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Review

A comprehensive review of indirect bridge health monitoring

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ABSTRACT

Indirect Bridge Health Monitoring (BHM) using indirect measurements of the response from passing vehicles has recently gained significant attention from researchers within the Structural Health Monitoring (SHM) domain. This approach requires only one or a few sensors installed on the vehicle, making it more cost-effective, efficient, and easier to implement than traditional methods, which demand numerous sensors on bridges. Recent advancements in both algorithms and hardware have further accelerated progress in this field. This paper aims to provide a comprehensive, one-stop review of indirect BHM using measured vehicle response since 2004. It systematically analyzes the connections and integrations within existing literature, incorporating rapidly emerging state-of-the-art studies. The review initiates with a bibliometric analysis, covering annual publication trends, keyword cooccurrence, and authorship networks, followed by a discussion on the fundamental theories of vehicle–bridge interaction. Subsequently, it summarizes the vehicle, bridge, and road roughness models used in indirect BHM. Furthermore, it explores current techniques and challenges in identifying bridge modal parameters, such as bridge frequencies, mode shapes, and damping ratios, as well as in indirect bridge damage detection using signal processing, modal-based, and data-driven methods. Additionally, this review includes affiliated studies that, while not directly related, contribute to the advancement of indirect BHM. Finally, recent developments in 2025, future investigation directions, and key conclusions are provided. It is intended to serve as a fundamental resource for researchers seeking to advance their studies in the field of indirect BHM.

Contents

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Nomenclature

2D	2-dimensional
3D	3-dimensional
ABA	Axle box accelerations
AE	Auto-encoder
AI	Artificial intelligence
ANN	Artificial neural network
APPVMD	Autonomous peak picking variational mode decomposition
ASLT	Adaptive superlet transform
BHM	Bridge health monitoring
BMI	Blind modal identification
BO-BiLSTM	Bidirectional long short-term memory neural network model
BPF	Band-pass filter
CE	Cross Entropy
CNN	Convolutional neural network
CP	Contact-point
CPDV	Contact-point displacement variations
CWT	Continuous wavelet transform
DI	Damage indicator
DL	Deep learning
DSC	Direct stiffness calculation
DSF	Damage-sensitive feature
EDDI	Euclidean distance damage index
EEMD	Ensemble empirical modal decomposition
EMD	Empirical mode decomposition
ESMD	Extreme-point symmetric mode decomposition
FDD	Frequency domain decomposition
FE	Finite element
FFT	Fast Fourier transform
FIrST	Filtered iterative reference-driven S-transform
FRF	Frequency response function
FSST2	Fourier transform-based second-order synchrosqueezing transform
GKF-UI	Generalized kalman filter with unknown inputs
HDBSCAN	Hierarchical density-based spatial clustering of applications with noise
HHT	Hilbert–Huang transform
HierMUD	Hierarchical multi-task unsupervised domain
HT	Hilbert transform
i-VNCMD	Iterative variational nonlinear chirp mode decomposition
IAS	Instantaneous amplitude squared
IC	Instantaneous curvature
IFFT	Inverse fast Fourier transform
IHA	Inverse Hessian approximation
IMF	Intrinsic mode function
IMSST	Improved multisynchrosqueezing transform
IoT	Internet of Things
IVRD	Iterative vehicle response demodulation
KF	Kalman filter
LSTM	Long short-term memory
MAC	Modal assurance criteria
MFCCs	Mel-frequency cepstral coefficients
ML	Machine learning

MOESP	Multivariable output error state-space
MOSS	Mode shape square
MRC	Moving reference curvature
MSAA	Maximum successive approximation approach
MUSIC	Multiple signal classification
NExT	Natural excitation technique
ODS	Operating deflection shape
ODSR	Operating deflection shape ratio
OMA	Operational modal analysis
PCA	Principal component analysis
PPI	Prominent peak identification
PSD	Power spectral density
RDT	Random decrement technique
RMSC	Regional mode shape curvature
RNN	Recurrent neural network
SAE	Stacked auto-encoder
SET	Synchroextracting transform
SHM	Structural health monitoring
SSA	Singular spectrum analysis
SSI	Stochastic subspace identification
SSMA	Spatial singular mode angle
SST	Synchrosqueezing transform
STFDD	Short-time frequency domain decomposition
STFT	Short-time Fourier transform
SVD	Singular value decomposition
SVM	Support vector machine
SVMD	Successive variational mode decomposition
SWT	Synchrosqueezed wavelet transform
TFR	Time–frequency representation
TSD	Traffic speed deflectometer
UMAP	Uniform manifold approximation and projection
VBI	Vehicle–bridge interaction
VMD	Variational mode decomposition
VSM	Vehicle scanning method
WT	Wavelet transform
WVD	Wigner–ville distribution

1. Introduction

1.1. Structural health monitoring for bridges

Bridge structures, as crucial components of transportation networks, play a significant role in enhancing the mobility of individuals, goods, and services, thereby contributing to economic development and societal welfare. The past century, particularly in the post-1950s, has witnessed a significant increase in bridge construction. Over time, many bridges constructed during this period may have surpassed their intended lifespan. In Europe, as reported, a significant number of bridges were built after 1945. The outdated design regulations are now facing challenges due to the growing traffic demands [1]. A comparable trend was also observed in the United States and Japan, where around 42% and 39% of bridges have been in service for over fifty years, respectively [2,3]. The increasing concern about gradual deterioration and aging issues has motivated researchers worldwide.

Structural health monitoring (SHM), emerging as a matured and multidisciplinary branch for the maintenance of infrastructures, can provide fundamental techniques for health condition assessment of bridge structures [4,5]. Typically, SHM includes modules such as sensor deployment, data acquisition, transmission, and management systems, data analysis and modeling components, structural damage detection, alarm devices, and graphical user interfaces [6]. Among all modules, structural identification is the core task and can provide fruitful information about bridge condition assessment. Typically, structural identification includes four levels: (1) structural damage detection, (2) localization of geometric location of the damage, (3) quantification of the damage severity, and

(4) prediction of remaining service life of the structure [7]. How to achieve these four levels of structural identification becomes a focus in existing studies on bridge health monitoring (BHM).

Traditionally, structural damage detection for bridges heavily relied on visual inspection approaches. It requires experienced engineers to perform comprehensive examinations on bridges. Such a method can be labor-intensive, time-consuming, dangerous, or even impossible nowadays [8]. Furthermore, since this approach is based on human vision, only surface, i.e. visually perceptible, defects can be detected, instead of deeper structural flaws like inner cracks and initiation of corrosion, which, however, can be crucial in practical engineering. Notable incidents, e.g., the collapse of the Morandi Bridge in Genoa, Italy, in 2018 due to tendon corrosion, highlight the severe consequences of inadequate monitoring and delayed maintenance. The increasing number of deteriorated and newly constructed bridges has triggered the consideration of scientific researchers to seek new ways for effective BHM.

One effective strategy for BHM involves the identification of damage-sensitive features (DSFs) from bridge vibration [9,10]. Modal parameters, including natural frequencies, mode shapes, and damping ratios, can provide essential information for BHM. Modal data are invaluable for developing accurate numerical models of bridges and supporting the implementation of digital twin methods. These techniques are essential for guiding structural design, maintenance, and control of bridges. Modal information serves to deliver indicators of bridge damage, and modal shifts can be linked to pathologies such as stiffness loss due to support settlement, and cracking due to aging problems. Conventionally, acquiring the modal parameters of a bridge requires the use of various sensors to collect suitably rich vibration data. Typical on-site testing includes logging of ambient response, but can also come in the form of targeted campaigns, such as forced vibration tests, impact tests, and more. In the last fifty years, many studies have been reported along this line [11]. Since this method involves the direct installation of sensors on the bridge structure, it is also known as the direct method for BHM. However, this method typically involves the installation of multiple sensors on the bridge to establish a sensing network that continuously gathers data, making it costly and labor-intensive for practical engineering applications. In addition, those sensors are typically installed during the construction phase. For bridges that are in operation, traffic disruption may be required when deploying vibration sensors [12], thus compromising availability of bridge assets. Another limitation of such fixed sensor networks is that each system is tailored to a specific bridge and cannot be easily transferred to another without modifications [13]. Due to these constraints, only critical bridges are usually chosen for installation of such monitoring systems. This has so far resulted in only a small fraction of bridges worldwide having undergone comprehensive monitoring. Short-span bridges and footbridges, which are vital for daily human activities, are often excluded from monitoring efforts, even though the failure of these structures can pose significant risks to human life and property. Hence, there is a pressing need for new technologies in BHM to address the maintenance requirements of deteriorating bridges.

1.2. Indirect bridge health monitoring

To resolve the current challenges associated with direct BHM, the indirect monitoring method was proposed by Yang et al. in 2004 [14] (also named Vehicle Scanning Method [15], drive-by method [16], or mobile sensing [17]). In the indirect method, vibration-based sensors (usually accelerometers) are installed on the vehicle to collect its vibration data during bridge crossings, thereby alleviating the cost and hurdles of fixed sensors installation. In this study [14], a sprung-mass model was utilized to simulate the passing vehicle, and the bridge was modeled as a simply supported beam. This work laid down the fundamental theory that the bridge frequency could be indirectly identified from the vehicle response measurements. Later in 2005, Lin and Yang [18] employed a tractor–trailer system on the Da-Wu-Lun bridge in Taiwan. The field test showed that the bridge's dynamic information could be transferred to the vehicle's vibrations through vehicle–bridge interaction (VBI). These two pioneering studies offered foundations to identify the bridge's modal parameters and to perform bridge damage detection for the latter investigation using vehicle response measurements.

As one can notice, a salient advantage of the indirect method is that it is more economical and easier to operate compared to the direct method since it only needs one or several sensors mounted on the vehicle rather than the bridge. Moreover, as the sensors are attached to the vehicle, it is convenient to check, maintain, and repair them once faults are noticed. Thirdly, it has the potential to properly monitor clustered bridges near each other at one time by driving the sensing vehicle to pass all bridges sequentially. Due to these advantages, researchers soon identified the concept of indirect BHM, which has gathered much attention worldwide. Currently, there are multiple projects ongoing toward the indirect BHM in Europe [19,20], as well as the United States, China, Japan, Canada, and Australia [13,17], which indicates the promising trend of the indirect method for BHM in the near future.

In the last two decades from 2004 to 2024, the indirect method has been greatly developed after the first publication in 2004 by Yang et al. [14]. In existing studies, the extraction of the bridge's modal parameters from vehicle response measurements has been extended from modal frequencies to mode shapes and damping ratios [21–23]. Several key techniques, such as the back-calculation of contact-point (CP) response from vehicular accelerations, have been proposed, which allow to remove the vehicle's dynamic contribution from the measured response [24]. Furthermore, advanced models for the VBI systems, e.g., 3-dimensional (3D) vehicles and bridges, have been deployed for refining the numerical simulations in engineering applications [12,25]. Beyond extraction of bridge modal parameters, the downstream tasks of BHM such as damage detection, localization, and quantification using vehicle vibrations have further been investigated. Moreover, capitalizing on the advent of artificial intelligence (AI) solutions in SHM [26], machine learning (ML) and deep learning (DL) techniques have been gradually adopted within this indirect framework to alleviate use of exhaustive models in extracting key DSFs [27,28].

Regarding reviews of the indirect method for BHM, several publications have gradually surfaced reporting step-wise developments. In 2015, Malekjafarian et al. [7] presented the first review paper including 73 publications related to bridge modal parameter identification and damage detection methods. Later, the first author and his colleagues extended the review to August 2022 [17], in which the existing laboratory experiments and field tests were elaborated. In 2018, Yang and Yang [29] provided a review of 102 publications covering works on bridge information extraction and damage detection for road bridges until April 2017. Later, Wang et al. [13] extended this contribution to damage detection for railway bridges, road roughness estimation, and the use of modern devices before February 2022, and Xu et al. [30] updated the references until April 2024. Several further articles have summarized the development of both the direct and indirect monitoring methods, [31–33], mainly focused on railway bridges [34,35], and provided relatively concise reviews [36–39]. As can be observed, the indirect method has become a hot topic for BHM, which has been documented in the aforementioned reviews. However, the bibliometric analysis, as a tool to examine the connections and integrations of existing studies, have not been so far comprehensively provided. However, such analysis can help researchers, especially those new to this field, to understand the development trend of this topic, select proper journals, know who the experts are in indirect BHM, and recognize cutting-edge techniques employed. Furthermore, there exist radically new and novel publications and developments in bridge modal parameter identification and indirect bridge damage detection techniques regarding both algorithms and hardware, which deserve review and summarization. A noticeable lack in existing reviews is the offering of methodological explanations and understanding, which lie at the core of this paper.

1.3. Contributions of this paper

This paper presents a comprehensive review of indirect BHM, encompassing both fundamental techniques and recent advancements. It is intended to serve as a one-stop reference for researchers to efficiently grasp the current state-of-the-art, identify key challenges, and explore future research opportunities. The review covers literature published between May 2004 and December 2024, along with recent developments from 2025, spanning over two decades. The main contributions of this paper are summarized as follows: (1) A structured, thematic organization of literature is provided. It systematically groups studies by modeling approach and application, offering comparative insights across VBI models as well as methods for modal identification and damage detection. (2) A rigorous bibliometric analysis of 436 publications is introduced, quantifying research trends, author networks, and keyword clusters. (3) A dedicated section that systematically reviews vehicle, bridge, and road roughness models used in indirect BHM is presented, offering a clear technical basis for understanding assumptions across studies. (4) The literature is systematically categorized by research subtopics and existing methods are carefully grouped into clear types. Their key features and validation approaches are summarized in comparative tables, which can help readers quickly understand differences across studies. (5) Affiliated topics such as road roughness estimation and railway track monitoring are introduced as essential extensions to indirect BHM, which frames them as essential components rather than side topics. (6) Recent developments in 2025, key challenges, and future investigations based on discussions in the field of indirect BHM are provided. Fig. 1 illustrates an overview of the review framework. It summarizes key applications related to indirect BHM. Certain listed techniques that have not been directly utilized for BHM, but have saliently contributed to the development of the indirect method and are, thus, included as affiliated investigations.

The remainder of the paper is organized as follows: Section 2 provides a bibliometric analysis for articles published between 2004 and 2024. Section 3 outlines the fundamental theories for indirect BHM. In Section 4, the models of vehicles, bridges, and road roughness utilized in existing studies are introduced. Section 5 provides a review of the extraction of bridge modal parameters from vehicle response measurements, and current research to remove the influence of vehicle information and road roughness is elaborated. Then, Section 6 offers current studies on indirect bridge damage detection using vehicle measurements, which is the core task for indirect BHM. Subsequently, Section 7 describes the affiliated investigations that facilitate the development of indirect BHM. Recent developments and future investigations based on discussions are provided in Section 8. Finally, Section 9 gives the conclusions of this paper.

2. Bibliometric analysis of the publications

This section will provide bibliometric analysis for 436 journal publications closely related to indirect method for BHM between 2004 and 2024 (until December 31, 2024). Annual publications, journals, keyword clusters, and author connections are reviewed and analyzed.

2.1. Publication numbers and journal analysis

Annual publication numbers can reflect researchers' interest and the progression within a field. Fig. 2(a) presents the trends in the publication of yearly journals in indirect BHM in the past two decades, highlighting a marked increase in articles in the last 2–3 years. In the early years (2004–2008), following the initial proposal of this concept, only a few studies were published. However, between 2009 and 2014, researchers began to recognize the method's potential for efficiently extracting bridge information, leading to a steady increase in publications. Two notable peaks occurred in 2014 and 2017, likely driven by the successful reconstruction of bridge mode shapes from vehicle response [40,41] and the introduction of the concept of CP response [24]. Although a temporary decline was observed in 2018, the number of publications has continued to increase in recent years, reflecting the growing interest in this research area.

Beyond publication numbers, another key metric is the distribution of research across journals. Fig. 2(b) presents the top 20 journals publishing work on indirect BHM. Notably, most articles appear in Q1 journals, as classified by the Journal Citation Report, underscoring the method's significance and potential in BHM. The five most prominent journals, based on publication volume, are *Engineering Structures*, *International Journal of Structural Stability and Dynamics*, *Mechanical Systems and Signal Processing*, *Journal of Sound and Vibration*, and *Structural Control and Health Monitoring*. Researchers in this field may consider these journals for submission, as their scopes closely align with indirect BHM. Additionally, 21.8% of the articles are published in other journals, reflecting the broader interest from various civil engineering-related publications.

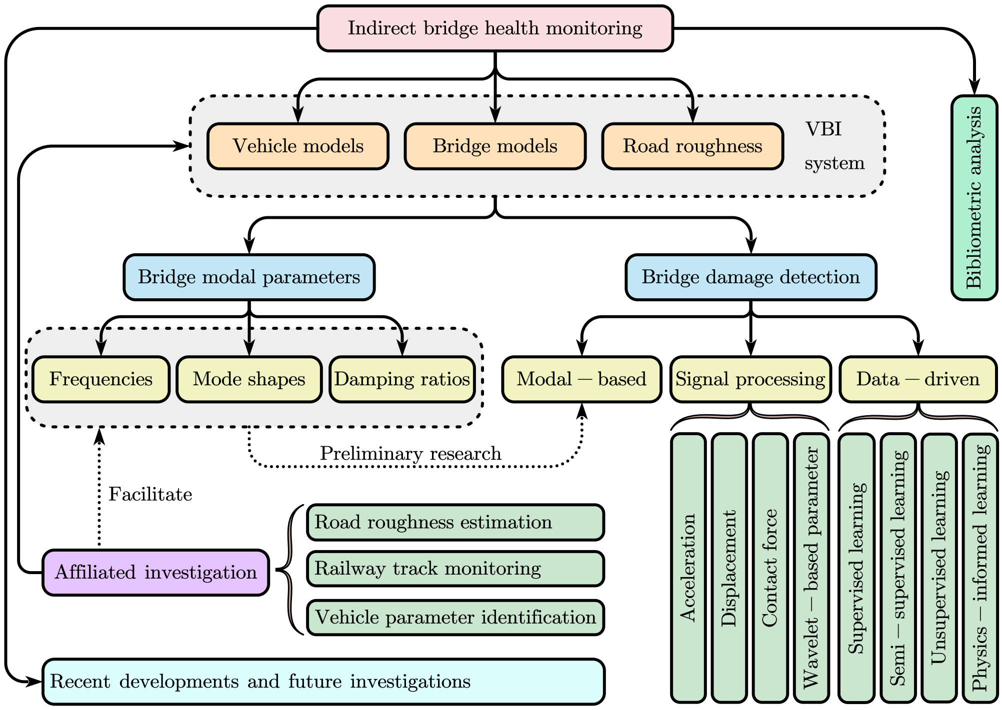


Fig. 1. Overview of the review of indirect BHM.

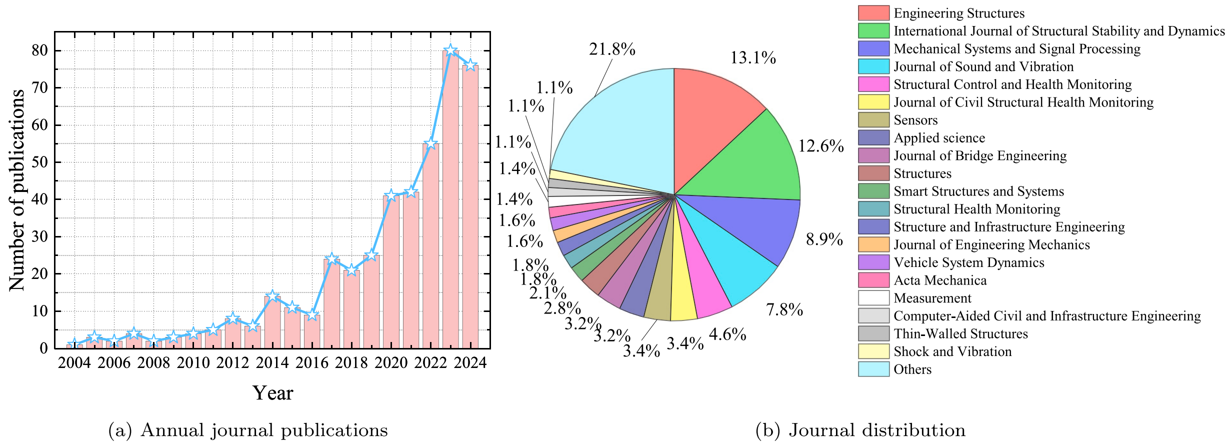


Fig. 2. Number and journal analysis of publications.

2.2. Keywords cooccurrence analysis

Keywords in publications offer valuable information about research hotspots and the dominant themes in current studies. To identify key topics in indirect BHM research, a keyword cooccurrence analysis was performed, with their relationships over the past five years visualized in Fig. 3. To emphasize their significance, only keywords that appeared more than five times were included. Notably, frequent terms such as “vehicle–bridge interaction”, “bridge”, and “vehicle scanning method” highlight the fundamental concepts underlying indirect BHM. Additionally, terms like “structural health monitoring” and “damage detection” are prevalent in existing publications. In recent years, there has been a growing focus on topics such as “bridge frequency identification”, “contact-point response”, “road roughness”, and “deep learning”, reflecting a shift from basic bridge parameter extraction to more comprehensive health condition monitoring using vehicle response measurements. Cutting-edge tools and algorithms, including smartphones, crowdsourcing, ML, and DL, are increasingly being applied in this field. At the same time, foundational research areas such as indirect frequency and mode shape identification have remained active and continue to evolve over the past two decades.

