined probabilistic neural network technique; a total of 15 damage cases in TsingMa suspension bridge located in Hongkong are considered in the numerical study to examine the performance of the method in which damage was introduced in bearings of the tower and deck, a side span cable and an anchorage, a tower saddle and a Tower cross-beam, hangers, deck members, and rail way beams; the reliability of the proposed damage identification technique is verified: The autoassociative neural network using flexibility coefficients performs better than that formulated using modal frequencies in identifying minor damage with noisy data; results based on the adaptive probabilistic neural network are much better compared with the traditional probabilistic neural network in the case of high noise level. Guan et al.[194] developed an optimization method of wavelet neural network for damage identification of the suspension bridge; the wavelet coefficients modulus maxima is employed to locate the damage and then the damage severity of the bridge is identified by the optimized neural network; the efficiency of the proposed approach was verified by numerical simulation.

6.2 | Bayesian theory-based damage identification methods

Arangio and Beck[195] developed a two-step Bayesian framework using the probability logic method for damage detection and quantification of suspension bridges; damage identification of large structural systems can be conducted using the Bayesian neural network approach without the information of the structural model. Chen and Wang[196] developed a probabilistic cumulative fatigue damage model using Bayesian learning for long-term SHM of long-span suspension bridges under wind excitation; the method was utilized to analyze the measurement data from the Tsing Ma Bridge in Hong Kong, and results show that the model is suitable for the probabilistic fatigue assessment. Alduse et al.[197] presented a Bayesian approach to estimate wind-induced fatigue damage of long-span bridges under the effect of uncertainties in wind speed and direction; this method makes the analysis of fatigue damage boundary and exceeding probability more comprehensive, because it provides the distribution of damage value; compared with the conventional fatigue damage assessment method, results show that the proposed method is more reliable. Cho et al.[198] developed a Bayesian correlation prediction model for analyzing the relativity of hydrogen-induced cracking in the cable wires of a steel suspension bridge; the model demonstrates better convergence and approximation capabilities when compared with a conventional linear prediction model.

6.3 | Damage identification methods with consideration of temperature variations

Miao et al.[199] proposed a damage alarming method for bridge expansion joints; the multiple regression models are established for obtaining influences of environmental factors, and the X-bar control chart is used for detecting abnormal expansion joints' displacements; the temperature and traffic condition are found to be dominant environment factors for displacements; based on the long-term monitoring data from Runyang Suspension Bridge, China, 0.1-cm damage-induced displacement variation of the expansion joint can be detected based on the X-bar control chart with confidence level of 0.003. Wang et al.[200] proposed an analytical model-free damage identification method based on the covariance matrix; the effect of the temperature variation on the matrix's diagonal elements is reduced by the application of a support vector machine; the damage simulated by the change of the covariance of covariance component of the deck in a suspension bridge, that is, the Pearl River Huangpu Bridge in China, is successfully detected. Xia et al.[201] proposed a structural damage identification method based on temperature-induced responses for the long-span suspension bridge; structural characteristics can be obtained through the structural transfer function by taking temperature load variation and temperature-induced strains input–output data, unlike the traditional vibration-based method only employs structural vibration responses from ambient testing; in the numerical study, for the single damage case, the 10th element has a 10% stiffness reduction; for the multiple damage case, the fourth, 10th, and 13th elements have a 10% stiffness reduction; results show that the method can localize the damage clearly in single and multiple damage cases; the proposed method was employed to evaluate the condition of the Jiangyin bridge after a ship collision in 2005, and results show that no obvious damage was found.

6.4 | Other damage identification methods

Guan et al.[202] proposed a damage detection and localization method for suspension bridges based on wavelet analysis of strain mode; the damage can be detected using the structural strain modal parameters solution by Lanczos method and also can be localized using the maximum of wavelet coefficients; the effectiveness of the proposed method is verified based on the FE model of a suspension bridge. Xu et al.[203] analyzed the fatigue reliability and fatigue damage accumulation of long-span suspension bridges under multiple fatigue loads using the continuum damage model; applicability of the nonlinear continuum damage model is validated through the comparison with the field monitoring data from TsingMa suspension bridge; the life-cycle fatigue assessment and the most dangerous loading scenarios of the bridge are given. Domaneschi et al.[204-206] proposed the interpolation damage identification method for long-span suspension bridges under the seismic excitation; by analyzing the changes in accelerations of the intact and damaged structures, several numerical damage cases are identified in a numerical model of the suspension bridge; the proposed method does not require the modal properties and shows strong robustness against noise, and therefore, it is promising to be applied in a real-suspension bridge. Cross et al.[207] present a principal component analysis-based approach, coupled with Response Surface Models, to assess the evolution of modal parameters on the Tamar bridge. Ubertini[208] introduced an application of a damage diagnosis method for the main cable in a suspension bridge using data continuously recorded under wind excitation; damage is located in the critical region close to one suppot: Damage intensity factor changes from 0 to 0.1 (i.e., 10% section reduction of the cable), and 5% of the cable length is assumed to be affected by the damage; small damage in main cables of suspension bridges can be detected accurately based on the frequency differences before and after damage; several simplifications are adopted in this study, such as ignoring the coupling between vertical and torsional/lateral modes, ignoring changes in environmental conditions, and assuming the stationary wind loading model and linear time-invariant structural behavior.