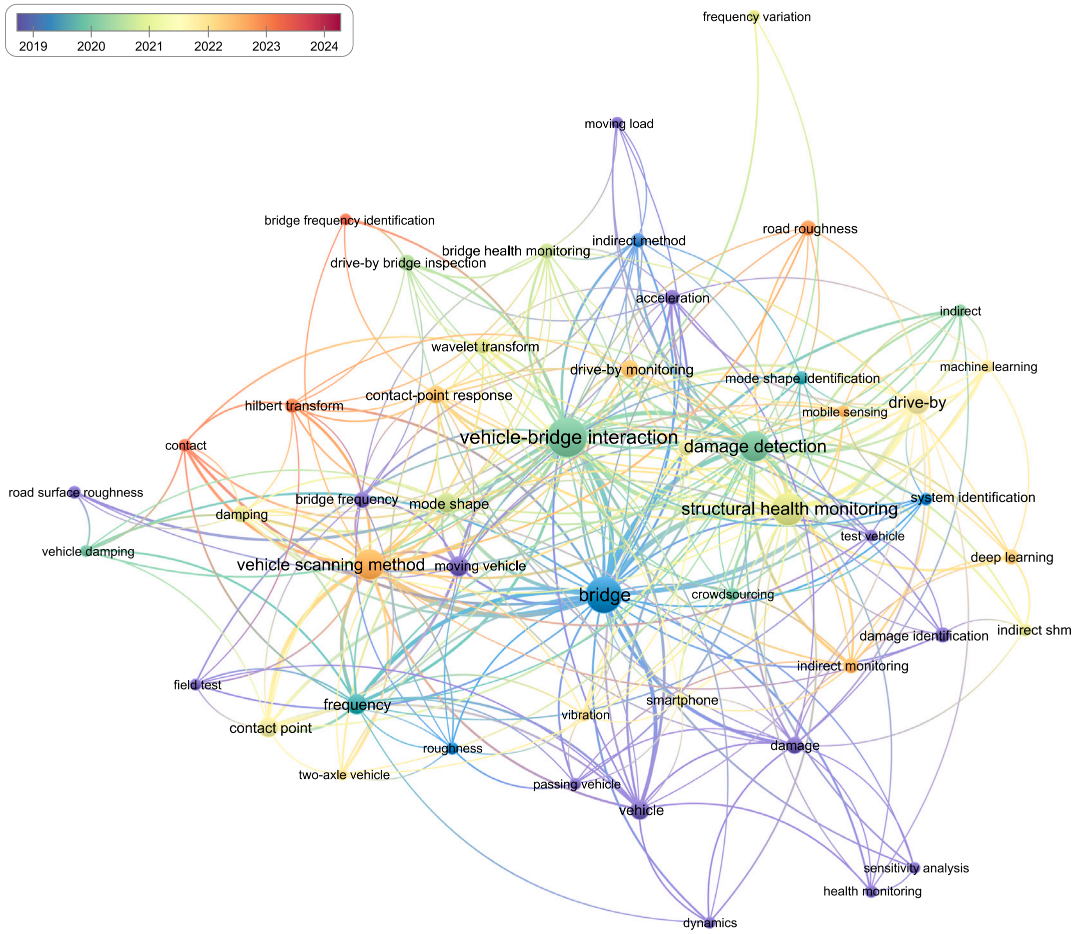


Fig. 3. Keywords cooccurrence network.

2.3. Authorship analysis

Fig. 4 presents an analysis of authors with more than three publications in the field of indirect BHM, along with their collaborative networks. The visualization highlights the involvement of multiple research groups worldwide, each represented by distinct color clusters, reflecting the growing global interest in using vehicle response measurements for BHM. Among these groups, the research teams led by Y.B. Yang and Eugene J. OBrien have emerged as key contributors, publishing the highest number of articles. Additionally, the figure reveals collaborative links between certain groups, facilitated by specific researchers, which have played a crucial role in fostering cooperation and accelerating advancements in this field.

Based on the analysis of publication trends, journal distribution, keyword cooccurrence, and authorship networks, it is clear that the indirect method for BHM has gained significant attraction among researchers worldwide. Its advantages have attracted numerous research groups, leading to growing contributions in this field. Additionally, state-of-the-art techniques are increasingly being utilized to extract crucial bridge health information from vehicle response measurements. The following sections will explore the fundamental theories and recent advances in this area in greater detail.

It should be noted that the bibliometric analysis in this section covers publications up to the end of 2024. However, research momentum has continued to accelerate in 2025, with notable progress particularly in practical implementation and data driven methods. These recent developments have been incorporated into Section 8.1 to ensure that the review remains up to date and reflects the latest evolution of the field.

3. Fundamental theories for indirect bridge health monitoring

The fundamental theories of indirect BHM are rooted in VBI [42]. As a vehicle passes a bridge, it interacts with the structure, transmitting excitation forces that induce bridge vibrations. In turn, these vibrations influence the vehicle's own dynamic response. This bidirectional interaction enables the extraction of dynamic characteristics of the bridge from vehicle vibrations. The primary

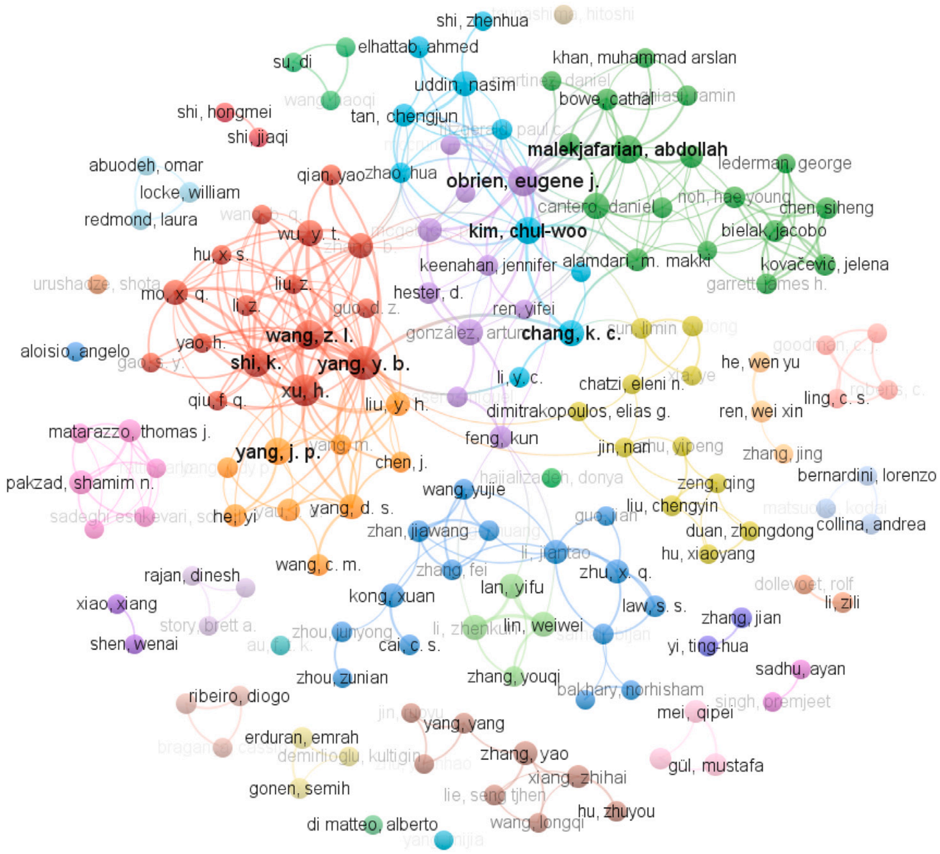


Fig. 4. Authorship analysis.

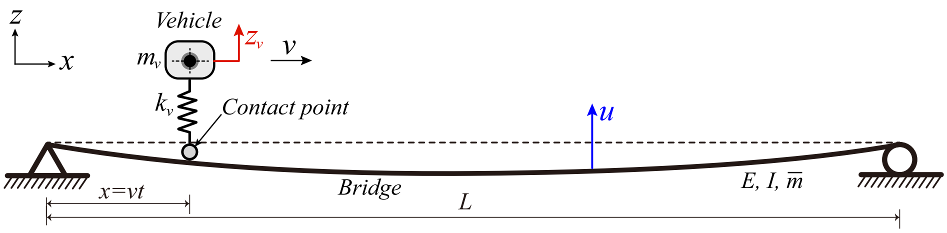


Fig. 5. VBI of a sprung-mass model and a simply supported beam.

objective of indirect BHM is to obtain critical bridge information through vehicle response measurements, facilitating continuous health monitoring throughout the bridge lifecycle. Essentially, the vehicle functions as a moving sensor, scanning and capturing the bridge's dynamic behavior without requiring direct instrumentation on the structure.

In this section, a single sprung-mass model for the vehicle and a simply supported beam model for the bridge are employed to illustrate the fundamental theories of indirect BHM [14]. While more advanced studies now utilize complex models, the core principles remain consistent with this foundational investigation.

For deriving analytical solutions of the vehicle's response, only the first mode of the bridge's vibration is considered. This simplification allows for a clearer understanding of the VBI mechanism. The corresponding VBI model is shown in Fig. 5.

As illustrated in Fig. 5, the vehicle's speed is denoted as v, while its body mass is represented by m_v, supported by a spring with stiffness k_v. The bridge is modeled as a simply supported beam with a unit-length mass of $\overline{m}$, total length L, Young's modulus E, and cross-sectional moment of inertia I. If the damping of the VBI system and road roughness are not considered, the dynamic equilibrium equations governing the vehicle and bridge can be expressed as Eqs. (1) and (2),

$$m_v \ddot{z}_v + k_v \left(z_v - u|_{x=vt} \right) = 0 \tag{1}$$

$$m\ddot{u} + EIu'''' = f_c(t)\delta(x - vt) \tag{2}$$

where z_v represents the vertical displacement of the vehicle body, and u denotes the vertical deflection of the bridge. The symbols $(\dot{})$ and $(')$ indicate derivatives of u with respect to time t and the spatial coordinate x, respectively. The function δ represents the Dirac delta function, which is equal to one only when its argument is zero; otherwise, it is zero. The contact force between the vehicle and the bridge, denoted as $f_c(t)$, varies at the contact point and can be determined using Eq. (3),

$$f_c(t) = k_v \left(z_v - u|_{x=vt}\right) + m_v g \tag{3}$$

where g represents the acceleration due to gravity. If only the first mode of the bridge is considered, its deflection $u(x,t)$ can be expressed as $u(x,t) = q_b(t)\sin(\pi x/L)$, in which $q_b(t)$ is the generalized coordinate corresponding to the bridge's first mode. In practical engineering applications, the vehicle's mass is typically much smaller than that of the bridge. By incorporating this assumption and applying zero initial conditions, the vehicle's response can be obtained using Duhamel's integral, as expressed in Eq. (4) [14],

$$\begin{aligned} z_v(t) = &\frac{\Delta_{st}}{2\left(1-S^2\right)}\left[\left(1-\cos\omega_v t\right) - \frac{\cos(2\pi vt/L) - \cos\omega_v t}{1-(2\mu S)^2}\right.\\ &\left. -S\frac{\cos\left(\omega_b - \pi v/L\right)t - \cos\omega_v t}{1-\mu^2(1-S)^2} + S\frac{\cos\left(\omega_b + \pi v/L\right)t - \cos\omega_v t}{1-\mu^2(1+S)^2}\right] \end{aligned} \tag{4}$$

where $\omega_v = \sqrt{k_v/m_v}$ is the vehicle frequency. $\omega_b = \pi^2/L^2\sqrt{EI/\overline{m}}$ represents the fundamental frequency of the bridge. $\Delta_{st} = -2m_v g L^3/\left(\pi^4 EI\right)$ denotes approximate static deflection of the bridge's mid-span point under gravity action of the vehicle mass m_v. $S = \pi v/L\omega_b$ means the speed parameter. $\mu = \omega_b/\omega_v$ means the frequency ratio between the bridge and vehicle. In engineering applications, accelerations can be easily measured by installing accelerometers on the passing vehicles. With Eq. (4), the analytical solution for the vehicle's accelerations can be obtained and rearranged as Eq. (5),

$$\ddot{z}_v(t) = \frac{\Delta_{st}\omega_v^2}{2\left(1-S^2\right)}\left[A_1\cos\omega_v t + A_2\cos\omega_d t + A_3\cos\left(\omega_b - \frac{\pi v}{L}\right)t + A_4\cos\left(\omega_b + \frac{\pi v}{L}\right)t\right] \tag{5}$$

where A_1, A_2, A_3, and A_4 are coefficients as shown in Eq. (6), which represent the relative contributions of the vehicle frequency ω_v, driving frequency $\omega_d = 2\pi v/L$, and the two shifting frequencies of the bridge, $\omega_s^l = \omega_b - \pi v/L$ and $\omega_s^r = \omega_b + \pi v/L$, respectively.

$$\begin{aligned} &A_1 = 1 - \frac{1}{1-(2\mu S)^2} - \frac{S}{1-\mu^2(1-S)^2} + \frac{S}{1-\mu^2(1+S)^2},\\ &A_2 = \frac{(2\mu S)^2}{1-(2\mu S)^2}, A_3 = \frac{S\mu^2(1-S)^2}{1-\mu^2(1-S)^2}, A_4 = \frac{S\mu^2(1+S)^2}{1-\mu^2(1+S)^2} \end{aligned} \tag{6}$$

From Eq. (5), it is evident that the vibration information about the bridge is embedded in the response of the passing vehicle, forming the fundamental principle of the indirect BHM method. Early research focused on extracting bridge modal parameters, such as natural frequencies, mode shapes, and damping ratios, from vehicle vibrations, as these serve as basic dynamic fingerprints for bridge damage detection. Subsequent studies have explored the direct use of vehicle response measurements for damage detection. These approaches typically involve identifying abnormalities in measured data after damage occurs, and some signal processing techniques may be utilized. Furthermore, with advances in computer science, data-driven methods have demonstrated exceptional sensitivity to minor changes in vehicle response data and are now widely employed in indirect BHM. The following sections will review VBI models and the latest developments in indirect BHM.

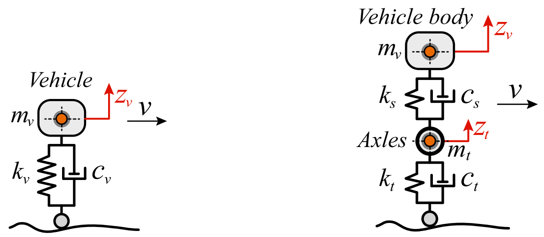
4. VBI models used for indirect bridge health monitoring

If the vehicle's speed is low and the road surface is in excellent condition, the passing vehicle can be approximated as a constant moving force along the bridge. This simplification is based on the assumption that interaction effects are negligible and can be ignored [43–45]. Such an approach is useful when the bridge response is the primary focus and only approximate calculations are needed. However, in practical scenarios, vehicles often travel at higher speeds and the roughness conditions of the road may be poor, leading to significant VBI effects. As the vehicle moves across the bridge, it forms a time-varying coupled system, resulting in non-stationary vibrations [46]. For indirect BHM, various VBI models and road roughness representations have been developed to facilitate the extraction of bridge information from vehicle response measurements. The following sections will discuss these models as explored in existing studies.

4.1. Vehicle models

4.1.1. Quarter-car models

In the early stages of the investigation of the indirect method, the sprung-mass model was the most commonly used. As illustrated in Fig. 6(a), this model includes a single degree of freedom (DOF), representing the vertical translation of the vehicle body (z_v). The suspension system's stiffness and damping are denoted by k_v and c_v, respectively, while the vehicle body mass is represented by m_v. In the pioneering study [14], the sprung-mass model was adopted without damping. The study demonstrated that the bridge's



(a) Sprung-mass model (b) 2-DOF quarter-car model

Fig. 6. Quarter-car models.

fundamental frequency could be identified from vehicle acceleration data, which laid the theoretical foundation for subsequent studies exploring higher-frequency components and the effects of road roughness.

The 2-DOF quarter-car model, as shown in Fig. 6(b), is another commonly used model in existing studies. This model has two DOFs: vehicle body bounce (z_v) and axle bounce (z_t). Unlike the sprung-mass model, it also accounts for the effects of the tire, incorporating its stiffness (k_t), damping (c_t), and axle mass (m_t). In general, the damping coefficient of the tires (c_t) is significantly lower than that of the suspension system and can often be neglected when only approximate calculations are required [47,48]. If tire effects are completely ignored, the 2-DOF quarter-car model simplifies to a two-mass model [49].

Quarter-car models, though simple, play a crucial role in deriving bridge information from vehicle vibrations. In addition, key concepts such as CP response originate from these models. They are particularly effective when the vehicle dimensions are negligible compared to those of the bridge. These models allow for initial theoretical analyses and foundational investigations. For instance, Shi et al. [50] systematically examined the influence of vehicle parameters on indirect bridge frequency identification using the sprung-mass model, providing valuable insights for vehicle selection and design. Lan et al. [51] introduced a physics-guided diagnosis framework that utilizes raw vehicle acceleration data from the 2-DOF quarter-car model. Corbally et al. [52] developed a deep convolutional neural network (CNN) to classify the type, location, and severity of bridge damage, using the quarter-car model to generate labeled training data.

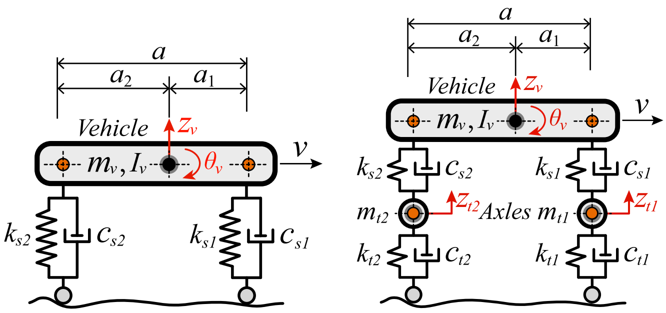
4.1.2. Half-car models

The half-car model is an advanced vehicle model commonly employed in indirect BHM. By incorporating the suspension systems of the front and rear axles, the sprung-mass model is generalized into a 2-DOF half-car model [53,54], as illustrated in Fig. 7(a). A 2-DOF half-car model includes two DOFs: vehicle body bounce (z_v) and vehicle body pitching (θ_v). It accounts for the vehicle body mass (m_v) and body moment of inertia (I_v). The front and rear suspension systems are characterized by their stiffness k_{s1}, k_{s2} and damping c_{s1}, c_{s2}. The vehicle's center of gravity is located by two parameters, a_1 and a_2. The 2-DOF half-car model is intuitive and widely used for various tasks, including identifying the frequency of the bridge, mode shape, damping ratios [55], stiffness loss [56], and model parameters of the railway bridge [57]. Notably, the vehicle's response in this model can be indirectly obtained using two sensors installed on the front and rear ends of the vehicle [58], as shown by the orange points in Fig. 7(a).

A 4-DOF half-car model, as shown in Fig. 7(b), extends the 2-DOF half-car model by incorporating the movement of the front and rear axles, with respective masses m_{t1} and m_{t2}. This model includes four DOFs: vehicle body bounce (z_v), body pitching (θ_v), and the bounce of the front and rear axles (z_{t1} and z_{t2}). Compared to the 2-DOF half-car model, the 4-DOF version further accounts for tire parameters, including stiffness (k_{t1} and k_{t2}) and damping (c_{t1} and c_{t2}). Since the unsprung-mass is typically around 1/10 of the sprung-mass [49], thus needs to be also considered in the procedure of building the vehicle model. Similar to the 2-DOF quarter-car model, tire damping can often be neglected for simplification purposes [59,60]. Furthermore, if tire stiffness is also excluded, the 4-DOF half-car model will degenerate to a three-mass model [61–63]. It should be noted that certain vehicles, such as heavy trucks, feature two or more axles, which can be seen as extensions of the half-car model [64–67]. For generating half-car models and simulating VBI response data using MATLAB, readers may refer to [68,69].

4.1.3. Train-track models

For railway bridges, trains serve as the primary vehicles passing over them. Researchers have recognized that train response measurements can also be utilized for railway track and bridge monitoring. A commonly used model in existing studies is illustrated in Fig. 8. This model consists of 10 DOFs, including four for the wheelsets ($z_{t1} - z_{t4}$), four for the bogies (z_{b1}, θ_{b1}, z_{b2}, and θ_{b2}), and two for the carriage (z_v and θ_v). The bogies are modeled as rigid bodies with masses m_{b1}, m_{b2}, and moments of inertia I_{b1}, I_{b2}. The carriage body is also considered rigid, with mass m_v and moment of inertia I_v. The wheelsets, with masses $m_{w1} \sim m_{w4}$, are connected to the bogies through suspension systems characterized by stiffness ($k_{p1} \sim k_{p4}$) and damping ($c_{p1} \sim c_{p4}$). The center of gravity of the carriage body is defined by L_{v1} and L_{v2}, while the distance between the two wheels connected to a bogie is given by L_{b1} or L_{b2}. A detailed explanation of all parameters can be found in [70]. For simulations of 2D train–track–bridge interaction in MATLAB, readers may refer to [71]. It is noted that a full-order train model can be quite complex [72], and the above-simplified model maintains the essential response information, while reducing the computational resources required in simulation. The model has been employed in diverse studies and promising results were obtained [35,73,74].



(a) 2-DOF half-car model (b) 4-DOF half-car model

Fig. 7. Half-car models.

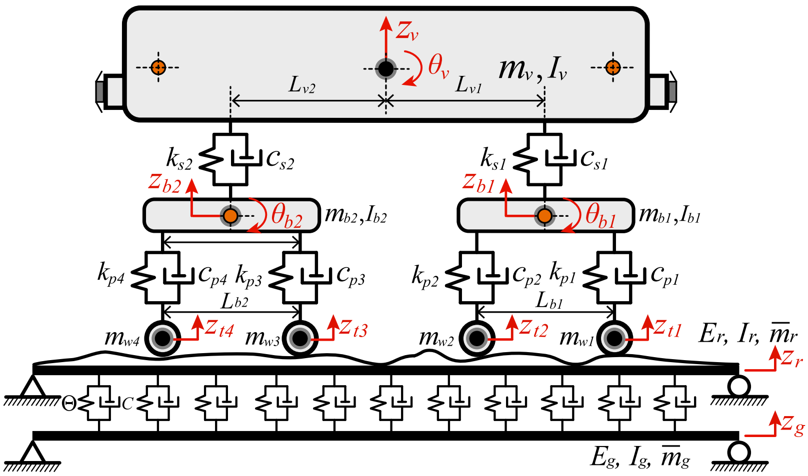


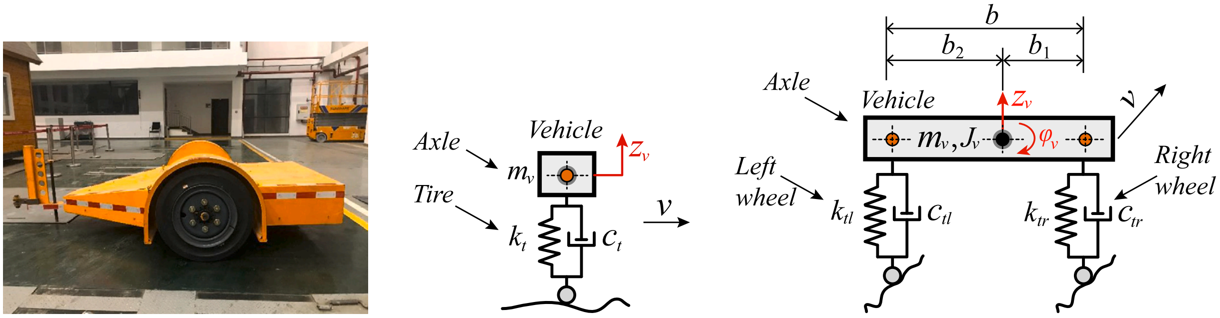
Fig. 8. Train model.

Furthermore, for the health monitoring of railway bridges, tracks play a crucial role in the train–bridge interaction process. To simplify the analysis, the track and bridge can be modeled as a dual-beam system, as illustrated in Fig. 8. In this system, the upper beam represents the rail, while the lower beam denotes the bridge girder. An interlayer with stiffness Θ and damping coefficient C per unit length is placed between the two beams to account for the effects of fasteners, sleepers, and ballast in the track structure [75]. For computational simplicity, both beams are typically assumed to be simply supported at their ends. The parameters m_r, E_r, and I_r represent the rail's mass per unit length, Young's modulus, and moment of inertia, respectively, while m_g, E_g, and I_g represent the corresponding properties of the bridge girder. This aforementioned model serves as a simplified representation of the train–track–bridge interaction system. More advanced track models have also been proposed in existing studies related to indirect BHM, particularly those that consider the individual effects of fasteners, sleepers, and ballast [76,77]. For a comprehensive overview of train-track interaction, readers may refer to [78].

4.1.4. Single-axle vehicle models

To align with the theoretical model developed in [14], Yang et al. conducted a comprehensive investigation of vehicle parameters [79] and designed a hand-drawn cart for measuring bridge modes [80–82]. While this test vehicle model is mathematically elegant, it cannot self-stand physically in practical applications and requires a tractor to pull [13]. Unlike conventional vehicles, the test vehicle does not feature a suspension system but is instead coupled with the bridge through its tires [83]. A real single-axle test vehicle is shown in Fig. 9(a) [84]. The corresponding 1-DOF single-axle model is plotted in Fig. 9(b), where the tire stiffness and damping are represented by k_t and c_t, respectively, while m_v represents the vehicle's body mass. The only DOF in this model is the vertical translation of the vehicle axle. This model is typically employed in tractor–trailer systems for identifying bridge modal parameters [85–88].

However, the previously discussed model does not account for the rocking effects of the test vehicle. When a single-axle vehicle is pulled across a bridge, the two wheels typically encounter different road roughness conditions, causing the vehicle to rock. To better capture the vehicle's response, a 2-DOF single-axle model has been developed, as shown in Fig. 9(c). This model introduces two DOFs: vehicle body translation (z_v) and rocking (φ_v). The vehicle body mass is represented by m_v, and its moment of inertia



(a) Real single-axle test vehicle [114]   (b) 1-DOF single-axle model   (c) 2-DOF single-axle model

Fig. 9. Single-axle test vehicle models.

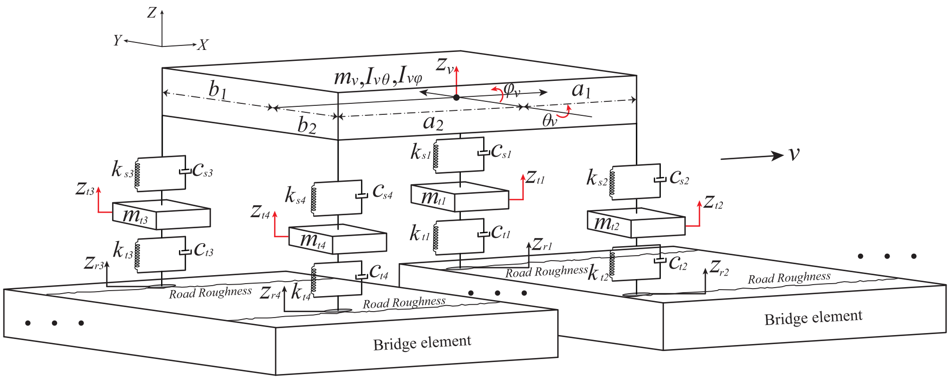


Fig. 10. Full-car model [94].

by J_v. The left tire's stiffness and damping are denoted by k_{tl} and c_{tl}, while the right tire's corresponding parameters are k_{tr} and c_{tr}. The center of gravity of the vehicle body is defined by the parameters b_1 and b_2. Since the two wheels follow different paths on the bridge, the identification of bridge modal properties extends to scanning its torsional-flexural frequencies [89–91]. Furthermore, when analyzing curved bridges, an additional DOF, lateral (radial) movement of the test vehicle, must be included, resulting in a 3-DOF single-axle vehicle model [92].

4.1.5. Full-car models

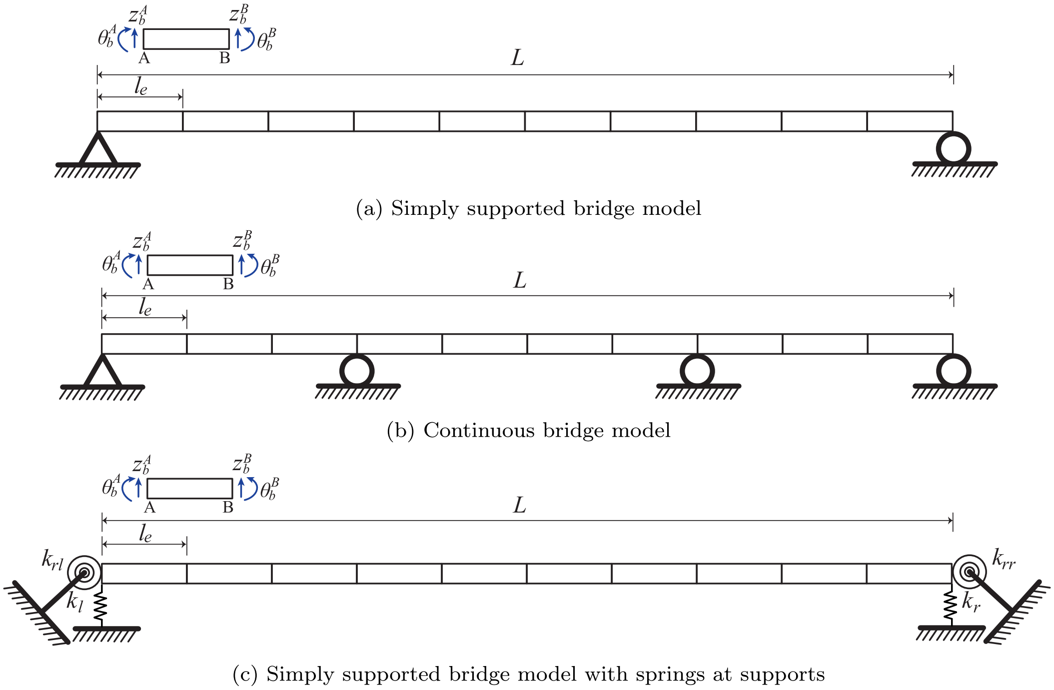
The simplified models discussed above effectively capture the key characteristics of different types of vehicles. However, in practice, real vehicles comprise complex structures and exhibit more complex response when interacting with bridges. Studies have shown that 2D vehicle models tend to generate larger bridge response compared to 3D vehicle models [93], leading to more conservative engineering recommendations. To better simulate real vehicle dynamics, more advanced models, known as full-car models (or 3D vehicle models), are utilized. For instance, a full-car model for a two-axle vehicle includes seven DOFs, as shown in Fig. 10. A detailed explanation of the model parameters can be found in [94].

In 2005, Kim et al. [25,95] introduced 3D vehicle models, including both two-axle and multi-axle configurations, coupled with bridges to simulate the VBI process. Experimental validation using strain sensors confirmed that this coupling approach effectively represents real VBI systems. A high-fidelity simulation of the VBI system was later conducted by Jian et al. [12], incorporating a 3D bridge model. Similar to the 2-DOF quarter-car and 4-DOF half-car models, tire damping can sometimes be neglected for simplified VBI response calculations [96]. Additionally, field tests have verified the accuracy of the proposed model in replicating real vehicle behavior [97]. Overall, 3D vehicle models provide a more advanced and realistic representation of the VBI process, making them highly valuable for engineering applications [98].

4.2. Bridge models

4.2.1. Line models

The simply supported bridge model is the most commonly used one for identifying bridge modal parameters and detecting structural damage. It is straightforward to construct and serves as a reliable benchmark for validating newly developed methods. A simply supported bridge model with a length of L is illustrated in Fig. 11(a). Typically, the bridge is discretized into multiple finite elements, with each node possessing two DOFs: vertical deflection (z_b) and rotation (θ_b), as indicated by the blue arrows in Fig. 11.



(a) Simply supported bridge model

(b) Continuous bridge model

(c) Simply supported bridge model with springs at supports

Fig. 11. Line bridge models.

In addition to the simply supported bridge model, another widely used one is the continuous bridge model. In practical engineering, most bridges consist of multiple continuous spans [99]. A typical three-span continuous bridge model is illustrated in Fig. 11(b). This model follows the same discretization approach as the simply supported bridge model. In recent studies on identifying bridge frequencies and mode shapes, multiple bridge types are often examined to validate the robustness of proposed methods [58,100,101]. Moreover, continuous bridge models are frequently used for railway bridge monitoring. Since trains are the primary vehicles traversing railway bridges, their wheelsets pass over the same track irregularities. This characteristic provides an advantage in mitigating the influence of track irregularities when extracting bridge modal properties [35,57]. Additionally, in railway bridge models, the track and ballast must be properly incorporated into the bridge deck to accurately simulate train–bridge interaction [102].

Accurate finite element (FE) modeling is essential for damage detection methods based on bridge models, such as model updating-based identification. In many studies, bridge boundary conditions are idealized as either perfectly pinned or fixed, as introduced in [103]. However, such ideal conditions rarely persist in real-world settings, particularly after extended service life. Bridge bearings may undergo corrosion or degradation, leading to deviations from their original functional behavior. To better represent these effects, several studies have proposed introducing spring elements at the supports to model vertical or rotational degrees of freedom [104–108], as shown in Fig. 11(c). These enhanced boundary models provide a more realistic representation of in-service bridge behavior and allow the study of support deterioration effects. Moreover, they improve the engineering applicability of indirect BHM methods by more closely aligning model assumptions with actual field conditions. This modeling strategy is particularly useful for simulating damage scenarios at bridge supports, thereby offering deeper insight into the practical implementation of indirect BHM.

Additionally, the above models typically build the bridge to be horizontal and straight. However, there can be bridge types different from these ones. Existing studies have also explored the identification of modal parameters for horizontally curved bridges [92]. In such cases, the bridge is modeled as a curved beam with a specific radius. For instance, for a bridge with length of 30 m, $R = 50$ m represents a bridge with very small radius, and $R = 850$ m means a nearly straight bridge [109]. Field tests have demonstrated the effectiveness of identifying the frequencies of curved bridges, particularly when the vehicle's natural frequencies are higher than those of the bridge [110]. Unlike horizontal straight bridges, curved bridges exhibit radial frequencies in addition to vertical ones. Consequently, both vehicle and bridge models must incorporate out-of-plane $(x - z)$ DOFs to accurately capture these radial frequencies. Studies have further shown that bridge frequencies and mode shapes can robustly be extracted using the passing vehicle response data, especially when CP response is employed. Moreover, inclined bridges have also drawn attention in engineering applications [111–113], suggesting a need for future investigations into how vehicle response can be utilized for information extraction of such structures.

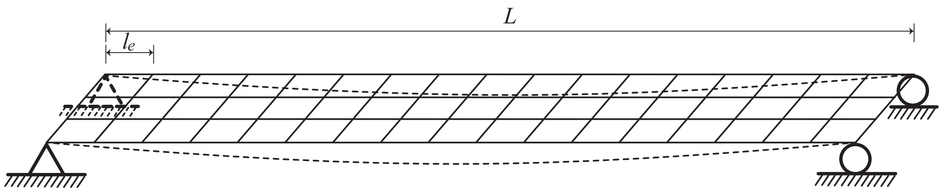
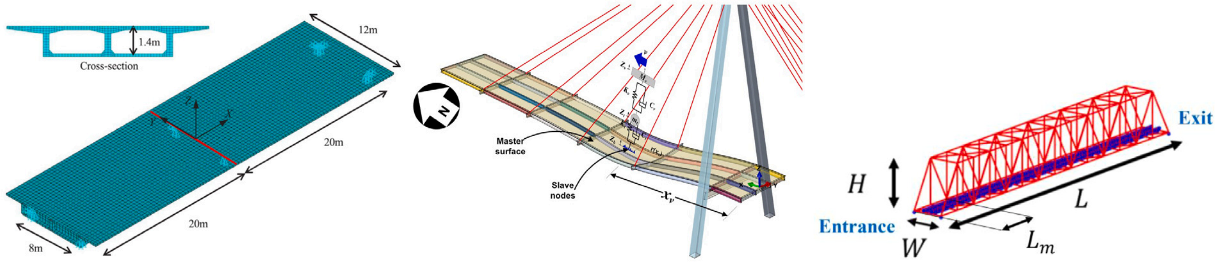


Fig. 12. Planar model for bridges.



(a) Bridge model built in ANSYS [12] (b) Bridge model built in ABAQUS [115] (c) Bridge model built in ADTReS [116]

Fig. 13. 3D bridge models.

4.2.2. Planar models

When line models are used for bridges, only vertical modes (or radial modes in the case of curved bridges) can be considered in the bridge information identification process. However, in practice, the width of some bridges cannot be ignored, especially for wide structures with multiple lanes and pedestrian pathways. In such cases, a passing vehicle may only traverse a single lane, making line models insufficient for accurately simulating the real VBI system, particularly when torsional modes are of interest. A more advanced approach is to use planar models to represent the bridge deck. These models allow for a more comprehensive analysis, including both vertical and torsional vibrations. An example of a simply supported bridge with a length of L, constructed using planar elements, is shown in Fig. 12.

In 2005, Kim et al. [95] utilized planar elements in the VBI model when incorporating a 3D vehicle. More recently, in 2022, Yang and He [114] investigated damage detection in plate-type bridges using translational response generated by a single-axle test vehicle. Compared to line models, bridge models constructed with planar elements offer a more advanced approach, allowing for the inclusion of torsional response. This makes them more suitable for practical engineering applications, as they better represent the complex dynamic behavior of real bridges under vehicle loads.

4.2.3. 3D models

Although planar models can capture a bridge's torsional modes, real bridge decks often feature diverse cross-sectional shapes, such as box girders. To accurately simulate bridges with varying cross-sections, 3D models are required. For example, Kawatani et al. [25] built a 3D VBI model, including a two-span continuous two-girder steel highway bridge (a total span length of 106 m) modeled by shell and beam elements. Jian et al. [12,87] utilized ANSYS to develop FE bridge models and then integrated them with MATLAB to simulate VBI. One such bridge model is shown in Fig. 13(a) [12]. Similarly, Kildashtia et al. [115] built a cable-stayed bridge model using the ABAQUS platform, as depicted in Fig. 13(b). Additionally, Bernardini et al. [116] constructed a Warren truss bridge model using ADTReS, a tool developed at Politecnico di Milano, as shown in Fig. 13(c). In this study, time-shifted accelerations from a 3D multi-body rail train were used for bridge frequency identification. While 3D bridge models offer clear advantages in simulating real bridges with high precision, they typically require significantly greater computational resources compared to line and planar models. In engineering applications, the selection of appropriate vehicle and bridge models need careful consideration based on the specific purpose of the study.

As introduced, in the context of indirect BHM, researchers have increasingly recognized the limitations of idealized boundary assumptions and have begun incorporating more realistic representations, such as elastic or viscoelastic supports modeled with a small set of parameters. These enhanced boundary models may also include constrained degrees of freedom, particularly rotational constraints shown in Fig. 11(c), to simulate common field conditions such as bearing deterioration. Several strategies have emerged to address boundary uncertainty in a systematic manner. One approach is model updating, where ideal boundary conditions (e.g., pinned and fixed) are refined by calibrating support stiffness, soil springs, or joint parameters using measurement data. Another strategy involves using measurements collected under varying environmental and operational scenarios, such as changes in temperature, traffic loading, or time of day, to separate boundary effects from intrinsic structural properties. Additionally, hybrid approaches that combine physics-based FE models with data-driven techniques have shown promise. These methods use simulated data from imperfect models to train algorithms that can better generalize field conditions. Finally, uncertainty modeling using ensembles of FE models can help quantify the influence of variability in boundary conditions and mitigate the risks associated with relying on a single assumed configuration.

Table 1
Road roughness classification.

Road class	Degree of road roughness: $G_d(n_{s,0})$ (10^{-6} m^3)		
	Lower limit	Geometric mean	Upper limit
A	–	16	32
B	32	64	128
C	128	256	512
D	512	1024	2048
E	2048	4096	8192
F	8192	16 384	32 768
G	32 768	65 536	131 072
H	131 072	262 144	–

4.3. Road roughness models

Road roughness plays a crucial role in amplifying the response magnitudes of the VBI system [117]. Therefore, generating appropriate road roughness profiles is essential for validating methodologies developed for indirect BHM.

Regarding road roughness modeling, Chang et al. [118] proposed that the contact between the road and the vehicle should be considered a "disk model" rather than a "point model". The latter is unrealistic, as wheels have finite size and cannot reach the bottom of road surface valleys. This disk model was later adopted by Corbally and Malekjafarian [47] and further modified by Xu et al. [119] to account for the wheel size effect, making it compatible with point-based models. In 2023, Yang and Feng demonstrated that wheel size influences bridge frequency identification using a three-mass vehicle model [120]. Yang et al. [121] further investigated the disk model and introduced a novel convolution method to directly address the disk effect in the spatial domain (i.e., road roughness). Additionally, Yang and Cao [122] analyzed wheel size effects using a two-mass vehicle model, revealing that a wheel radius of $R = 0.3$ m could facilitate bridge frequency identification. Meanwhile, Shi et al. [123] suggested that wheels with a higher elastic modulus enhance the identification of higher maximum identifiable frequencies. In existing indirect BHM studies, three primary methods are used to generate point-wise road roughness for validating proposed methodologies. The generation process can be carried out using MATLAB or Abaqus [124]. The following sections will introduce the established approaches for road roughness generation.

4.3.1. Models in ISO 8608

The International Organization for Standardization has defined eight classes for road roughness, namely classes A-H from the best to poorest one, by ISO 8608 [125]. The generation of road roughness follows the power spectral density (PSD) function that can be represented by Eq. (7),

$$G_d(n_{s,i}) = G_d(n_{s,0}) \left(\frac{n_{s,i}}{n_{s,0}}\right)^{-w} \tag{7}$$

where $n_{s,0}$ is the reference spatial frequency taken as 0.1 cycle/m, $n_{s,i}$ represents the spatial frequency taken as numbers ranging from 0.01 to 10 m^{-1} with an interval of 0.01 m^{-1}, and w is the fit exponent, which is usually set as 2. The roughness coefficient $G_d(n_{s,0})$ is determined by the road roughness class, as shown in Table 1. Once $G_d(n_{s,i})$ is determined, the road roughness can be generated by a normal zero-mean, real-valued stationary Gaussian process, as shown in Eq. (8),

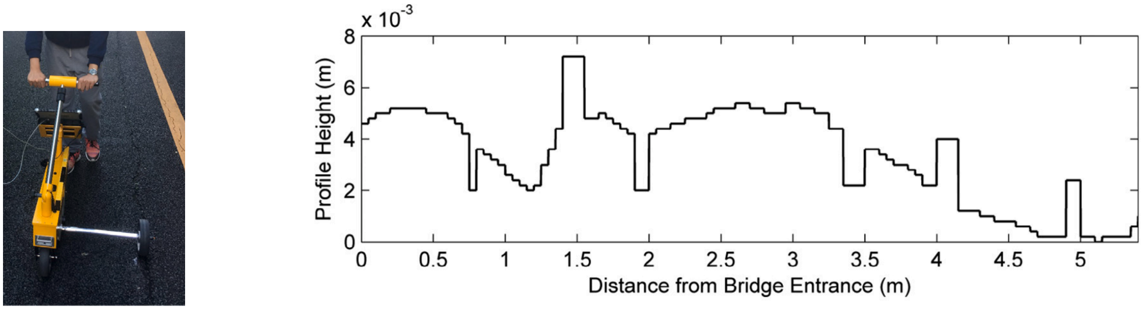
$$z_r(x) = \sum_{i=1}^{N} \sqrt{2G_d\left(n_{s,i}\right)\Delta n_s} \cos\left(2\pi n_{s,i} x + \theta_i\right) \tag{8}$$

where $z_r(x)$ represents the generated road profile, while N denotes the number of generated harmonic waves, corresponding to the length of the spatial frequency vector, $\boldsymbol{n}_s = \{n_{s,i}\}$. Here, $n_{s,i}$ is the ith spatial frequency. The interval of spatial frequency, Δn_s, is set at 0.01 cycle/m. Additionally, θ_i denotes the random phase angle, which is randomly sampled from a uniform distribution in the range $[0, 2\pi]$.

4.3.2. 3D road roughness models

In engineering, the bridge width cannot always be ignored, especially when using planar or 3D bridge models. In this case, a 3D carpet model for roughness on the road can be used [66]. Here, the road roughness generated by ISO 8608 is employed along the width direction of the bridge with a certain distance, and the 3D roughness can be built accordingly. Every time a vehicle crosses the bridge, its wheels can experience different road roughness. However, generated 3D road roughness will only be subjected to a class in ISO 8608 along one direction.

Another method to simulate a 3D road roughness profile is based on the 2D inverse fast Fourier transform (IFFT) [12]. Initially, the approach broadens the PSD of the 1D road roughness profile to a 2D PSD. Subsequently, the 3D road roughness surface is generated by implementing a 2D IFFT on the 2D PSD [126]. In this method, the generated 3D road roughness has good isotropic properties, which means that it will follow the same class in ISO 8608 in all directions.



(a) Portable pavement profiler [127]

(b) Scaled road roughness [56]

Fig. 14. Measuring and scaling road roughness.

4.3.3. Scaled/real road roughness models

In existing studies, researchers have also employed scaled road roughness based on measured road profiles. The measurement of real roughness can be accomplished by the portable pavement profiler, as shown in Fig. 14(a) [127]. An example of scaled road roughness is achieved in laboratory experiments by McGetrick et al. [56] using layered tapes and plastic strips, which was scaled from real road roughness studied by Kim et al. [95] from a 40.4 m road bridge, as shown in Fig. 14(b). Road roughness is classified as Class A according to ISO 8608.