Several vibration-based damage diagnosis algorithms for the Alfered Zampa Memorial suspension bridge, that is, changes in the flexibility matrix method, changes in the stiffness matrix method, changes in the uniform load surface method, and uniform load surface curvature method are implemented by Talebinejad et al.[209] to detect various damage cases in different structural components with different severities, and the corresponding numerical analysis is conducted in which the damage intensity is increased from 50% to 100% for a suspender and increased from 25% to 90% for the deck; damage in the deck and suspenders is easily detected even with low damage intensity of 25%, whereas damage in the tower leg cannot be detected. Chen et al.[210] introduced a damage diagnosis method utilizing stress influence lines (SIL) to locate the damage on different suspension bridge members; the first-order difference of SIL is selected as damage index, and the location of single and double damage cases simulated in TsingMa suspension bridge can be effectively identified; damage is simulated by reducing cross-sectional area of the diagonal truss element and the flexural rigidity of the railway beam member to 1% of their original values respectively; damage in the diagonal truss element is more likely to be identified by SIL-based indices for neighboring top and bottom chords, vertical posts, and suspenders; damage in the railway beam is more likely to be identified by SIL-based damage indices for neighboring railway beams, cross frames and bracings, vertical posts, and suspenders. Miao et al.[211] proposed a damage identification method for the main girder in the long-span suspension bridge based on the mean-value control chart method and dynamic displacement data collected from GPS subsystem; 3% abnormal change of position coordinates in the longitudinal direction, and 5% in the vertical direction can be effectively detected. An et al.[212] proposed two model-free test methods for damage diagnosis of suspender cables, that is, the mean normalized curvature difference of waveform damage feature-based method and the curvature difference probability of waveform damage feature based method; simulation results indicate that 5% stiffness reduction in long suspender cables can be identified, and small damage in long suspender cables can be more easily diagnosed than in short ones; the method has strong noise immunity, and it changes manual inspection from observation to a more quantified method. Guan et al.[213] proposed a method that combines wavelet transform and artificial immune algorithm to detect the damage in the suspension bridge; numerical results show that the proposed method not only can quickly and accurately identify the damage location but also can calculate the extent of the damage.

Wickramasinghe et al.[214] proposed a new method to detect and locate damage in cables using component-specific damage indices using the modal flexibility method; the efficiency of the proposed approach was verified by the case studies on a cable and a suspension bridge structure, respectively. Wickramasinghe et al.[215] proposed a damage index for identifying and locating damage in cables of a suspension bridge; a suspension bridge model with three different types of cables was constructed in laboratory to gain the vilified FE model, and 10 damage scenarios were generated through changing the Young's modulus in the FE model; results show that the method can successfully detect damage for all three types of cables in all damage scenarios. Heo and Jeon[216] developed a structural identification technique consists of the kinetic energy optimization technique and the direct matrix updating method for SHM of suspension bridges, which is used to determine the most appropriate location of sensors and minimize its quantities at the most extent for accurately assessing the structural state and FE model updating; experimental results show that only 20% measurement location are required compared before, and the margin of error of FE model derived from experiment is limited to 1% compared with the eigenvalue of the modal experiment. Domaneschi et al.[217] extended a recently proposed damage localization method, and the structural response of an existing long-span suspension bridge under the wind excitation was simulated by a calibrated FE model; the sensitivity of the method is checked by simulation of several damage scenarios. Xu[218] proposed an SHM-based fatigue damage prognosis framework for long-span bridges under combined traffic and wind loadings; results based on the proposed fatigue damage prognosis framework for Tsing Ma suspension bridge in Hong Kong show that its health condition during design life is satisfactory with current traffic conditions. Wei et al.[219] proposed a statistical paradigm for detecting crack based on the features of the strain response using dense fiber Bragg grating strain sensors; the ratio of strain related to structural conditions is used to eliminate the vehicle weight information; different types of cracks are detected precisely though comparing the strain ratio distributions; the proposed statistical paradigm for crack detection is validated based on dense fiber Bragg grating strain sensors on a long-span suspension bridge.