5. Identification of bridge modal parameters using vehicle response

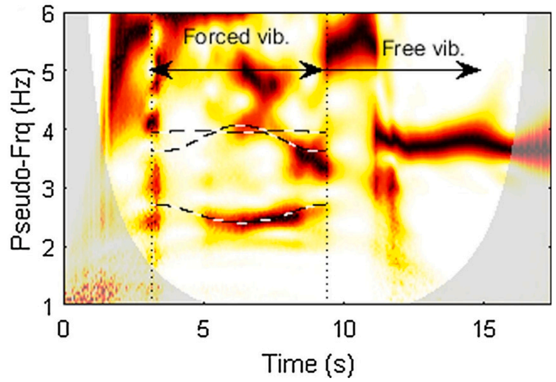
For indirect BHM using response from passing vehicles, identification of bridge modal parameters, including bridge frequencies, mode shapes, and damping ratios, has been a primary focus in early studies, as changes in these parameters can indicate structural damage. Following the groundbreaking study by Yang et al. [14], which demonstrated the feasibility of identifying a bridge's fundamental frequency from vehicle accelerations, researchers quickly recognized the advantages of the indirect method. These benefits include high efficiency, cost-effectiveness, and ease of operation [128]. However, the initial study did not account for the effects of road roughness, which was later confirmed to be a major inverse factor that influences the extraction of dynamic bridge information from vehicle response [117]. Additionally, since accelerations are recorded by sensors mounted on the vehicle, the vehicle's own dynamic characteristics tend to dominate the response, making it challenging to extract bridge-related information. To address this issue, researchers have proposed various approaches to improve the visibility of dynamic bridge features in vehicle response. The following sections will discuss the identification of bridge modal parameters from vehicle response, reviewing key challenges, and promising solutions. Since bridge frequency identification serves as the foundation for the extraction of mode shapes and damping ratios, if the study focused on mode shape identification, it will be included in Section 5.2, while those related to damping ratio identification will be covered in Section 5.3.

5.1. Identification of bridge frequencies

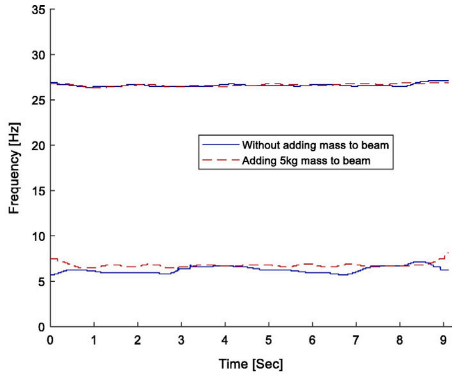
5.1.1. Time-varying nature of the VBI system's frequencies

Indirect BHM is fundamentally based on VBI theory, where dynamic information from the bridge is transferred to the vehicle as it traverses the structure. However, the VBI system is inherently time- and space-variant, meaning that, in theory, its modal parameters also change over time [129]. Given this complexity, most existing studies on indirect bridge frequency identification assume that the vehicle's mass is significantly smaller than that of the bridge. This assumption simplifies the problem and helps maintain relatively stable bridge frequencies during the interaction process. However, for a more accurate understanding of indirect bridge frequency identification, it is crucial to analyze how bridge frequencies evolve throughout the VBI process. Identifying conditions in which bridge frequencies experience significant variations due to interaction effects will help improve the reliability of indirect BHM methods.

Following this research direction, scholars have first explored the theoretical foundations of the time-varying characteristics of the VBI system. In 2013, Cantero and OBrien [130] numerically demonstrated that variations in bridge frequencies were highly dependent on the vehicle-to-structure frequency ratio and the mass ratio. In the same year, Yang et al. [46] derived an analytical solution for time-varying VBI frequencies using the sprung-mass model. Their findings indicated that when resonance occurred between the vehicle and the bridge and the vehicle–bridge mass ratio was high, the frequencies of the VBI system exhibited significant changes. Interestingly, in some cases, bridge frequencies increased rather than decreased, highlighting that the vehicle's effect differed from that of a moving mass [131–133]. To monitor the time-varying frequencies of the VBI system, sensors can be installed on either the vehicle or the bridge. Since installing sensors on bridges is generally more straightforward, this approach is often preferred. In two field tests conducted by Cantero et al. [134] in 2017, researchers observed an increase in bridge frequencies during vehicle crossings, further validating these theoretical predictions. To capture the time-varying frequencies of the VBI system,



(a) CWT of vehicle acceleration [135]



(b) Instantaneous frequencies [138]

Fig. 15. Measuring time-varying characteristics of VBI systems.

Cantero et al. [135] employed WT to analyze both bridge and vehicle vibrations in laboratory experiments. They found that even when two vehicles had the same mass, differences in suspension stiffness resulted in varying frequency shifts. The TFRs generated by continuous wavelet transform (CWT) using one vehicle were shown in Fig. 15(a). This highlighted the complex dynamic nature of the VBI system.

However, traditional time–frequency representations (TFRs) generated by short-time Fourier transform (STFT) and WT often lack sufficient clarity to accurately extract the time-varying features of VBI vibrations. Hence, researchers began exploring more advanced methods to improve resolution and better track changes during the VBI process. In 2020, Li et al. [136] investigated time-varying parameter identification of bridges under moving vehicles. They introduced a ridge extraction method based on empirical WT to estimate the instantaneous frequencies of the VBI system. Their study utilized 24 accelerometers installed on a bridge connecting the south and north campuses of Western Sydney University, demonstrating that the bridge's time-dependent frequency evolution due to vehicle crossings could be effectively tracked. Further advancements were made in 2021 when Zhang et al. [137] proposed a new Gaussian window function for the S-transform to enhance time–frequency resolution. Since both the vehicle and bridge are part of the VBI system, researchers have also explored the feasibility of capturing time-varying frequencies using vehicle vibrations. In 2020, Li et al. [138] applied synchroextracting transform (SET) combined with ridge detection to successfully extract time-varying vehicle and bridge frequencies from vehicle response. Their results were validated through both simulations and laboratory experiments. Combined with ridge extraction, the time-varying frequencies of the VBI system were shown in Fig. 15(b), in which the scenario when 5 kg was added to the bridge was also explored. The effectiveness of SET was later confirmed by Singh and Sadhu [139] in field tests, further demonstrating its applicability in real-world bridge monitoring scenarios. In 2022, Yang et al. [140] introduced the filtered iterative reference-driven S-transform (FIrST) to analyze the relationships between frequency components from both vehicle and bridge response. Their study explored key influencing factors, including vehicle speed, road roughness, and environmental noise. By employing a multisensory system and FIrST, they successfully extracted time-varying bridge frequencies with high accuracy. In 2023, Tan et al. [141] proposed a method for identifying bridge frequencies using the drive-by approach combined with an adaptive STFT-based second-order synchrosqueezing transform (FSST2). Experimental results demonstrated the effectiveness of FSST2 in extracting the bridge's fundamental instantaneous frequencies. In the same year, He et al. [142] investigated variations in higher-order modal parameters of the VBI system using synchrosqueezing transform (SST) and multi-ridge extraction. Their findings, supported by numerical simulations and experiments, highlighted the feasibility of detecting higher-order modes through indirect BHM. In 2024, Li et al. [143] applied an improved multisynchrosqueezing transform (IMSST) to extract time-varying bridge frequencies using a two-axle vehicle and a simply supported bridge. Their study provided a comprehensive discussion on different vehicle-to-bridge frequency and mass ratios, further clarifying their impact on indirect frequency identification. Additionally, in 2024, Yang et al. [144] derived an analytical solution for a vehicle–plate interaction system, emphasizing the importance of considering the transverse spatial path of vehicles. Their results showed that when a vehicle traveled along one side of a plate-like bridge, the bridge's frequencies exhibited the most significant variations, underscoring the spatial effects in VBI. Further advancing this research direction, Chen et al. [145] proposed the iterative variational nonlinear chirp mode decomposition (i-VNCMD) method to extract time-varying instantaneous frequencies from the dynamic response of a passing heavy vehicle. Their study specifically targeted the detection of bridge bearing disengagement, demonstrating the potential of vehicle-based sensing for structural anomaly identification. From these studies, it is evident that when employing indirect BHM for bridge parameter extraction, VBI effects must be carefully considered. This implies that the vehicle's mass should not be excessively large and resonance between the vehicle and bridge should be avoided to ensure reliable frequency identification.

From the above analysis, we can see that the traffic can make the VBI system a time-dependent dynamic system. In a VBI system, the dynamic properties of the bridge can vary continuously as vehicles enter, traverse, and leave the bridge. For the downstream assignments, such as damage detection, instead of relying solely on stationary modal parameters such as natural frequencies, mode shapes, and damping ratios, damage detection can be based on the extraction of time-varying modal features. While many of the

(a) Car and smartphone used in [162] (b) Bus used in [163] (c) IoT vehicle in [165]

Fig. 16. Several field testing examples.

above techniques have been validated in laboratory environments, their accuracy and reliability still require further enhancement for full-scale bridge applications.

5.1.2. Direct extraction from vehicle accelerations using data processing

After the initial research using the sprung-mass model, the concept of indirect BHM was further explored through simulations, laboratory experiments, and field tests. These studies commonly applied the fast Fourier transform (FFT) or other frequency estimation methods directly to vehicle acceleration data [146–159]. In 2020, Sitton et al. [101] extended the analytical solution of the sprung-mass model to a continuous bridge. They observed six distinct frequency components in the frequency spectrum of vehicle accelerations, including the vehicle driving frequency, half of the vehicle driving frequency, bridge frequencies, two shifting frequencies, and the vehicle frequency. A similar phenomenon was also identified when a 2-DOF half-car model was used [160]. Recognizing that bridge frequencies only appear in vehicle response while the vehicle is on the bridge, Erduran et al. [102] employed WT, the widely used time–frequency analysis technique, to distinguish bridge frequencies from vehicle accelerations. If there are simultaneous passing vehicles on the bridge, the common component in the vehicles' vibration should be related to the bridge, instead of road roughness or vehicles. In 2018, based on this concept, Matarazzo et al. [161] introduced the concept of "peak scores", which represent the normalized cumulative prominences of selected peaks in the vehicle's frequency spectrum, as a method to estimate the bridge's first three frequencies. Field tests on the Harvard Bridge demonstrated the effectiveness of this approach. Building on this idea, as shown in Fig. 16(a), in 2022, Matarazzo et al. [162] further refined their approach by utilizing TFRs generated through synchrosqueezed wavelet transform (SWT). Two datasets collected on the Golden Gate Bridge, a controlled dataset (102 runs conducted by researchers) and a ridesourcing dataset (72 runs by Uber drivers), showed that several bridge frequencies could be effectively identified. In 2023, Lan et al. [163] introduced the coherence-Prominent Peak Identification (PPI) method, which utilized the coherence of multiple vehicle runs rather than directly relying on frequency-domain peaks to identify bridge frequencies. Their study, which employed city buses (shown in Fig. 16(b)) as passing vehicles, demonstrated that the bridge's fundamental frequency could be successfully estimated. Similarly, Lu et al. [164] proposed a method using cross-power spectra of vehicle dynamics at multiple moving speeds to mitigate the inverse effects of road roughness. Their approach was validated through numerical simulations and laboratory experiments, confirming its effectiveness in identifying bridge frequencies. In engineering applications, vehicle traffic distribution is typically in-deterministic. For instance, traffic volume tends to be higher during morning and evening rush hours, and on weekdays compared to weekends. In addition, vehicle weights and speeds are not uniformly distributed. Employing an increasing number of measurements and using averaging or ensemble techniques can reduce the influence of unpredictable traffic distribution. For example, a sensing vehicle can cross a bridge multiple times a day during the monitoring period, and the use of city bus response can be a good strategy to investigate. Employing multiple runs of sensing vehicles can be feasible in engineering applications. Furthermore, Peng et al. [165] developed a single-board computer-based Internet of Things (IoT) sensing system, as shown in Fig. 16(c), for continuous and real-time drive-by BHM. This system integrated accelerometers, a temperature sensor, GPS, and a 4G module. Field tests with this setup successfully captured both bridge and vehicle frequencies in the vehicle's frequency spectrum. The concept of drive-by bridge monitoring has also influenced the use of shared micro-mobility systems [166]. In 2024, McSweeney et al. [167] mounted smartphones on an electric scooter to monitor bridge vibrations during crossings. Field tests demonstrated that the fundamental frequency of the bridge could be clearly extracted from the scooter's frequency spectrum. Moreover, in the same year, May et al. [168] identified the fundamental frequency of a bridge using a bicycle equipped with a wireless sensor, where pedal forces were used as the driving input.

The above studies have confirmed the presence of dynamic bridge information in the vibrations of passing vehicles, laying a strong foundation for further research. Since vehicle response contains multiple vibration components, time-domain signal decomposition techniques can be explored to effectively separate signals of different frequencies.

In 2009, Yang and Chang [169] proposed using empirical mode decomposition (EMD) to improve the probability of identifying bridge frequencies. Originally introduced by Huang et al. [170], EMD is designed for non-stationary and nonlinear data, decomposing signals into several intrinsic mode functions (IMFs). Applying FFT to each IMF allows for the identification of higher bridge mode frequencies individually. Later, OBrien et al. [171] applied this technique to detect the pseudo-frequency related to vehicle speed. Building on this approach, Eshkevari et al. [172] combined EMD with the expectation maximization algorithm [173] and found that the ensemble empirical mode decomposition (EEMD) method was an effective tool for bridge modal identification. They demonstrated that EEMD could successfully deconvolute drive-by signals without requiring prior information about the vehicle. Comparing EMD and EEMD, Zhu and Malekjafarian [174] highlighted that EEMD helped mitigate mode mixing issues in vehicle response. EEMD, combined with the Hilbert–Huang transform (HHT), has also been applied for railway bridge frequency identification and track anomaly detection [175,176]. Beyond EMD and its variations, other signal decomposition techniques have been explored for vehicular response analysis. These include blind modal identification (BMI) using singular spectrum analysis (SSA) [177], complete ensemble EMD with adaptive noise [178], and successive variational mode decomposition (SVMD) [179], all of which have demonstrated effectiveness in isolating bridge frequencies from vehicle response. To further automate bridge frequency identification, Abuodeh and Redmond [180] employed a peak-picking technique combined with VMD. Their approach was validated using various types of vehicles and bridges, achieving a 69. 2% success rate in identifying bridge frequencies across four vehicle classes while accounting for road roughness effects.

Pre-processing time-domain signals significantly enhances the likelihood of successfully identifying bridge frequencies using vehicle accelerations. However, prior knowledge of the vehicle's dynamic properties is typically required so that the researcher can identify the bridge's frequencies after the signal decomposition, e.g., selecting IMFs for bridge frequency identification may still require manual operations by researchers. To address this limitation, researchers have increasingly turned to operational modal analysis (OMA) techniques. In 2016, Yang and Chen [181] tailored the stochastic subspace identification (SSI) method for indirect BHM and applied it to bridge frequency identification using a quarter-car vehicle model. Their study found that adding damping to the vehicle system helped suppress the vehicle's own frequencies, improving bridge frequency extraction. In 2021, Jin et al. [182] introduced the short-time SSI method, which estimated bridge frequencies based on traversing vehicle vibrations. To eliminate road roughness effects, their approach relied on two vehicle passes at different speeds. However, this method proved feasible only when temporal variations in the VBI system were negligible, posing limitations for high-speed vehicles. To overcome this drawback, Jin et al. [183] later adopted the multivariate output error state-space (MOESP) algorithm, using a half-car vehicle model. Their results demonstrated that the improved approach was effective in identifying the frequencies of a three-span bridge, even under high vehicle speeds and significant road roughness conditions. More recently, in 2024, Quan et al. [21] further enhanced the short-time SSI algorithm, eliminating the need for prior bridge information or vehicle parameters. Beyond SSI, other OMA techniques, such as peak-picking and frequency domain decomposition (FDD), have also proven effective in extracting bridge frequencies from vehicle response [184]. Among these methods, FDD has been found to be more efficient than simple FFT in revealing bridge frequencies [110,185]. Despite advancements in OMA-based methods, fully suppressing vehicle frequencies remains a challenge, particularly without prior knowledge of vehicle dynamics. Consequently, eliminating the influence of vehicle self-information remains a critical task in indirect bridge modal parameter identification.

At the same time, researchers have observed that the parameters of the VBI system play a crucial role in accurately identifying bridge frequencies [186]. This suggests that selecting an appropriately designed vehicle, rather than relying on a randomly chosen commercial one, is essential for optimizing bridge frequency identification. In [186], the authors found that the initial vehicle-to-bridge acceleration amplitude ratio significantly influenced bridge frequency extraction. They recommended a ratio below three for optimal results. Although tuning this parameter for a specific VBI system is challenging, the study provided a theoretical foundation for further investigations. In 2017, Yang and Lee [187] conducted an in-depth analysis of the effects of vehicle damping on indirect bridge frequency identification using the sprung-mass model. Their results showed that higher vehicle damping helped suppress vehicle frequencies and reduce the influence of road roughness, improving bridge frequency extraction. Later, in 2021, Shi and Uddin [50] systematically examined bridge frequency identification using the sprung-mass model. Their key findings include: (1) high bridge damping can hinder the transmission of bridge vibration information to the vehicle, making frequency extraction more challenging, whereas high vehicle damping has a minimal impact; as an addition, Yang et al. [188] analyzed a monosymmetric 3D bridge model and found that the damping ratio in each direction primarily affects vibration amplitudes along that specific direction; (2) the vehicle's fundamental frequency is a crucial parameter and should ideally be higher than the target bridge frequencies for effective identification; (3) high vehicle speeds amplify acceleration magnitudes and can intensify the "camel hump" phenomenon observed in frequency spectra. These effects were also observed even when the bridge was not simply supported [189]. A similar conclusion was drawn by Luo et al. [99], who emphasized the importance of carefully selecting trailer frequencies to prevent potential resonance between the vehicle and the bridge. Their findings reinforce the necessity of optimizing vehicle parameters to enhance the accuracy and reliability of indirect BHM. It is worth noting that even if the vehicle mass did not attenuate the bridge frequency spectrum, as it was moving mass (contacted by tires) over the bridge, heavy vehicles might cause incorrect frequency identification of the bridge [190].

In long-term indirect BHM, a key challenge is closely related to the uncertainty of vehicle model parameters in different periods. For approaches directly identifying bridge information from vehicle accelerations, the successful extraction of bridge modal parameters can depend on the properties of the vehicle and the bridge much, e.g., the vehicle–bridge mass and frequency ratios, as shown above. Even though the mass of the vehicle may not change very much over time, changes in vehicle model parameters may have an influence on vehicle frequencies. If such a change is relatively small, it will not significantly influence the identification of bridge modal parameters from vehicle response. However, if the vehicle parameters vary quite much in different periods, which can induce failure of some proposed methods, for example, the use of EMD and OMA methods. Therefore, it is highly recommended to check the vehicle's parameters before new testing if vehicle accelerations are directly utilized.

Furthermore, for methods based on coherence of multiple vehicular runs, vehicle parameter variability can be beneficial. That is because in vehicle response, there are three components, including the vehicle's self-information, road roughness, and bridge

(a) PU type of wheels [79] (b) Bridge with speed bumps [195]

Fig. 17. Examples of investigating vehicle parameters.

vibrations. While the vehicle and road roughness may vary from one run to another, the underlying structural response of the bridge remains consistent among different runs. Studies such as Refs. [163,164,191] have demonstrated that coherence-based approaches can effectively isolate the bridge-related component despite variability in vehicle conditions.

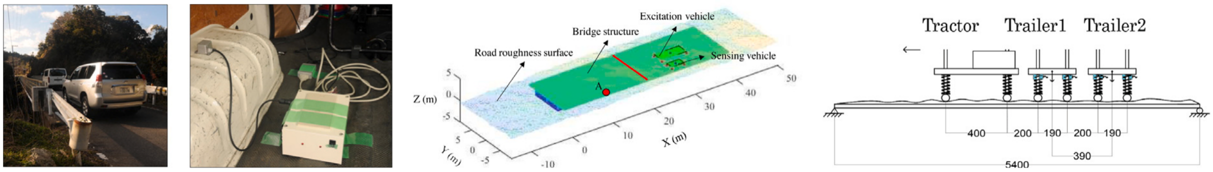
5.1.3. Investigating and modifying vehicle/bridge parameters

In 2022, Jayakumar and Vasamsetti [192] explored vehicle parameters using a quarter-car model and recommended higher vehicle damping, the use of CP response, and the presence of ongoing traffic to improve bridge frequency identification from vehicle accelerations. A key challenge for long-term indirect BHM involves the time variation of vehicle parameters. Tire properties, in particular, change due to factors like temperature and wear, and these variations play an important role in the reliability of bridge frequency identification. Empirical studies, such as the field test conducted by Yang et al. [79] using a hand-drawn cart, confirmed the advantage of specific materials, finding that polyurethane (PU) wheels (shown in Fig. 17(a)) were more effective for bridge frequency extraction than either inflatable or rubber wheels. Additionally, they observed that heavier test carts exhibited smaller self-response, improving the visibility of bridge frequencies in the vehicle's frequency spectrum. The selection of vehicle speed is another critical factor. Higher speeds induce stronger VBI response but reduce the passing time, leading to poor frequency resolution. While wavelet analysis can partially mitigate the low-resolution limitations of FFT [193], lower speeds are often necessary to collect sufficient data and suppress excessive vehicle vibrations [153,194]. In 2024, field tests conducted by Gkoktsi et al. [195] (see Fig. 17(b)) revealed that the effectiveness of drive-by bridge frequency identification is highly dependent on the relative dynamic properties of the VBI system. They identified four key parameters affecting the accuracy of frequency extraction: (1) the filtering properties of the vehicle, particularly the influence of tires and the suspension system; (2) the effective signal length in the presence of road discontinuities; (3) the trade-offs associated with vehicle speed; (4) the level of vehicle-induced bridge vibration and its transmission back to the vehicle. The analysis of VBI system parameters provides essential insights for designing optimized test vehicles for bridge modal identification and offers valuable perspectives for future research on indirect BHM.

5.1.4. Weakening effects of road roughness and/or vehicle information in vehicle accelerations

To minimize the influence of vehicle dynamics in indirect BHM, a logical approach is to filter out vehicle frequencies, thereby enhancing the visibility of bridge frequencies [196]. Several filtering-based techniques have been explored to achieve this objective. SSA combined with a band-pass filter (BPF) has been demonstrated to be effective, particularly when the vehicle's frequency is either significantly lower or higher than the bridge frequencies of interest. Additionally, the combination of variational mode decomposition (VMD) and BPF has been identified as a preferable method for extracting the bridge's fundamental frequencies [197]. Compared to EMD, VMD exhibits greater efficiency and sophistication in identifying the bridge's initial frequencies from vehicle response. It requires fewer decompositions while effectively mitigating mode-mixing issues. In 2022, Yang and Wang [198] proposed the use of a tuned elliptic filter combined with the advanced moving internal node element method [199]. Their study incorporated factors such as bridge damping and road roughness, demonstrating the effectiveness of this approach in accurately identifying bridge frequencies. However, filter-based methods generally require prior knowledge of the target frequency band to effectively isolate vehicle frequencies. This can pose challenges in practical applications when vehicle parameters are unknown. Given the difficulty in accurately measuring vehicle properties, Shirzad-Ghaleroudkhani and Gül [200] proposed an inverse filtering approach. Their method involved recording the vehicle's vibration spectrum when it was off the bridge, designing a filter based on this spectrum, and then applying it to suppress vehicle frequencies when the same vehicle traversed the target bridge. To address the limitations associated with constant speed and similar roughness conditions on the road surface in field tests, the authors further refined their inverse filtering technique [201]. These advancements highlight the potential of filter-based strategies for improving indirect bridge frequency identification, though challenges related to practical implementation remain.

As readers may observe, when multiple vehicles cross an identical bridge, the accelerations recorded by each vehicle contain both vehicle-specific and bridge-induced vibrations. The common components in these signals are associated with the bridge rather than individual vehicle dynamics. This fundamental principle has inspired several studies aimed at improving bridge frequency identification through multi-vehicle sensing. In 2017, Nagayama et al. [191] applied the cross-spectral density function to extract



(a) Measurement and instrumentation in [191] (b) Diagram of the VBI case in [12] (c) Tractor and trailer models in [211]

Fig. 18. Examples to weaken road roughness effects using vehicle accelerations.

bridge frequencies from the shared vibration components of two commercial vehicles crossing the Tsukige Bridge. The measurement and instrumentation of the vehicle system could be found in Fig. 18(a). Their numerical simulations and field tests confirmed the effectiveness of this approach in identifying the bridge's fundamental frequency. Building on this concept, in 2020, Shirzad-Ghaleroudkhani et al. [202] proposed a method to identify bridge frequencies using multiple vehicle runs with varying properties. The key idea was that when different vehicles passed the same bridge, the common spectral features in their response would correspond to the bridge's frequencies rather than the vehicle dynamics. Experimental validation demonstrated that this method could distinguish minor differences between two bridges with similar fundamental frequencies, highlighting its potential for damage detection using smartphone-based vehicle sensing. A similar approach was adopted by Sitton et al. [160], who used the multiple signal classification algorithm (MUSIC) to identify the fundamental frequency of the bridge by leveraging shared spectral components across different vehicle runs. Expanding on these ideas, Lan et al. [203] installed sensors at different positions within the same vehicle to capture common bridge-induced vibrations. Their method utilized a distinct peak in the cross-spectrum between different sensor locations to extract the bridge's frequencies.

Apart from vehicle frequencies, road roughness is another critical factor influencing the accuracy of bridge frequency identification using vehicles [204,205]. While poor road conditions can amplify VBI response, they also obscure bridge frequencies in vehicle response. The generation and classification of road roughness have been introduced in Section 4.3. To mitigate the inverse effects of road roughness, early studies suggested that its influence could be partially reduced by either amplifying bridge vibrations using ongoing traffic or increasing the vehicle's traversing speed [206]. Using ongoing traffic means that the other simultaneous passing vehicles have also been considered in the indirect BHM. However, ongoing traffic is not always available, and high vehicle speeds significantly reduce frequency resolution in vehicle response [207,208]. A more effective approach is to employ two or more connected vehicles [117], which considers the other ongoing vehicle apart from the sensing vehicle. When two vehicles move in a straight line, they experience the same road roughness traces. A classical strategy involves subtracting the spectrum of the rear vehicle from that of the front vehicle, thereby significantly reducing the contribution of road roughness [209]. In 2022, Jian et al. [12] proposed bridge frequency identification using a 3D vehicle model shown in Fig. 18(b). Their method first transformed the equations of motion of the wheels into the frequency domain, then subtracted the frequency response of the front and rear axles with a time delay to eliminate the effects of road roughness. A similar approach was implemented in the time domain instead of the frequency domain [210], where residual response of two connected sprung-mass trailers, was used to extract bridge frequencies more effectively by minimizing road roughness effects. This method was later validated through laboratory experiments by Kim et al. [211] at Kyoto University, as illustrated in Fig. 18(c), as well as numerical simulations using real bridge properties [86]. Furthermore, the effectiveness of two connected two-axle vehicles (modeled as 2-DOF half-car models) or residual response from adjacent railway vehicles in reducing track irregularity effects was confirmed [57,212]. While these strategies have been widely adopted for bridge modal parameter identification and possible damage detection, they present practical challenges. One limitation is the strict requirement for synchronizing response from two vehicles in the time domain [213,214]. Additionally, deploying multiple identical connected vehicles in real engineering applications can be operationally complex [215]. Given these challenges, developing new and more practical approaches to mitigate road roughness effects remains a crucial research direction in indirect BHM.

5.1.5. Eliminating effects of road roughness and/or vehicle information using CP response

From the above analysis, two major challenges must be addressed for identifying bridge frequencies from vehicle response: (1) the interference of the vehicle's self-dynamic information. (2) the adverse effects of road roughness. To tackle the first challenge, Yang et al. [24] proposed the concept of the CP response in 2017, utilizing a sprung-mass model. The CP response represents the interaction between the vehicle and bridge. When a vehicle passes a bridge, the CP response predominantly reflects two sources: the bridge vibrations and the roughness of the road. Importantly, it is independent of the vehicle's own frequencies, effectively eliminating vehicle-related interference. Numerical studies have shown that CP response outperforms the accelerations of raw vehicles in identifying bridge frequencies, especially higher modes [109,216,217]. The enhanced sensitivity of CP response to bridge dynamics makes them a valuable tool for indirect BHM. Several approaches for calculating CP response have been developed, which are introduced here. The CP response can be back-calculated from the vehicle's accelerations. Still, the calculation equations may vary for different vehicle models and the number of sensors, e.g., CP response calculation for the sprung-mass model with one sensor [24], the 2-DOF quarter-car model with two sensors [47,218], the 2-DOF half-car model with two sensors [58], a 4-DOF scooter model with three sensors [219], and the 4-DOF half-car model with two sensors [100,220,221]. Other methods were also developed by researchers. For example, in 2020, Nayek and Narasimhan [222] tried to extract the CP response of a quarter-car model

(a) VBI model in [107]   (b) Excitation location, tire pressure sensor, and laser displacement sensor in [225]

Fig. 19. CP response and force estimation from accelerations.

using only one sensor installed on the vehicle body. The deduction depended on the knowledge of the multi-DOF vehicle dynamics using a Gaussian process latent force model-based joint input-state estimation approach. In 2022, Li et al. [223] proposed to utilize dual Kalman filters (KFs) to obtain the input forces of two successive vehicles accurately using vehicle response and to identify the CP response. Then, the residual CP response was employed by automatic SSA to identify the bridge's frequencies. Addressing the coupling of unknown vehicle parameters and road roughness, Liu et al. [224] proposed a combined identification method using an extended KF. By leveraging the time lag between front and rear axles, the method accurately identified vehicle properties and road roughness profiles, as verified by numerical studies. In 2023, Feng et al. [107] derived the transfer functions of a VBI system (shown in Fig. 19(a)) to obtain the CP response instead of traditional complex differential equations. Also, the number of vehicle parameters is another factor influencing the calculation process, among which the most essential one is the consideration of tire damping because it transfers the equation into a problem of solving first-order linear differential equations.

In addition to the CP response, an alternative approach is to calculate the contact force, which is also effective for identifying bridge information, since it is independent of the vehicle's dynamic modes. In 2019, Wang et al. [96] proposed estimating the tire force using only the vehicle's body response. A KF with augmented tire forces in the system state vector was employed, and field tests confirmed the effectiveness of this estimation method. In 2018, Wang et al. [60] proposed using a particle filter approach to estimate the excitation at the front and rear tires of a commercial vehicle for bridge frequency identification. The influence of road roughness was reduced by subtracting the estimated excitation at the rear tire from that at the front tire. The results indicated that the bridge's natural frequency was estimated with an error of 3.2%. In 2023, Liu et al. [225] developed and calibrated a tire pressure model to calculate the relative displacement between the axle and the contact point. This relative displacement was then used to determine the CP displacement of the rear tire. By conducting two vehicle runs, the effects of road roughness were mitigated. Field tests in Fig. 19(b) had demonstrated that the bridge's fundamental frequency could be clearly identified.

The CP response can outperform the original vehicle accelerations in indirectly identifying bridge frequencies. In 2021, Xu et al. [226] derived a method to back-calculate CP response using a damped sprung-mass model. Their findings indicated that the damping of a single-axle test vehicle had minimal influence on the CP response. In 2022, Yang et al. [227] automated the indirect bridge frequency identification process by employing K-means, a well-known unsupervised learning algorithm, to cluster peak frequencies of the CP's principal components based on SSA. Furthermore, based on a dual-beam model simulating the track–bridge system subjected to a moving test vehicle, the concept of CP response was extended to identify dual frequencies corresponding to the track and bridge components [228]. The CP response can be further explored using time-domain or frequency-domain signal processing techniques. For instance, extreme-point symmetric mode decomposition (ESMD) can be applied to extract IMFs, which are useful for identifying bridge frequencies from the CP response of a vehicle [229]. Additionally, the efficacy of the VMD-BPF technique is significantly enhanced when CP response, rather than original accelerations, are utilized [197]. Using a full-scale study, Singh and Sadhu [230] demonstrated that employing robust EMD to decompose vehicle CP response allowed for the identification of the bridge's first three frequencies from IMFs. Moreover, multiple vehicle runs were shown to significantly improve the accuracy of bridge frequency identification.

Nonetheless, since the CP response encapsulates both road roughness and bridge vibrations, the influence of road roughness can overshadow the bridge's response [231]. This occurs because, in general, the magnitude of bridge vibrations is significantly smaller than that of road roughness. To mitigate the effects of road roughness in the CP response, several approaches can be employed:

Firstly, since the road roughness will only present its influence when the vehicle runs on the bridge, the transmissibility of the vibration of the bridge will not be affected by it when the vehicle is parked on the bridge when other vehicles are simultaneously passing the bridge; instead, only the vehicle's information remains [232]. As a compromise between moving and stationary conditions, Yang et al. [81] introduced a non-moving period for the indirect method using a single-axle test vehicle. They observed that when the vehicle was resting on the bridge, torsional modes of the bridge could also be identified from the vehicle's CP response. This concept was later extended to account for the rocking effects of the single-axle test vehicle [233]. Further developments explored bridge frequency identification using a fully stationary vehicle (without a moving period) [234,235]. By employing this approach, the frequencies identified from the parked vehicle's CP response closely matched those obtained directly from the bridge [236]. Zhang et al. [237] conducted a comprehensive analysis comparing moving and stationary vehicles, illustrated in Fig. 20, for indirect bridge frequency identification. Their findings indicated that the "camel hump" phenomenon disappeared

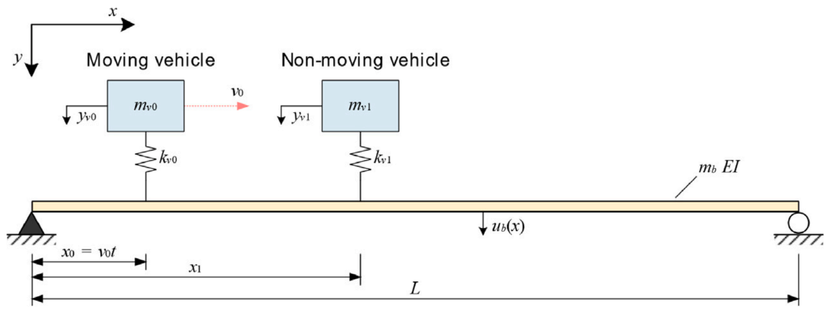
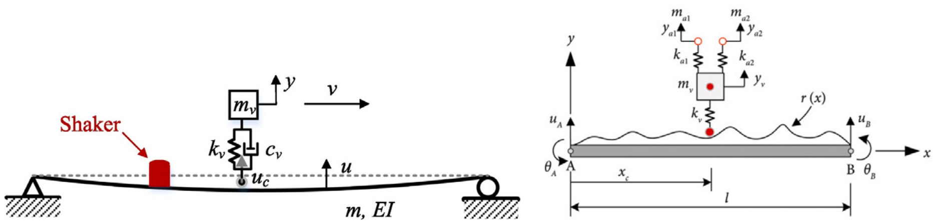


Fig. 20. Weakening road roughness effects using moving and non-moving vehicles [237].

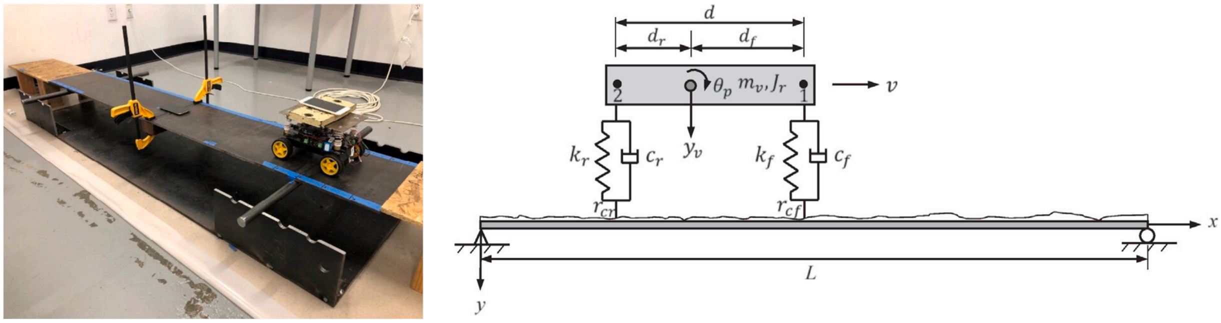


(a) Shaker on the bridge [247] (b) Amplifiers on vehicles [248]

Fig. 21. Weakening road roughness effects using shakers or amplifiers.

in the stationary vehicle's frequency spectrum, and higher-order bridge modes could be more effectively extracted compared to the moving vehicle case. Additionally, if the test vehicle's frequency is designed to be significantly different from the bridge's target frequencies, the stationary condition can help suppress the effects of road roughness, allowing the vehicle to function as a "frequency-free" system for bridge modal identification [80]. Based on this concept, vehicles with adjustable frequencies could potentially serve as monitoring tools for bridge frequency identification [238,239]. Furthermore, it was found that higher vehicle frequencies enhance the transmissibility of bridge vibrations to the vehicle, making bridge frequencies more prominent in the vehicle's frequency spectrum [240]. While temporary parking or a purely stationary vehicle can effectively reduce road roughness effects and enhance bridge frequency identification, this approach requires a longer data collection period. Consequently, the monitoring efficiency may be lower compared to using continuously moving vehicles.

In addition, a key challenge in identifying bridge frequencies is the relatively small amplitude of its vibrations. An effective approach to improving bridge modal identification is to amplify these vibrations, making them more distinguishable from road roughness. Then, when the CP response is utilized under such conditions, the bridge's modal parameters can be extracted more effectively. One advantage of the indirect method is that it does not require traffic pauses. Consequently, ongoing traffic loads can be regarded as an external energy input that enhances bridge vibrations [91,217]. This technique has been successfully applied, where a single-axle vehicle was used to scan the vertical and radial frequencies of curved bridges [109]. Similarly, in the case of footbridges, walking and running pedestrians contribute additional energy to the bridge, facilitating the extraction of its frequencies [219,241]. However, ongoing traffic may not always be available, necessitating alternative excitation methods. One such approach is the use of active excitation on bridges. This can be implemented in two ways. On the one hand, active excitation can be applied to the vehicle, which then transfers energy to the bridge. For instance, Zhang et al. [242] utilized the tap-scan method [243], in which a harmonic exciter mounted on the vehicle amplified bridge vibrations, allowing its frequencies to be clearly identified from vehicle accelerations. Such a technology was later utilized by Zhang et al. using advanced bridge models [244]. In 2021, Yang et al. [245] proposed installing an amplifier on the vehicle, recommending that its frequency be slightly higher than the target bridge frequency. Their results showed that the first two bridge frequencies could still be identified despite road roughness and damping effects. In 2022, Yang et al. [246] investigated the use of an amplifier within a three-mass vehicle model. The additional DOF provided by the amplifier enhanced the vehicle's response, which in turn amplified the bridge's response, improving the likelihood of identifying bridge frequencies using the indirect method. On the other hand, active excitation can be applied directly to the bridge. Typical approaches involve using a shaker (see Fig. 21(a)) on the bridge, as demonstrated in studies [247]. In 2023, Xu et al. [248] explored a dual-amplifier system shown in Fig. 21(b), revealing that a bridge-mounted amplifier was more effective than a vehicle-mounted one in extracting bridge frequencies. In 2024, Yang and Wang [249] derived analytical solutions for an amplifier-enhanced VBI system and semi-analytical solutions for a system incorporating two amplifiers, using a three-mass vehicle model. To further enhance the force exerted by the vehicle on the bridge, alternative solutions such as cogwheels [250,251] or modified wheels [252,253] have been proposed. These methods can increase the amplitude of bridge vibrations, thereby reducing the influence of road roughness and improving the accuracy of bridge frequency identification.



(a) Using crowdsensing vehicles [257] (b) Using residual CP response of axles [215]

Fig. 22. Weakening road roughness effects using vehicle CP response.

Thirdly, as the CP response contains information on both road roughness and bridge vibrations, researchers have explored methods to eliminate the influence of road roughness using the residual CP response from two different vehicle runs. Zhan et al. [254] proposed a double-pass double-vehicle technique to mitigate road roughness effects. In this method, two vehicles with different parameters (e.g., mass) traverse the same bridge under identical road roughness conditions. After extracting their CP response from acceleration data, the residual CP response between the two vehicles was used to identify the bridge's frequencies. Simulation results demonstrated that this approach effectively identified bridge frequencies across different road roughness classes. A similar concept was applied by Zhan et al. [255] for damage detection in laboratory experiments and later validated in a field test by Liu et al. [225] under varying road conditions. In 2023, González et al. [256] introduced a method to separate vehicle, road, and bridge contributions from drive-by accelerations using the same vehicle at different speeds. By normalizing the amplitude of the CP response in the spatial frequency domain (using v^4) within a 2-DOF quarter-car model, the authors demonstrated that the influence of road roughness could be eliminated by subtracting the PSDs of the estimated CP response at two different speeds (real and imaginary parts were subtracted separately). In 2024, Sitton et al. [257] utilized CP response from crowdsensing vehicles for bridge frequency identification. By analyzing different vehicles with various parameters passing over the bridge and averaging the frequency spectrum, they demonstrated that bridge vibrations, being the common component in CP response, could be effectively extracted. The results of laboratory experiments (as shown in Fig. 22(a)) confirmed the successful identification of the bridge's fundamental frequency. Also, Zhou et al. [258] proposed a frequency-domain approach using the residual frequency spectrum of different vehicles' CP response. They derived that when tire stiffness approaches infinity, axle response closely approximate vehicle CP response. Experimental validation showed that this method effectively identified the bridge's first three frequencies.

Last but not least, as a similar approach to using vehicle accelerations, one state-of-the-art technique to eliminate the inverse influence of road roughness is to utilize the residual CP response of several connected vehicles or multiple axles of one vehicle. The concept was first explored using two single-axle test vehicles to identify the frequencies of a simply supported bridge [108,259,260]. Given the promising performance of CP response, the method was theoretically extended to scan the torsional modes of a thin-walled box girder bridge by employing the residual CP response of two connected identical single-axle test vehicles [89] and two two-wheel test vehicles [90]. In practical applications, commercial vehicles such as cars and trucks generally have two or more axles. To address the challenges associated with using multiple connected vehicles in engineering settings, employing the residual CP response of a single vehicle's multiple axles offers a more efficient and operationally feasible alternative. In 2022, Yang et al. [58] attempted to identify bridge frequencies using the residual CP response of a single 2-DOF half-car vehicle model's two axles. Their findings demonstrated that bridge modal information could be effectively extracted despite poor road conditions, environmental noise, and varying bridge types. In the same year, He and Yang [215] investigated the residual CP response of a two-axle vehicle, shown in Fig. 22(b), in the frequency domain, successfully extracting the bridge's fundamental frequencies under different conditions. Similarly, in the time domain, residual CP response from the two axles of a 4-DOF half-car model was shown to effectively mitigate the inverse effects of road roughness [216,220,221]. In 2023, Li et al. [94] extended this approach by employing a 3D vehicle model for bridge frequency identification. They derived equations for calculating the residual CP response and analyzed practical factors such as sensor placement on the vehicle body and axle distance measurements. This technique was further adapted for identifying footbridge frequencies using the residual CP response of a shared scooter model's axles [219]. Additionally, the method was investigated in the frequency domain through residual frequency spectrum analysis of vehicle axle response. Laboratory experiments carried out by Liu et al. [261] demonstrated that when using a smartphone, the residual CP response between the axles significantly reduced the negative influence of road roughness. In 2024, Yang et al. [262] proposed an enhanced integration algorithm to calculate the contact response of the wheelset in a multi-DOF train model for the identification of the frequency of the railway bridge. Numerical simulations showed that using residual contact response from two consecutive wheelsets was effective, even in the presence of track irregularities, enabling the identification of the first five bridge frequencies. The consideration of residual CP response in vehicle-based bridge monitoring has significantly improved the extraction of bridge information. By largely removing vehicle and road roughness effects, this technique enhances the reliability of downstream applications, such as damage detection using data-driven methods [28].

The indirect identification of bridge frequencies from the response of passing vehicles serves as a foundation for extracting other bridge modal parameters. For example, in the identification of mode shapes and damping ratios, the first step is to isolate bridge frequency-related components from the vehicle response. The approaches, techniques, and challenges discussed above have provided valuable insights into mitigating influencing factors in indirect BHM, such as vehicle dynamics, road roughness, and environmental noise. Table 2 has listed a comprehensive overview of research on bridge frequency identification using vehicle response. The studies are categorized based on their validation methods, including simulations, laboratory experiments, and field tests. For each work, details on vehicle and bridge models, the types of response analyzed, techniques for mitigating the effects of road roughness, and key methodologies are systematically documented. Additionally, studies focusing on damage detection, listed in Table 2, will be further discussed in Section 6.2.