6.5 | Summary for suspension bridges

Great progress has been made in damage identification of suspension bridges; however, the proposed methods' anti-noise ability and sensitivity to small damage are still required to be improved. Little has been published about the damage identification for long-span suspension bridges based on field monitoring data, which indicates that damage identification of large and complicated bridge structures is a difficulty and requires development in the future studies. The possible points are listed as follows: (a) employ division of the bridge to individual components (dissection). Suspender cables, joints, and key steel truss members are the most vulnerable components of a suspension bridge; damage identification should be conducted from the level of these components, and in such a case, measured nodes are set on these components directly, which can reduce the influence of uncertainties, improve the damage sensitivity of the damage identification methods. (b) Many damage identification methods require the accurate FE model of the measured bridge, which is often difficult if not impossible especially for those large and complicated bridges. Therefore, it is recommended to continually develop model-free damage identification methods or methods with low dependence on accuracy of structural FE models; this can avoid the heavy workload of model development and updating and also decrease the influence of model error.

7 | CONCLUSIONS

Despite extensive research on structural damage identification in the last several decades, most of them rely on numerical simulation and laboratory experiments, while full-scale validation remains limited. Three major challenges are met in the vibration-based damage identification for bridge structures: First, accurate structural damage identification, and damage severity identification in particular, is challenging due to three main difficulties: high noise, low sensitivity to small damage, and low accuracy of the numerical model.[124] Second, studies on damage identification for beam bridges and truss bridges have been extensively published; however, little has been published concerning arch bridges, cable-stayed bridges, and suspension bridges, and even fewer works deal with experiments and engineering application. Third, little has been published regarding long-term monitoring data analysis of bridge. The main reason is that generally the long-term monitoring data are not openly accessible to researchers. The outcome of long-term monitoring data analysis[155,220] is critical for validation of the SHM methods, and it is one of the current trends and most promising directions in the fields of SHM. The conclusions of this review paper are summarized as follows:

(1) In vibration-based damage identification studies, a focus should be on damage localization rather than quantification, because vibration-based damage quantification generally requires an accurate numerical model. In particular, damage localization methods, which can provide good performance in three points, should be pursued, that is, high anti-noise ability, high sensitivity to small damage, and model-free/low dependence to the accuracy of numerical model. At the same time, this is also dependent on the evolution and potential of the employed sensor technologies (hardware), which are nonetheless continuously improving. Machine learning techniques, such as the deep learning-based method, bear new promise in the fields of damage localization and damage quantification.
(2) Nondestructive evaluation methods bear more promise for damage quantification. Many nondestructive evaluation methods exist ranging from acoustics to optical, with most of them operating through measuring sound, light, intensity of electromagnetic field, temperature, or displacements.[9] Many researchers have conducted damage identification studies based on nondestructive evaluation methods: the guided ultrasonic wave-based method,[221] the ground penetrating radar-based method,[222-225] the ultrasonic testing-based method,[226,227] the acoustic emission-based method,[228] thermography method,[224] impact echo method,[224,225] etc.
(3) The coupling of real-time monitoring techniques (i.e., vibration-based damage identification methods) and nondestructive evaluation methods may form a powerful tool for model updating and damage identification of large and complicated structures. It is recommended that vibration-based damage identification methods are used to detect the approximate location of damage within a bridge, with nondestructive evaluation methods then used to localize the exact flaw location and evaluate the severity of the damage. Combination of the long-term monitoring data analysis, numerical simulations, experimental model tests, and the analysis of periodical inspection-based damage database paves the way to damage identification of large and complicated bridge structures.
(4) Damage identification of complex structures should rely on a divide and conquer logic, allowing for assessment on the critical component level, with sensing nodes placed more densely on such key/critical components. Damage

identification methods for hangers/suspender cables/stay cables can be validated in operating bridges through the following two methods: (a) by adjusting the cable tension to simulate the damage of anchor head looseness during the construction stage of a new bridge and (b) when the cables of an old bridge require replacement.

(5) For some historic or complex structures, an accurate numerical model is very difficult to be established due to incomplete drawings and complexity. In this case, 3D laser scanner-based FE modeling techniques may serve as enabling tools for the fast modeling. Moreover, image processing-based damage identification methods have recently surfaced as promising model-free methods for detecting certain types of damage, such as cracking, corrosion, and undesirable deformations and displacements.

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