The preceding sections have introduced key techniques utilizing the CP response for bridge frequency identification. Most of these approaches require known vehicle parameters to back-calculate the CP response. Consequently, in the context of long-term indirect BHM, methods relying on CP response back-calculation may be sensitive to uncertainties in vehicle model parameters. Nevertheless, existing studies have demonstrated that even when vehicle parameters are estimated and lack precision, the back-calculated CP response can still outperform raw acceleration signals for frequency identification [218]. This suggests that such methods utilize a degree of robustness against small parameter deviations, including variations in tire properties. However, the influence of vehicle model parameter uncertainties in engineering applications has not been investigated when contact-point response is utilized, and such methods deserve further attention.

5.2. Identification of bridge mode shapes

In the traditional direct method, obtaining the bridge's mode shape typically requires multiple accelerometers installed at various locations on the bridge. A key advantage of the indirect method is that a passing vehicle traverses every point of the bridge, offering the potential to identify high-resolution mode shapes. Moreover, mode shapes contain spatial information about the bridge, which can be leveraged for damage localization. However, similar to bridge frequency identification, the extraction of mode shapes is affected by various influencing factors. The following section will discuss the techniques employed to estimate bridge mode shapes using vehicles.

5.2.1. Using FFT/STFT

The investigation of mode shape construction using passing vehicles dates back to 2012. Zhang et al. [242] successfully applied the tap-scan method and STFT to identify the mode shape square (MOSS) of a plate. The strategy had been illustrated in Fig. 23(a). Their study, conducted at low vehicle speeds, recommended tuning the tapping frequency close to the target structure's frequency for optimal results. In 2013, Zhang et al. [263] introduced a method to obtain the operating deflection shape (ODS) of a bridge using a pre-filtering process based on wavelet decomposition. The tap-scan technique was employed to amplify bridge vibrations, while STFT was used to transform vehicle signals into the time–frequency domain for ODS extraction. A similar strategy was later adopted by Qi and Au [264], who applied impact excitation to the moving vehicle. Their approach was found to improve the accuracy of mode shape identification by mitigating environmental noise and road surface roughness. In 2014, Oshima et al. [265] successfully estimated bridge mode shapes using the response of a sprung-mass vehicle model and singular value decomposition (SVD). However, further improvements were needed to enhance the robustness of the reconstructed mode shapes against noise. Lakshmi et al. [266] proposed a modal identification technique using SVD and the Teager-Kaiser Energy Operator on output-only response from a traversing vehicle. Numerical and experimental studies showed the algorithm effectively extracted bridge frequencies and mode shapes even under conditions of high vehicle speed and road surface roughness. In 2016, Kong et al. [85] demonstrated that the residual time-domain response of trailers could be effectively used to extract MOSS, finding this approach to be more reliable than using residual response in the frequency domain. Later, the proposed method was demonstrated effective with properties of real bridges and practical five-axle trucks [86]. In 2017, Marulanda [267] proposed a method using a mobile and a stationary sensor to identify spatially dense bridge mode shapes. By leveraging ambient excitation, STFT was applied to extract time–frequency components from the mobile sensor's signals. Experimental results showed that the first three mode shapes of an I-shaped beam were successfully reconstructed for 21 modal coordinates. In 2018, Nayek et al. [268] introduced a mass-normalized mode shape identification method using a single actuator–sensor pair. In this approach, a sensor-equipped vehicle was moved and excited along the bridge, while another sensor, fixed on the bridge, collected acceleration data. Numerical simulations and laboratory experiments confirmed that the identified mode shapes closely matched those obtained using multiple sensors installed on the bridge. Later, Zhang et al. [269] proposed a technique for identifying bridge mode shapes using a moving sensor-installed mass. In their method, the mass traversed a beam with artificially installed humps, while its vertical accelerations were recorded. By applying FFT to the acceleration data of the passing vehicle, the bridge's mode shapes were successfully reconstructed. Numerical simulations and laboratory-scale experiments demonstrated that this method performed well, even at high vehicle speeds [270]. In 2021, Yang et al. [271] employed a passing tractor with two identical trailers for bridge mode shape reconstruction. The residual response between the two trailers was first utilized to eliminate the adverse effects of road roughness. Subsequently, BPF was applied to extract bridge-related vibrations, and STFT was used to reconstruct bridge mode shapes. Field test results showed that the indirectly identified mode shapes closely matched those obtained using the SSI method.

Table 2
Bridge frequency identification from vehicle response.

Validation	Refs.	Vehicle	Bridge	Res.	Roughness and its elimination	Techniques
Simulations	[12]	Full-car	3D	Acc.	Residual response of one vehicle	FFT
	[14]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	FFT
	[21]	4-DOF half-car	3D	Acc.	Residual response of one vehicle	ST-SSI, MOESP
	[24]	Sprung-mass	Line	CP	Ongoing traffic	FFT
	[216]	4-DOF half-car	Line	CP	Residual response of one vehicle	FFT
	[49]	Two-mass	Line	Acc.	Smooth/normal road roughness	FFT
	[50]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	FFT
	[53]	2-DOF half-car	Line	Acc.	Smooth/normal road roughness	FFT
	[58,215]	2-DOF half-car	Line	CP	Residual response of one vehicle	FFT
	[57]	2-DOF half-car	Line	CP	Residual response of multiple vehicles	FFT
	[61]	Three-mass	Line	Acc.	Smooth/normal road roughness	FFT
	[89]	1-DOF single-axle	3D	CP	Residual response of multiple vehicles	FFT
	[90]	2-DOF single-axle	3D	CP	Residual response of multiple vehicles	FFT
	[91]	2-DOF single-axle	3D	CP	Smooth/normal road roughness	FFT
	[94]	3D	Line	CP	Residual response of one vehicle	FFT
	[101]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	FFT
	[102]	Sprung-mass	3D	Acc.	Smooth/normal track irregularity	WT
	[105]	Sprung-mass	Line	CP	Smooth/normal road roughness	FFT
	[106]	2-DOF half-car	Line	CP	Residual response of mutiple vehicle runs	FFT
	[108]	Sprung-mass	Line	CP	Residual response of multiple vehicles	FFT
	[109]	2-DOF single-axle	Line	CP	Ongoing traffic	FFT
	[116]	Train model	3D	Acc.	Smooth/normal track irregularity	FFT
	[117]	Sprung-mass	Line	Acc.	Residual response of multiple vehicles	FFT
	[120]	Three-mass	Line	Acc.	Modifying vehicle parameters	FFT
	[146]	Train model	Line	Acc.	Smooth/normal track irregularity	EKF
	[147]	3D	3D	Acc.	Smooth/normal road roughness	FFT, STFT
	[149]	2-DOF half-car	Line	Acc.	Smooth/normal road roughness	FFT
	[158]	Tractor–trailer	Line	Acc.	Residual response of multiple vehicles	FFT
	[169]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	EMD, FFT
	[171]	2-DOF quarter-car	Line	Acc.	Smooth/normal road roughness	EMD, FFT
	[174]	2-DOF quarter-car	Line	Acc.	Smooth/normal road roughness	EEMD, FFT
	[180]	4-DOF half-car	Line	Acc.	Smooth/normal track irregularity	APPVMD, FFT
	[181]	Sprung-mass	Line	Acc.	Ongoing traffic	SSI
	[182,183]	4-DOF half-car	Line	Acc.	Residual response of mutiple vehicle runs	ST-SSI, MOESP
	[186]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	FFT
	[187]	Sprung-mass	Line	Acc.	Modifying vehicle parameters	EMD, FFT
	[188]	2-DOF single-axle	3D	CP	Residual response of multiple vehicles	FFT
	[189]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	FFT
	[192]	2-DOF quarter-car	Line	Acc.	Smooth/normal road roughness	FFT
	[190]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	FFT
	[193]	2-DOF quarter-car	Line	Acc.	Smooth/normal road roughness	WT
	[196]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	SSA-BPF
	[204]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	FFT
	[206]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	FFT
	[207]	2-DOF quarter-car	Line	Acc.	Smooth/normal road roughness	HT
	[209]	Sprung-mass	Line	Acc.	Residual response of multiple vehicles	FFT
	[210]	Tractor–trailer	3D	Acc.	Residual response of multiple vehicles	FFT
	[212]	Train model	Line	Acc.	Residual response of multiple vehicles	FFT
	[217]	2-DOF quarter-car	Line	CP	Ongoing traffic	FFT
	[219]	4-DOF scooter	Line	CP	Residual response of one vehicle	FFT
	[221]	4-DOF half-car	Line	CP	Residual response of one vehicle	FFT
	[222]	2-DOF quarter-car	Line	CP	Smooth/normal road roughness	FFT
	[228]	Sprung-mass	Line	CP	Smooth/normal track irregularity	FFT
	[232]	Sprung-mass	Line	Acc.	Stationary vehicles	FFT
	[234]	Sprung-mass	Line	Acc.	Stationary vehicles	FFT
	[235]	Sprung-mass	Line	CP	Stationary vehicles	FFT
	[237]	Sprung-mass	Line	Acc.	Stationary vehicles	FFT
	[245]	Sprung-mass	Line	Acc.	Amplifiers on vehicles	FFT
	[246]	Sprung-mass	Line	Acc.	Amplifiers on vehicles	FFT
	[247]	Sprung-mass	Line	CP	Active excitation on bridges	FFT
	[248]	Sprung-mass	Line	Acc.	Amplifiers on vehicles	FFT
	[249]	Sprung-mass	Line	Acc.	Amplifiers on vehicles	FFT
	[259]	Sprung-mass	Line	CP	Residual response of multiple vehicles	FFT
	[262]	Train model	Line	CP	Stationary vehicles	FFT

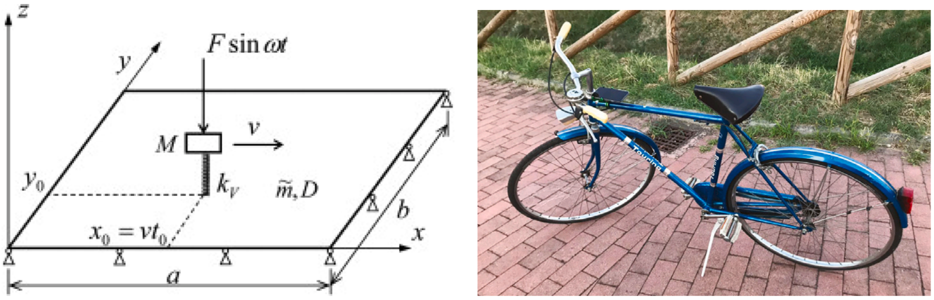
(continued on next page)

Table 2 (*continued*).

Validation	Refs.	Vehicle	Bridge	Res.	Roughness and its elimination	Techniques
Lab Experiments	[47,218]	2-DOF quarter-car	Line	CP	Smooth/normal road roughness	FFT
	[135]	2-DOF half-car	Line	Acc.	Smooth/normal road roughness	WT
	[138]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	SET
	[140]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	FIrST
	[141]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	FSST2
	[142]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	SST
	[143]	2-DOF half-car	Line	Acc.	Smooth/normal road roughness	IMSST
	[145]	2-DOF half-car	Line	Acc.	Smooth/normal road roughness	i-VNCMD
	[148]	Three-mass	Line	Acc.	Smooth/normal road roughness	FFT
	[160]	2-DOF half-car	Line	Acc.	Smooth/normal road roughness	FFT, MUSIC
	[164]	Sprung-mass	Line	Acc.	Crowdsensing from mutiple vehicle runs	FFT
	[177]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	BMI, SSA
	[202]	——	——	Acc.	Crowdsensing from mutiple vehicle runs	FFT
	[203]	——	——	Acc.	Crowdsensing from mutiple vehicle runs	FFT
	[214]	——	——	Acc.	Smooth/normal road roughness	FFT
	[223]	4-DOF half-car	Line	CP	Residual response of one vehicle	DKF, SSA
	[231]	2-DOF quarter-car	Line	CP	Smooth/normal road roughness	FFT
	[238]	——	——	Acc.	Modifying vehicle parameters	FFT
	[239]	——	——	Acc.	Smooth/normal road roughness	FFT
	[244]	Sprung-mass	3D	Acc.	Active excitation on vehicles	FFT
	[257]	2-DOF half-car	Line	CP	Crowdsensing from mutiple vehicle runs	FFT
	[258]	2-DOF quarter-car	Line	CP	Smooth/normal road roughness	FFT
	[261]	4-DOF half-car	Line	CP	Residual response of one vehicle	FFT
Field tests	[18]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	FFT
	[60]	4-DOF half-car	Line	CP	Residual response of one vehicle	FFT
	[79]	1-DOF single-axle	Line	Acc.	Ongoing traffic	FFT
	[81]	1-DOF single-axle	Line	CP	Vehicle resting periods	FFT
	[99]	Tractor–trailer	Line	Acc.	Smooth/normal road roughness	FFT
	[110]	——	——	Acc.	Smooth/normal road roughness	FFT
	[139]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	WT/SET
	[150]	Three-mass	Line	Acc.	Smooth/normal road roughness	FFT
	[153]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	FFT
	[154]	——	——	Acc.	Smooth/normal road roughness	FFT
	[157]	——	——	Acc.	Smooth/normal road roughness	FFT
	[159]	——	——	Acc.	Smooth/normal track irregularity	FFT
	[161]	——	——	Acc.	Crowdsensing from mutiple vehicle runs	FFT
	[162]	——	——	Acc.	Crowdsensing from mutiple vehicle runs	WT
	[163]	2-DOF quarter-car	Line	Acc.	Crowdsensing from mutiple vehicle runs	FFT
	[165]	——	——	Acc.	Smooth/normal road roughness	FFT
	[168]	2-DOF quarter-car	Line	Acc.	Smooth/normal road roughness	FFT
	[176]	——	——	Acc.	Smooth/normal track irregularity	HHT
	[184]	——	——	Acc.	Smooth/normal road roughness	OMA techniques
	[195]	——	——	Acc.	Smooth/normal road roughness	FFT, CWT
	[194]	2-DOF quarter-car	Line	Acc.	Smooth/normal road roughness	FI-UPSR
	[197]	Sprung-mass	Line	CP	Smooth/normal road roughness	VMD-BPF
	[200,201]	——	——	Acc.	Smooth/normal road roughness	Inverse Filtering
	[191]	2-DOF quarter-car	Line	Acc.	Crowdsensing from mutiple vehicle runs	FFT
	[225]	2-DOF quarter-car	Line	CP	Residual response of mutiple vehicle runs	FFT
	[226]	Sprung-mass	Line	CP	Ongoing traffic	FFT
	[227]	Sprung-mass	Line	CP	Ongoing traffic	FFT, SSA
	[229]	Sprung-mass	Line	CP	Ongoing traffic	ESMD, FFT
	[230]	Sprung-mass	Line	CP	Smooth/normal road roughness	REMD
	[233]	2-DOF single-axle	——	CP	Vehicle resting periods	FFT
	[241]	——	——	Acc.	Walking or running pedestrians	FFT

5.2.2. Using HT

Without external excitation, Yang et al. [40] proposed in 2014 a method to reconstruct a bridge's mode shape from a passing vehicle's response using the Hilbert Transform (HT). Once the bridge frequency was determined and its corresponding component response was separated from the vehicle's response, the instantaneous amplitude history of the extracted signal was interpreted as a representation of the bridge's mode shapes. This technique was later adopted by He et al. [272,273] and Yang et al. [84,114] to extract high-resolution first-order bridge mode shapes. Erduran et al. [274] analyzed the influence of bridge damping on modal reconstruction in detail through simulations. Their findings indicated that bridge damping led to asymmetry in the first mode shape and caused inaccuracies in higher-order mode shapes. In 2021, Tan et al. [275] improved this technique by incorporating multiple filters to enhance the identification of higher-order mode shapes and bridge MOSS. In 2022, Yang and Wang [276] designed an elliptic filter to extract narrowband signals from the CP response of vehicles, after which HT was applied to extract bridge mode shapes. Corbally and Malekjafarian [277] extended this approach by utilizing residual CP response from multiple axles to extract bridge operating deflection shape ratios (ODSRs), with HT employed to derive the ODS from acceleration signals. In the same year,



(a) A passing vehicle on a plate in [242] (b) Bicycle in [166]

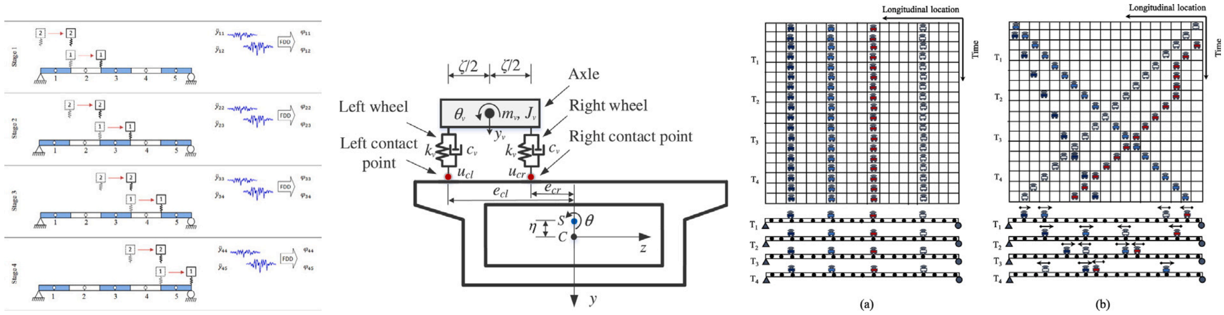
Fig. 23. Several tests of estimation of bridge mode shapes using STFT/HT.

Zhang et al. [278] attempted to identify the spatial mode shape of a T-girder bridge using HT. Their method involved analyzing the CP response of a vehicle at different positions, with numerical results confirming its effectiveness. Later, Liu et al. [279] used the virtual CP response of two two-axle vehicles combined with HT to construct bridge mode shapes. Their approach successfully identified the first four mode shapes. Additionally, Zhang et al. [280,281] proposed a method involving a stationary excitation vehicle on the bridge and another passing vehicle collecting vibration data. The mode shape was then extracted from vehicle acceleration using HT. Numerical simulations with two sprung-mass vehicle models and a 3D bridge confirmed the effectiveness of this method for extracting the bridge's fundamental mode shape.

Employing the HT, Quqa et al. [166] explored the feasibility of identifying footbridge mode shapes using shared micromobility vehicles such as bicycles and scooters. A smartphone was mounted on a bicycle (see Fig. 23(b)) while the researcher rode, walked, and stood on the footbridge. Their results demonstrated that the footbridge's mode shape could be effectively measured through multiple experiments. In another approach using vehicular accelerations, Zhou et al. [282] proposed a novel two-peak spectrum idealized filter function to extract bridge mode shapes. However, simulations revealed that this method could be significantly affected by high levels of road roughness. To amplify bridge vibrations, Zhang et al. [283] suggested using a stationary shaker to induce steady-state forced vibrations in the bridge. Field tests on a two-span continuous girder bridge, successfully identified its first six mode shapes using HT. In 2024, Hu et al. [284] introduced a method for reconstructing bridge mode shapes using a test vehicle equipped with auxiliary wheels of identical characteristic frequencies. The Adaptive Superlet Transform (ASLT) was applied to extract time–frequency response of the vehicle. Numerical simulations indicated that ASLT performed similarly to HT, though large errors were observed at both ends of the identified mode shape ratio curve. Also in 2024, Yang et al. [22] proposed a normalization formula to mitigate the effects of damping in bridge mode shape reconstruction using moving and stationary vehicles. They first extracted bridge-related instantaneous amplitudes using HT and then removed damping effects by normalizing these amplitudes with those from a stationary vehicle. Their findings suggested that ongoing traffic could partially counteract the adverse effects of road roughness, while high vehicle speeds were not recommended for constructing bridge mode shapes from vehicle response. In the same year, Demirlioglu and Erduran [285] introduced the reference-based component scaling method for retrieving bridge mode shapes using both stationary and moving vehicles. Acceleration signals recorded from both vehicles were processed using VMD and HT. The modal components from the moving vehicle were then normalized using those from the stationary vehicle to extract the bridge's mode shapes. To further eliminate the effects of road roughness, they employed two strategies: residual CP response from a two-axle vehicle and a normalization procedure. Numerical studies demonstrated that this method was also effective in estimating the mode shapes of asymmetrical bridges.

5.2.3. Using FDD

In 2014, Malekjafarian and OBrien [286] employed Short-Time Frequency Domain Decomposition (STFDD) to extract a bridge's global mode shape vector from vehicle accelerations, as shown in Fig. 24(a). The influence of road roughness was mitigated by other traffic and by subtracting signals from two trailers. Their results indicated that when environmental noise was relatively low, the bridge's mode shape could be accurately extracted. The STFDD method was later refined to enhance the resolution of mode shapes [287]. To further reduce the effects of road roughness, Malekjafarian et al. [41] introduced two key modifications: (1) employing a truck–trailer system with exciters on one trailer and (2) using two connected trailers to cancel out road roughness effects. Their findings demonstrated that despite the presence of road roughness, bridge mode shapes could still be extracted with acceptable precision. In 2020, Malekjafarian et al. [288,289] utilized FDD to derive bridge global mode shapes from vehicle response, validating the method's effectiveness through laboratory experiments. In 2023, Talebi-Kalaleh and Mei [290] proposed a novel approach that combined SVD and FDD to estimate bridge mode shapes using predicted displacements and accelerations separately. Their study revealed that increasing the number of vehicle axles did not significantly enhance mode shape recovery, while lower vehicle speeds were found to be more suitable for accurate identification. In 2024, Jian et al. [291] introduced the stop-and-go mobile sensing scheme using an output-only FDD algorithm. In their approach, one vehicle remained parked as a reference, while another was sequentially stopped at different positions on the bridge to collect acceleration data. Field tests demonstrated that this technique successfully identified the first six mode shapes of the bridge.



(a) A 5-segments example in [286] (b) Vehicle over a thin-walled girder [293] (c) Demonstrations of sparse matrices [300]

Fig. 24. Several methods of estimation of bridge mode shapes using FDD/WT/matrix completion.

5.2.4. Using WT

Apart from STFDD, wavelet transform (WT) has proven to be an effective tool for identifying bridge mode shapes. In 2020, Jian et al. [87] proposed a wavelet-based modal analysis method combined with iterative multiplication to determine bridge mode shapes. The effects of road roughness were mitigated using multiple connected trailers, provided that the vehicle's speed was known. Their results demonstrated the method's effectiveness even under conditions of high vehicle speed, road roughness, and measurement noise levels of up to 10%. In 2022, Eshkevari et al. [292] introduced a 3D reconstruction approach for bridge mode shapes by incorporating data collected from various bridge lanes using the crowdsourced modal identification via CWT method. The blind source separation technique was applied to filter out unwanted shared content such as road roughness and expansion joints. Experimental results confirmed that bridge mode shapes could be successfully estimated through multiple vehicle runs. In 2023, Yang et al. [92] developed the VMD-SWT technique using a 3-DOF single-axle test vehicle to extract vertical and radial mode shapes of a curved bridge based on CP response. Their simulation results indicated that ongoing traffic could facilitate the extraction of higher-order mode shapes. In the same year, Xu et al. [293] employed WT to detect and separate vertical and torsional mode shapes of a 3D bridge using a 2-DOF single-axle vehicle, as illustrated in Fig. 24(b). Numerical simulations validated the approach, further demonstrating the positive influence of ongoing traffic on indirect mode shape identification. In 2024, Xu et al. [294] derived a recursive formula utilizing the spatial correlation between the front and rear contact points of a 4-DOF half-car vehicle model to eliminate damping distortion effects in bridge mode shape recovery. Their findings suggested that WT was more effective than HT in reconstructing undistorted bridge mode shapes. In the same year, Kong et al. [295] combined EMD with various time–frequency analysis methods to compare the performance of STFT, Wigner–Ville distribution (WVD), and CWT in retrieving mode shapes from vehicle response. Their laboratory experiments indicated that CWT provided the most accurate mode shape identification. Also in 2024, Cronin et al. [296] extracted mode shapes from four road bridges using data from over 800 crowdsensing trips with vehicles equipped with smartphones. They employed SWT to convert each vehicle acceleration time series into the time–frequency domain, subsequently calculating instantaneous magnitudes to obtain bridge mode shapes.

5.2.5. Using matrix completion

Another up-to-date technique for reconstructing bridge mode shapes is matrix completion. In 2020, Eshkevari et al. [297] proposed utilizing matrix completion methods, specifically alternating least squares [298], to recover a full matrix from sparse entries. The completed matrix was then analyzed to extract high-resolution mode shapes from vehicle accelerations. Under impulse excitation, their approach successfully reconstructed the bridge's mode shape with a resolution of 5000 points. Building on this, Mei et al. [299] applied matrix completion for indirect mode shape extraction. Unlike previous methods, their approach operated entirely in the time domain, making it applicable to a broader range of vehicle speeds. By completing a sparse matrix generated using virtual fixed points, the "soft-imputing" technique provided a non-parametric solution that required no prior knowledge of the VBI system. Their results demonstrated that the first three bridge modes could be identified with acceptable accuracy. More recently, in 2023, Peng et al. [300] employed the generalized Kalman Filter with unknown inputs (GKF-UI) method to estimate CP forces between the vehicle and the bridge. BPF was then applied to decompose the CP response. To reconstruct spatially dense mode shapes, they formulated an objective function based on a sparse response matrix and optimized it using matrix completion techniques (shown in Fig. 24(c)). Their study leveraged crowdsensing vehicle runs to mitigate the influence of road roughness. Field tests conducted on a double-girder concrete footbridge validated the proposed method, successfully retrieving the bridge's first-order mode shape.

5.2.6. Other methods

Additionally, the extraction of mode shapes often requires the normalization of vibration amplitudes, for which a reference (fixed) sensor can be highly beneficial. In 2015, Kong et al. [301] proposed two methods for extracting bridge mode shapes using vehicle vibrations. Method I involved one reference vehicle parked permanently at a fixed position on the bridge, with another vehicle parked at various positions to collect vibration data. However, this method may encounter challenges at positions where the mode shape approaches zero. Method II employed two parked vehicles at a fixed distance apart. By iteratively moving these vehicles along the bridge, the mode shapes were effectively constructed. Different from Method I in [301], Li et al. [302] introduced a method using one stationary and one moving vehicle to identify the bridge's mode shapes. Measured accelerations from the vehicles were divided into segments, and each segment pair formed a state-space identification problem. Local mode shapes were first derived using reference-based SSI and then rescaled to construct the global mode shape. Demirlioglu et al. [303] extended the reference-based SSI method to identify mode shapes of bridges with elastic supports. However, this approach was found to be sensitive to the negative effects of higher vehicle speeds and road roughness. The authors recommended the use of the half-car model, which demonstrated robustness under such adverse conditions. Similar to Method II in [301], Yang et al. [304] utilized the CP response to extract mode shapes while addressing the adverse effects of road roughness. Two stationary single-axle vehicles were deployed, and their CP displacements were measured iteratively along the bridge until one vehicle approached the bridge's end. Once all locations were tested, a matrix similar to the frequency response matrix was constructed, and the mode shapes were extracted using the SVD method. The feasibility of this approach was validated through field tests on the Li-Zi-Wan bridge. In 2017, He et al. [305] proposed a mass-normalized mode shape identification method based on frequencies measured by a two-axle vehicle parked at different positions on the bridge. Verification using a self-designed two-axle vehicle and a simply supported aluminum beam demonstrated that the bridge's fundamental frequency and mode shapes could be effectively identified. More recently, in 2024, Yang et al. [306] introduced an innovative iterative vehicle response demodulation (IVRD) technique for bridge mode shape scanning. When a vehicle traverses a bridge, the IVRD technique extracts the instantaneous amplitudes of the response. By applying a flipping procedure to these amplitudes, the mode shapes are derived. These studies demonstrate that employing one or more stationary vehicles as reference points facilitates the construction of global mode shapes. This advancement provides valuable insights for downstream applications, such as damage detection and localization.

Table 3 summarizes the techniques used in recent studies to construct bridge mode shapes based on vehicle response. Additionally, it highlights the approaches implemented to mitigate the adverse effects of road roughness, offering valuable insights for researchers interested in this area.

5.3. Identification of bridge damping ratios

Damping ratios are more complex than bridge frequencies and mode shapes, making their accurate identification challenging. Even with direct measurement methods, numerous uncertainties arise, particularly due to factors such as temperature fluctuations, wind effects, environmental noise, and traffic loads. However, changes in bridge damping can serve as indicators of structural damage. This paper will focus on two key aspects of indirect damping identification: (1) detecting changes in bridge damping and (2) quantifying damping ratios.

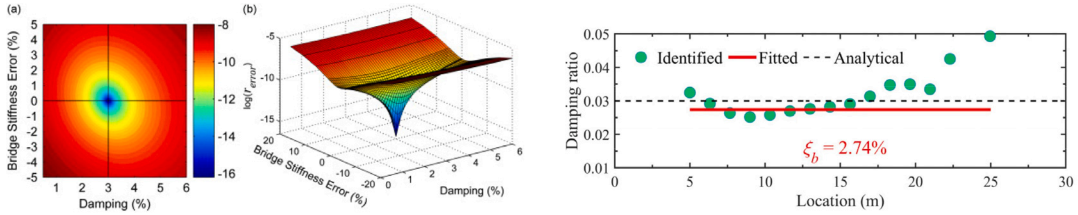
The research firstly focusing on identifying changes in bridge damping was reported by McGetrick et al. in 2010 [307]. It discovered that variations in bridge damping could be detected in vehicle spectra. Building on this, Keenahan et al. [158] conducted an initial investigation in 2014, proposing a dynamic truck–trailer drive-by system for monitoring bridge damping changes. To mitigate the influence of road roughness, they subtracted the axle accelerations of two trailers with identical properties or used a two-axle trailer. In the PSD spectrum of the trailers' residual accelerations, damping, simulated using the Rayleigh damping assumption, was clearly identifiable within a range of 0%–5%. A similar phenomenon was observed when a two-axle vehicle was used [308]. Further experimental validation was provided by Kim et al. [148], who confirmed that changes in bridge damping could be detected through vehicle spectra. Their findings indicated that low vehicle speeds and vehicles with bounce motion frequencies similar to the bridge's fundamental frequency yielded more accurate identification results.

For damping identification, González et al. [55] conducted one of the earliest studies on quantifying damping ratios using vehicle vibrations. They formulated the identification process as an optimization problem, minimizing the difference between road profile estimations obtained from the two wheels of the vehicle. Their results demonstrated that, even when road roughness was considered, the estimated damping ratios remained within a 10% error. An estimation result when the real damping ratio was 3% could be found in Fig. 25(a). In 2019, Yang et al. [309] proposed a method to identify bridge damping ratios using a two-axle test vehicle equipped with laser sensors. These sensors measured the relative displacement between the vehicle and its contact points on the bridge. The effects of road roughness were mitigated by subtracting response obtained from adjacent contact points. The damping ratios were then extracted based on their attenuation characteristics over time, utilizing the HT. In the same year, Tan et al. [310] also applied HT to simultaneously extract bridge mode shapes and damping ratios. As introduced in Section 5.2.5, Eshkevari et al. [297] introduced a matrix completion method, which could be used for identifying bridge damping. Their study demonstrated that, with the aid of Principal Component Analysis (PCA) and structured optimization analysis, bridge damping could be effectively identified under both impulsive and ambient loads. Similar to the identification of bridge frequencies and mode shapes, CP response has shown advantages in capturing dynamic characteristics, making it a promising approach for damping estimation. In addition, Eshkevari et al. [172] proposed two methods for estimating bridge damping. In the first approach, vehicle deconvolution was performed using the vehicle frequency response function (FRF) combined with second-order blind identification to extract bridge vibrations from the mixed vehicle–bridge response. In the second method, EEMD was used as an alternative technique for vehicle deconvolution. Numerical simulations demonstrated that the accuracy of the estimated damping ratios using both methods was generally comparable to that of traditional methods. In 2021, Yang et al. [311] explored the use of VMD and the Random Decrement Technique (RDT) to extract bridge damping ratios using a 1-DOF test vehicle. Initially, the mono-component of the CP response was extracted using VMD. Then, RDT was applied to compute the free-decay response of each mode, from which damping ratios were identified using the HT. This approach was later validated through experiments on the two-span

Table 3
Bridge mode shape identification from vehicle response.

Validation	Refs.	Vehicle	Bridge	Res.	Roughness and its elimination	Techniques
Simulations	[22]	Sprung-mass	Line	CP	Ongoing traffic	HT, stationary and moving vehicles
	[40]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	HT
	[85,86]	Tractor–trailer	Line/3D	Acc.	Residual response of multiple vehicles	STFT
	[87]	Tractor–trailer	Line	Acc.	Residual response of multiple vehicles	WT
	[92]	3-DOF single-axle	Line	CP	Ongoing traffic	VMD, SWT
	[100]	4-DOF half-car	Line	CP	Ongoing traffic	WT
	[114]	Tractor–trailer	Planar	CP	Residual response of mutiple vehicle runs	HT
	[198]	Sprung-mass	Line	CP	Smooth/normal road roughness	Elliptic filter
	[254]	Sprung-mass	Line	CP	Residual response of mutiple vehicle runs	HT
	[264]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	BPF
	[265]	Truck–trailers	Line	Acc.	Residual response of multiple vehicles	SVD
	[274]	Sprung-mass	Line	CP	Smooth/normal road roughness	HT
	[276]	Sprung-mass	Line	CP	Smooth/normal road roughness	Elliptic filter, HT
	[278]	Sprung-mass	Planar	CP	Smooth/normal road roughness	HT
	[279]	2-DOF half-car	Line	CP	Residual response of multiple vehicles	VMD-BPF,HT
	[284]	Sprung-mass	Line	Acc.	Auxiliary wheels	ASLT
	[286]	Truck–trailers	Line	Acc.	Residual response of multiple vehicles	STFDD
	[287]	4-DOF half-car	Line	Acc., Disp.	Residual response of one vehicle	Improved STFDD
	[41]	Truck–trailers	Line	Acc.	Residual response of multiple vehicles	HHT
	[288]	4-DOF half-car	Line	Acc.	Smooth/normal road roughness	FDD
	[290]	Multi-DOF half-car	Line	Acc.	Smooth/normal road roughness	SVD, FDD
	[293]	2-DOF single-axle	3D	CP	Ongoing traffic	WT
	[294]	4-DOF half-car	Line	CP	Ongoing traffic	HT, WT
	[299]	4-DOF half-car	Line	Acc.	Smooth/normal road roughness	Matrix completion, SVD
	[280,281]	Sprung-mass	3D	Acc.	Smooth/normal road roughness	HT, stationary and moving vehicles
	[303]	Sprung-mass/2-DOF half-car	Line	Acc.	Residual response of one vehicle	Reference-based SSI
	[285]	2-DOF half-car	Line	CP	Residual response of one vehicle	VMD, HT
Lab Experiments	[302]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	Reference-based SSI
	[242]	Sprung-mass	Planar	Acc.	Tap-scan	STFT
	[263]	Sprung-mass	Line	Acc.	Tap-scan	GFM, STFT
	[267]	——	Line	Acc.	Smooth/normal road roughness	STFT
	[268]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	Movable actuator and fixed sensors
	[269,270]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	STFT
	[272,273]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	HT
	[275]	2-DOF quarter-car	Line	Acc.	Smooth/normal road roughness	HT
	[277]	Sprung-mass	Line	Acc.	Residual response of multiple vehicles	HT
	[282]	2-DOF half-car	Line	Acc.	Smooth/normal road roughness	Two-peak spectrum idealized filter
	[289]	——	——	Acc.	Smooth/normal road roughness	FDD
	[292]	2-DOF quarter-car	3D	Acc.	Crowdsensing from mutiple vehicle runs	CMICW
	[295]	Tractor–trailer	3D	Acc.	Smooth/normal road roughness	STFT, WVD, CWT
	[305]	2-DOF half-car	Line	Acc.	Stationary vehicles	Frequency changes
	[306]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	IVRD
Field tests	[84]	Tractor–trailer	Line	Acc.	Residual response of mutiple vehicle runs	HT
	[166]	——	——	Acc.	Crowdsensing from mutiple vehicle runs	HT
	[271]	Tractor–trailer	Line	Acc.	Residual response of multiple vehicles	BPF, STFT
	[283]	Sprung-mass	3D	Acc.	Active excitation	HT
	[291]	Sprung-mass	Line	Acc.	Vehicle resting periods	STFT
	[296]	2-DOF quarter-car	3D	Acc.	Crowdsensing from mutiple vehicle runs	Synchrosqueezed WT
	[300]	2-DOF quarter-car	Line	Acc.	Crowdsensing from mutiple vehicle runs	Matrix completion
	[304]	Sprung-mass	Line	Acc.	Stationary vehicles	SVD

Turtle Hill Bridge at Chongqing University, where the damping ratios obtained from a stationary frequency-free test vehicle closely matched those derived from direct methods [80]. In 2022, Zhang [88] employed the well-known vehicle-trailer system for bridge damping identification. The adverse effects of road roughness were mitigated by employing the residual response of one trailer–bridge contact point to another one. Theoretical analysis demonstrated that damping could be evaluated by applying a 1-DOF model-based curve-fitting technique to several discrete values obtained from the FFT of the residual response. In the same year, Li et al. [179] compared the capability of SVMD and singular spectrum decomposition in identifying bridge frequencies from vehicle response. They found that the identification of damping ratios was more sensitive to the random operational load. Also in 2022, He et al. [260] proposed a semi-analytical solution to first identify the bridge's frequencies. Then, the SSA was conducted to extract bridge-frequency-related mono-components, from which the bridge damping ratios were estimated by curve-fitting. In the following year, He et al. [312] proposed a method using residual CP response from three connected vehicles to estimate bridge damping ratios.



(a) Damping ratio estimation results in [55]   (b) Damping ratio estimation results in [23]

Fig. 25. Several damping ratio estimation results.

Table 4
Bridge damping ratio identification from vehicle response.

Validation	Refs.	Vehicle	Bridge	Res.	Roughness and its elimination	Techniques
Simulations	[23]	4-DOF half-car	Line	CP	Ongoing traffic	WT
	[55]	2-DOF half-car	Line	Acc.	Smooth/normal road roughness	Optimization
	[123]	Sprung-mass	Line	CP	Smooth/normal road roughness	FFT
	[172]	2-DOF quarter-car	Line	Acc.	Smooth/normal road roughness	FRF, EEMD,STRIDEX
	[260]	Sprung-mass	Line	CP	Residual response of multiple vehicles	Curve-fitting, HT
	[297]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	Newton's methodIHA
	[309]	2-DOF half-car	Line	Acc., Disp.	Residual response of one vehicle	HT
	[311]	Sprung-mass	Line	CP	Ongoing traffic	VMD, RDT
	[312]	Sprung-mass	Line	CP	Residual response of multiple vehicles	VMD, curve fitting
	[314]	3-DOF single-axle	Line	CP	Ongoing traffic	VMD, SWT
	[315]	2-DOF half-car	Line	CP	Ongoing tra±c	HT
	[316]	Sprung-mass	Line	CP	Smooth/normal road roughness	VMD, NExT
Lab Experiments	[173]	——	——	Acc.	Smooth/normal road roughness	STRIDEX
	[310]	2-DOF quarter-car	Line	Acc.	Smooth/normal road roughness	HT
Field tests	[80]	1-DOF single-axle	Line	CP	Modifying vehicle parameters	VMD, RDT
	[82]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	Trial-and-error
	[179]	Sprung-mass	Line	Acc.	Smooth/normal road roughness	SVMD, NExT, RDT
	[313]	2-DOF single-axle	3D	Acc.	Smooth/normal road roughness	WT, SVD

Their approach involved curve fitting of free-decay components extracted via RDT and VMD. However, they observed that ongoing traffic hindered the extraction of bridge frequency-related mono-components, potentially introducing significant errors in damping ratio identification.

In 2023, Yang et al. [313] proposed a method for identifying bridge damping ratios using multiple sensors mounted on a single vehicle. Their approach combined WT and SVD to process the cross-covariances of multi-sensor vehicle response. Field tests on a three-span girder bridge demonstrated the effectiveness of this method in retrieving the first four damping ratios. Later, Yang et al. [82] developed a trial-and-error method for determining bridge damping ratios using a single-axle test vehicle. Unlike previous techniques, this method did not require subjective judgment or prior knowledge of bridge damping. Compared to the Empirical Decomposition Technique used in [311], the new approach accurately identified bridge damping ratios up to 5%. The concept of using the correlation of CP response was subsequently extended to two connected vehicles [314] and to the front and rear CP response of a single vehicle [315]. For curved bridges, the study found that vertical and radial damping ratios could be extracted from CP response using the VMD-SWT technique. In 2024, Mazzeo et al. [316] applied VMD to determine bridge modal frequencies and introduced the Natural Excitation Technique (NExT) alongside a noise-robust area ratio-based approach to estimate bridge damping ratios. Compared to traditional HT-based methods, the area ratio-based approach exhibited greater accuracy and robustness in estimating modal damping ratios. In the same year, Xu et al. [23] explored the relationship between modal damping and mode shapes for the identification of bridge damping. After employing WT to obtain the instantaneous amplitudes of bridge-related CP response, they developed a new formula based on the correlation of front and rear CP response. Damping ratio estimation results in practical scenarios could be found in Fig. 25(b). Their findings suggested that data collected from the first span could be representative for calculating bridge damping ratios. Additionally, Shi et al. [123] discovered that vehicle accelerations were more effective than displacements in damping identification. Using the instantaneous amplitude of Hilbert-transformed response, they extracted multiple damping ratios with an average error of 0.28% and a maximum error of less than 0.5%. Table 4 summarizes current techniques used in recent studies to identify bridge modal shapes using response of passing vehicles.

From the above introduction to modal parameter identification using vehicle response, we can see that the influence of simultaneous passage of multiple vehicles on bridges can be a key issue to explore for indirect BHM. Several key insights and their practicality in engineering are summarized here.

If only one vehicle is utilized for sensing, ongoing vehicles (other simultaneously passing vehicles) will amplify bridge vibrations, which benefits the extraction of bridge information from vehicle response. However, if there are many ongoing vehicles or their masses are large, the extracted modal parameters may no longer reflect the true bridge dynamics, as stated in Section 5.1.1, which can potentially affect damage assessment based on these parameters. Therefore, when other vehicles are present, it is preferable that they are relatively light and few in number. This condition is often met in practice, as the indirect method is generally applied to short- and medium-span bridges where simultaneous vehicle presence is limited. Therefore, in real-world practice, this approach is highly feasible. Another potential method, if there are several ongoing vehicles, is to connect two of them to weaken the influence of road roughness. Theoretically, the use of connected vehicles can significantly help with eliminating the influence of road roughness, both when accelerations and contact-point response are utilized. However, in a real environment, this is difficult to implement due to synchronization challenges and vehicle connections. Also, most studies assume the use of identical vehicles, but replicating identical configurations in practice can be challenging. Crowdsensing-based method also provides the potential to overcome the influence of simultaneous vehicle passages. In this method, all simultaneously passing vehicles with different parameters are installed with sensors to collect vibration data. The bridge-related component is extracted from the shared vehicle response, while vehicle-specific characteristics are removed. Typical methods include coherence analysis and data-driven approaches (introduced in Section 6.3). In the approach used parked vehicles, stationary vehicles are used for sensing, while moving vehicles serve as exciters. This method helps reduce road roughness interference and shows strong potential in practical implementation. However, when extracting modal shapes, the parked vehicle needs to be moved sequentially [291], which may be inconvenient in engineering applications. Probably the most straightforward method to remove the influence of simultaneously passing vehicles is to monitor the bridge when there is no traffic or during nighttime. This is typically manageable in engineering practice with careful timing.

In addition, as introduced, the traffic distribution on the bridge is typically in-deterministic. To avoid the interference from random traffic, other auxiliary tools, e.g., computer vision techniques [317], can be combined with vehicle-based measurements. The cameras installed on the bridge can be used to measure traffic patterns. Then, time windowing can be applied to isolate periods where the sensing vehicle is dominant on the bridge. This can significantly reduce the uncertainty introduced by varying traffic distribution.

6. Indirect bridge damage detection using vehicle response

Typically, bridge damage includes changes in supports [156,318], cracks [64,319], stiffness loss [320], tension loss in cables [115], and prestress loss [321,322], among others. In the preceding sections, it was demonstrated that a passing vehicle's accelerations can capture dynamic information about the bridge, such as natural frequencies, mode shapes, and damping ratios. Modal parameters have been widely used as effective damage indicators (DIs) for detecting, localizing, and assessing bridge damage in the direct method and can serve as valuable references for applying the indirect method in damage detection. With advancements in devices, algorithms, and computing power, novel techniques have been adapted to enhance the indirect method for identifying bridge damage. For example, damage indices can now be estimated directly from data, eliminating the need to identify bridge modes. This section introduces three categories of indirect approaches for bridge inspection: direct signal processing, modal-based methods, and data-driven techniques.

6.1. Direct signal processing methods

6.1.1. Using accelerations

For indirect BHM, accelerometers are commonly used due to their ease of installation and cost-effectiveness in engineering applications. In addition, existing studies have confirmed that the dynamic characteristics of vehicle vibrations contain key information about the bridge, making vehicle accelerations a primary focus of initial investigations. In 2010, Xiang et al. [243] introduced the tap-scan method, which required a sensor and a tapping device mounted on the vehicle. Their study demonstrated the potential of vehicle acceleration for bridge damage detection. This method was later improved by Hu et al. [252,253,323], who proposed a passive tap-scan method using specially a designed toothed wheel (see Fig. 26), eliminating the need for an active tapping device. Their work also explored prestress loss in bridges. In 2006, Bu et al. [324] developed a damage identification algorithm based on dynamic response sensitivity analysis, implemented using a regularization technique applied to vehicle acceleration measurements. Their approach successfully identified reductions in flexural stiffness in the FE model of a beam, even in the presence of measurement noise, VBI model errors, and road surface roughness. In 2008, Kim and Kawatani [325] proposed using the element stiffness index for bridge damage detection, employing a time-varying pseudo-static formulation derived from the equations of motion for coupled vibrations. This approach was later adopted by Chang et al. [326] to detect bridge damage using vehicle vibrations. Their results indicated that bridge damage could be accurately localized and quantified. Furthermore, higher vehicle speeds and vehicle frequencies close to the bridge's fundamental frequency were found to enhance the effectiveness of indirect damage detection. In 2014, Li et al. [327] applied the generalized pattern search algorithm to optimize vehicle acceleration response obtained from a sprung-mass model. When road roughness was neglected, the algorithm accurately identified the fundamental frequency and flexural stiffness of the bridge. In 2015, Hester and González [328] discovered that the area under the filtered bridge acceleration response was effective for identifying different levels of damage using the direct method. This finding provided valuable insights for utilizing vehicle accelerations. However, they also observed that vehicle accelerations were more sensitive to noise and road roughness than bridge accelerations, making them less reliable. In the same year, McGetrick et al. [56] proposed detecting bridge stiffness loss using a calibrated bridge model. Their approach employed estimated profiles from the two wheels of a 2-DOF half-car model as an objective function for damage detection. Laboratory experiments demonstrated that bridge stiffness values could be identified with an error margin of less than 5%. In 2024, Lu et al. [329] proposed a model-free damage localization method using the low-frequency acceleration component of a bridge under a moving vehicle. Theoretical and experimental results revealed that a

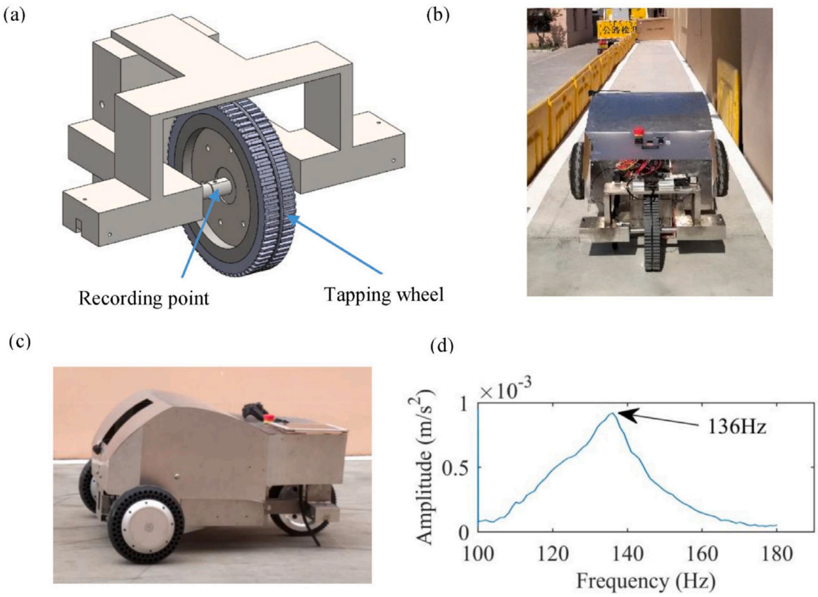


Fig. 26. Passive tap-scan method in [253].

distinct "bump" in the low-frequency response directly corresponded to the damage location, enabling detection through low-pass filtered acceleration histories.

In 2016, Li et al. [330] proposed identifying distributed bridge damage (e.g., cracks) using the accelerations of a 4-DOF vehicle, directly based on dynamic response sensitivity. Simulation results indicated that the fractional change in bridge elements could be determined, and the method demonstrated robustness against measurement noise. In 2018, Zhong and Yang [322] introduced a method for identifying prestress loss in prestressed bridges. Their study found that vehicle peak acceleration could be used to detect prestress loss when road roughness was ignored. In 2019, Carnevale et al. [331] conducted a numerical study on train–track–ballast–bridge interaction for trains crossing railway bridges. Accelerations within a suitable frequency range were employed to detect both the presence and location of damage. Additionally, the study observed that accelerations measured on the leading bogie were the most effective for damage detection. In 2020, Kildashti et al. [115] numerically investigated damage detection in the cables of a cable-stayed bridge (see Fig. 13(b)). Using EMD, vehicle signals were decomposed into several IMFs, and the summation of their absolute values was employed to detect, localize, and quantify damage. Numerical simulations verified that the method effectively detected damage under different vehicular parameters and damage scenarios. Also in 2020, Krishnanunni and Rao [332] proposed a two-stage approach for indirect BHM to address measurement noise and road roughness. Their method included estimating the road roughness profile from recorded vehicle accelerations using Tikhonov regularization and minimizing the roughness residual function, which depended on the location and magnitude of damage. Results indicated that damage located farther from bridge supports was more sensitively identified, and vehicle frequencies significantly higher than the bridge's fundamental frequency enhanced detection efficiency. In 2021, Aloisio and Alaggio [333] developed a method for identifying the elastic modulus of prestressed concrete girders. The highest cross-correlation between the bridge response obtained from an elementary analytical model and the experimental response, measured using a moving force-balance accelerometer, was used to determine the unknown model parameter. The effects of VBI were removed through proper signal filtering. The elastic moduli of seven prestressed concrete bridges were successfully measured using an sensing vehicle, showing a strong correlation with values obtained from static load tests. In 2021, Micu et al. [334] analyzed the static and dynamic effects of a railway bridge subjected to train loads to assess its health condition. Multiple dynamic measurements (accelerations) from a passing train were used to evaluate bridge condition. The study observed significant changes in the acceleration of the train when crossing a damaged bridge span. However, it was also noted that indirect detection could be highly influenced by variations in train speed.

In 2023, Shi et al. [335] proposed a multistage health monitoring method using bogie accelerations for damage localization and quantification in heavy-haul railway bridges. First, the bogie accelerations were preprocessed using the time-domain correlation analysis denoising method to mitigate the influence of track irregularities. Next, EMD was applied to decouple VBI vibrations, and a confidence classification threshold based on Mahalanobis distance was defined using the Gaussian inverse cumulative distribution function for damage detection. A sliding window strategy was then employed to localize the damage, followed by a combination of the classification threshold and k-means clustering analysis to quantify damage severity. Blind-test numerical simulations demonstrated the framework's effectiveness for damage detection, localization, and quantification without requiring prior knowledge. Subsequently, Shi et al. [336] developed a comprehensive train-track–bridge interaction model and analyzed the sensitivity of the train bogie's vertical accelerations. The sensitivity equation of the coupling system was constructed, and bridge damage was identified through numerical model updating. In 2023, Wang et al. [337] proposed a method that combined

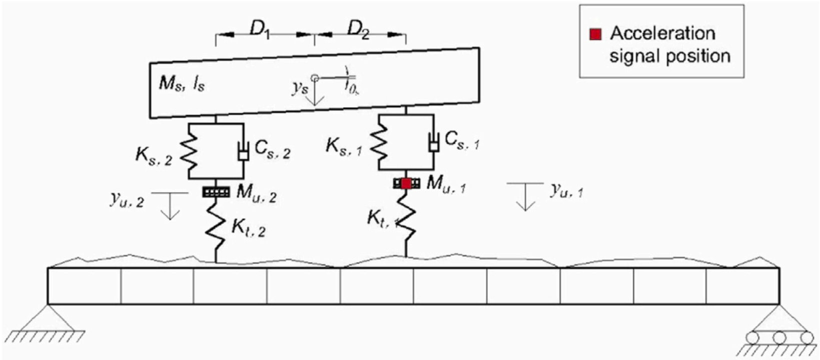


Fig. 27. Half-car model on a simply supported beam in [351].

response from multiple vehicles to address the challenge posed by the short passing time of high-speed vehicles, which limits sensitivity analysis. The method demonstrated robustness to variations in train speed, body mass, track irregularities, and interlayer connection properties, proving effective for bridge damage detection even under high speeds and measurement noise. Also in 2023, OBrien et al. [338] introduced a novel approach for road roughness estimation and bridge damage detection using accelerations from a fleet of passing vehicles. When a vehicle was not on the bridge, a Bayesian approach updated the estimation of road roughness and vehicle properties based on its accelerations. The updated vehicle properties were then used to assess bridge damage. Simulated measurements indicated that the method could effectively detect bearing and local crack damage in bridges. Later, Shokravi et al. [339] explored the potential of connected and autonomous vehicles for indirect damage detection and fleet-based SHM. In 2024, McGeown et al. [318] investigated the use of passing trains' rotational or pitching accelerations as indicators of bridge foundation scouring. Laboratory experiments involving a tractor–trailer crossing a four-span simply supported bridge on piers demonstrated that scouring damage could be effectively identified through the pitching accelerations of train carriages.

6.1.2. Using displacements

Another potential measurement from a vehicle passing a bridge is its displacement or relative displacement to the bridge deck. This can be obtained using traffic speed deflectometers (TSDs) or by performing a double integration of accelerations. In 2011, Yin and Tang [340] sought to distinguish between healthy and damaged bridges by analyzing the disparity in vehicle displacements as they passed over the structure. Their method successfully identified cable tension loss and deck damage. The study demonstrated that damage could be detected when proper orthogonal decomposition was applied to extract an optimal set of basis vectors from the relative vehicle displacements. In 2012, Miyamoto and Yabe [341] proposed integrating the accelerations of a public bus to obtain the characteristic deflection of the bridge. Their study found that the average characteristic deflection in undamaged cases was −0.4464 mm. They concluded that serious structural anomalies could occur if the average characteristic deflection dropped below −0.625 mm. In 2015, OBrien and Keenahan [342] suggested using TSDs installed on vehicles for BHM. The displacement collected by two TSDs was used to determine the apparent profile through the CE optimization method. The time-shifted difference between the obtained apparent profiles served as a DI for identifying and localizing damage, which was simulated as a loss in stiffness. In 2016, Elhattab et al. [343] proposed using the difference in bridge displacement profiles as a measure of bridge damage. The apparent profiles, derived from TSD data, were used to calculate displacement differences. When a quarter-car model and a plate bridge model were employed, results showed that damage could be identified and localized. However, the algorithm was sensitive to road profile variations, warranting further investigation. The concept of the apparent profile was later extended to railway bridges, where it included the true profile along with components of ballast and bridge deflection under the moving train. Later, Ren et al. [344] introduced a method in which the reference deflection influence line was calculated from the apparent profile, serving as a DI for monitoring bridge stiffness. In 2017, OBrien et al. [345] compared the effectiveness of IC and moving reference curvature (MRC) of vehicle displacement for bridge damage detection using a half-car model and TSDs. Curvature was defined as the second derivative of deflection with respect to distance and was approximated using a central difference method, while MRC was determined using measurements from three different positions. The study demonstrated that IC could effectively detect local stiffness loss in various parts of the bridge, while MRC provided a means for quantifying the damage. Later in 2017, Quirke et al. [346] demonstrated the effectiveness of using the apparent profile for damage detection in a 3D train–bridge interaction model. This work was later extended to various damage detection techniques, including the rate of IC [347], time-shifted curvature [348], and the moving reference influence function [349,350]. In 2024, OBrien et al. [351] introduced the concept of drive-by fleet monitoring, which utilizes a partially vehicle fleet without requiring knowledge of individual vehicle properties. In this study, vehicle wheel displacement was successfully derived from accelerations collected by the vehicle (shown in Fig. 27) for indirect BHM. The apparent profile difference was employed as a surface-profile-independent measure, relying instead on vehicle axle weight differences and moving reference influence function. A new DI was proposed, which proved effective for localizing and quantifying damage in bridge support bearings.

In 2018, Yang et al. [352] proposed measuring vehicle displacement through double integration of its acceleration response. Using a statistical moment-based damage detection method, they calculated fourth-order moment vectors to assess bridge conditions.

In a field test, the time-domain method proved to be highly accurate for determining bridge stiffness, outperforming frequency-domain methods in identifying both damage locations and severities. In 2020, Martinez et al. [353] employed eight sensors placed at different locations on the vehicle to measure deflections. The measured deflections were corrected for vehicle motion based on its known characteristics. Using the unit load theorem, the deflections were related to the reciprocals of flexural rigidity at various locations on the bridge. Their study demonstrated that bridge flexural rigidity could be derived from drive-by deflection measurements. In 2021, Lan [354] applied the Monte Carlo simulation method to optimize vehicular parameters for enhancing the sensitivity of vehicle deflections to local bridge damage. The proposed approach successfully detected and localized damage using an optimal vehicular configuration. To address the time and economic constraints associated with static tests, Aloisio et al. [355] proposed using an sensing vehicle for bridge bending stiffness estimation. Their system incorporated a swinging pendulum equipped with a laser sensor. Bridge bending stiffness was estimated by optimizing the correlation function between the pendulum's displacement in experimental tests and numerical simulations. In 2021, Zhan et al. [255], building on their previous study [254], introduced the double-pass mass-addition method for bridge damage identification. This method enabled the detection of multiple damage locations by performing WT on the difference in CP displacement and using coordinate modal assurance criteria (MAC) to analyze the constructed mode shapes. In 2024, Li et al. [356] proposed a joint input-state estimation approach based on Bayesian expectation–maximization for reconstructing CP displacement between the vehicle and bridge. Their experimental results indicated that bridge crack damage could be detected from the reconstructed CP displacement. Additionally, the influence of road roughness was mitigated by analyzing the residual CP response at the front and rear axles. Similarly, Guo et al. [357] utilized residual CP displacement from a 4-DOF half-car model, estimated using a generalized GKF-UI developed by the authors. Sensitivity analysis of the wheel's residual CP response was performed using l_1-norm regularization for bridge damage detection.

6.1.3. Using contact forces

Similar to displacements, monitoring the tire-contact force between the vehicle and bridge can serve as an effective method for damage detection [358]. In 2015, OBrien et al. [359] proposed using the mean of force histories from fleets of similar vehicles as DIs, thereby reducing the influence of vehicular parameters on damage detection. Their results demonstrated that this method was particularly sensitive when damage occurred away from the bridge's midpoint. Building on previous research on identifying bridge damping ratios [55], OBrien et al. [360] explored bridge global stiffness estimation using vehicle accelerations. Their approach involved identifying the contact force between the vehicle and bridge while minimizing the error between estimated road profiles detected by the front and rear wheels. In 2018, Zhu et al. [361] observed that accelerations from passing vehicles or the bridge were less sensitive to local damage compared to the interaction force between the tire and the bridge. Numerical results indicated that local anomalies could be estimated from interaction forces using Newton's iterative method based on the homotopy continuation approach. In 2020, Li et al. [362] introduced a two-step method for bridge damage detection using the dynamic response of passing vehicles. In the first step, road roughness was identified using a dual KF based on vehicle vibrations. In the second step, bridge damage was detected through interaction force sensitivity analysis with Tikhonov regularization. The study found that bridge damage induced significant changes in VBI forces. Results confirmed that the proposed method was both effective and reliable in identifying interaction forces and assessing bridge surface roughness.

In 2021, Kumar et al. [363] proposed a method for BHM using tire pressure, which could indicate the presence of bridge damage. Their approach consisted of two stages: (1) estimating tire model parameters using Bayesian inference based on calibration data, and (2) using the calibrated tire model to reconstruct changes in VBI forces. Damage was identified by minimizing an objective function using the Cuckoo search algorithm. Numerical simulations demonstrated the effectiveness of the method for damage detection, even in the presence of measurement noise and other uncertainties. In 2022, Eshkevari et al. [364] proposed estimating a quarter-car model's input excitation (i.e., contact point force) based on its dynamic response, highlighting its potential for indirect BHM. However, previous research [365] indicated that vehicle displacement as a DI could be overshadowed by road roughness effects. Since ensuring that the same vehicle experiences identical road roughness over several years is impractical in engineering applications, the effectiveness of this method remains a challenge. In 2023, Wang et al. [366] used bogie accelerations from passing marshaling trains to detect damage in high-speed railway bridge substructures. A new DI was developed on the basis of changes in interaction forces within a coupled vehicle-girder-pier-foundation model. These forces were estimated using a dual KF applied to train response before and after damage when the vehicle crossed a pier. The proposed method demonstrated robustness against variations in pier damage combinations, vehicle parameters, and track irregularities.

6.1.4. Using wavelet-based parameters

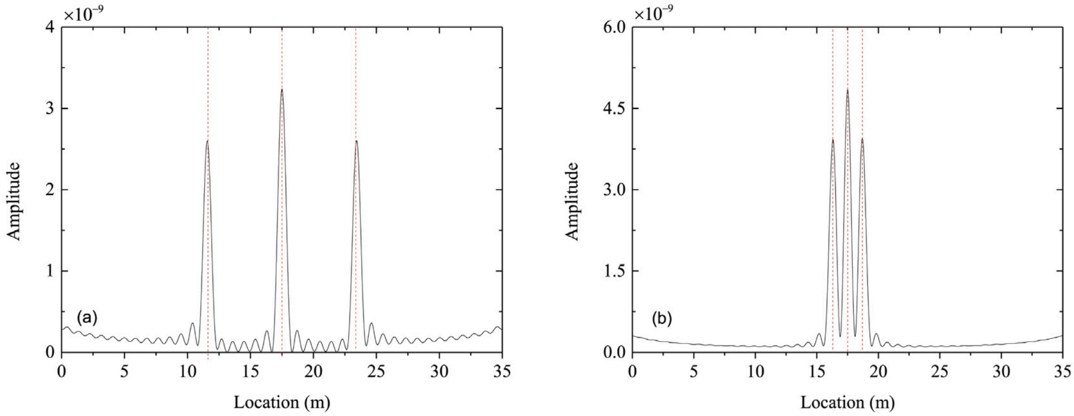
Even though vehicle response contain valuable bridge damage-related information, extracting DSFs directly can be challenging due to environmental noise, road roughness, and variations in vehicle parameters. To improve damage detection efficiency, vehicle accelerations or displacements can be processed before analysis. One of the most widely used techniques for this purpose is WT. In 2010, Nguyen and Tran [319] employed vehicle displacement data to detect bridge cracks. Their study found that damage locations could be identified using vehicle velocity and peaks in the WT, provided that the road surface was uniformly smooth. In 2013, McGetrick and Kim [367] conducted a comprehensive analysis of vehicle parameters when using the Morlet wavelet for indirect bridge damage detection based on vehicle accelerations. Their results indicated that vehicle mass had no significant impact on damage detection outcomes. However, distinguishing different damage scenarios in laboratory tests remained difficult. Additionally, when road roughness was considered, variations in the road profile had a greater influence on global VBI response than the damage itself [368]. In 2015, Cantero and Basu [369] demonstrated that WT could be effectively applied to vehicle response analysis for localizing railway damage, specifically detecting local track irregularities caused by weaker sections. Their study introduced a DI based on the sum of normalized absolute wavelet coefficients, which was evaluated using Monte Carlo analysis. In 2016, Yau et al. [370] proposed a wavelength-based technique that utilized a moving test vehicle as a traveling sensor for girder bridge damage detection. Their findings showed that for a healthy simply supported bridge, the characteristic wavelength corresponded to the span length, and the wavenumber-based response of the test vehicle remained independent of vehicle speed. Based on this property, damage could be detected by comparing the wavenumber response of an intact bridge with that of a potentially damaged one.

In 2019, Fitzgerald et al. [371] proposed detecting bridge scour by subtracting CWT coefficients between healthy and damaged bridge runs. Blind tests, where the bridge condition was unknown, demonstrated that the scour state could be accurately identified. In subsequent experiments by Zhang et al. [372], it was observed that wavelet energy increased with higher scour damage levels. However, the study also noted that real-world factors such as sensor noise and environmental variability could interfere with scour identification in practical applications. In 2020, Tan et al. [373] introduced a method that combined Shannon entropy with WT to identify both the location and severity of bridge damage. The inclusion of Shannon entropy facilitated the selection of optimal CWT parameters, enhancing signal interpretation and making discontinuities easier to detect. Later, in 2022, Tan et al. [374] further demonstrated that changes in wavelet energy could serve as an effective metric for assessing bridge conditions. In 2021, Bernardini et al. [375] analyzed train bogie accelerations under various operating conditions and damage intensities. They evaluated two time–frequency algorithms, CWT and HHT, under multiple influencing factors. Numerical studies involving a 3D rail vehicle and a short-span Warren truss bridge indicated that both CWT and HHT were effective for bridge damage detection, even in the presence of time-invariant track irregularities. However, CWT was found to be more robust against changes in rail irregularity profiles. In 2022, Tsunashima et al. [376] further confirmed that time–frequency analysis using HHT was also effective for track monitoring. In 2022, Liu et al. [377] utilized WT to transform acceleration response differences between two vehicles. The maximum successive approximation approach (MSAA) was then applied to process the WT coefficients, allowing for bridge damage localization. The severity of the damage was quantified using the processed MSAA coefficient. In 2024, Demirlioglu and Erduran [378] proposed a novel framework for bridge damage detection based on continuous wavelet analysis of accelerations recorded by two sensors installed on a vehicle. Their study found that changes in the static response of the bridge were more sensitive to damage than dynamic response, highlighting the potential of static-based indicators for improved damage detection accuracy.

6.2. Modal-based methods

Since it has been verified that bridge frequencies can be extracted from vehicle response, frequency changes have been one of the earliest methods used for damage detection. The variations in bridge frequencies before and after damage have been observed in numerical simulations and experiments. For instance, Yang et al. [147] detected changes in the bridge's fundamental frequency in a 3D VBI system modeled in ABAQUS. In laboratory experiments, Kim et al. [148] demonstrated that the bridge's frequency shift was identifiable in vehicle response following bridge damage when combining direct and indirect measurements. Similar observations were reported by Nguyen et al. [155] in a laboratory setup and by Nakajima et al. [156], who employed a homemade tractor–trailer system on a real bridge. In 2022, Cheng et al. [157] developed a mobile vehicle platform designed to drive across bridges and indirectly collect vibration frequency data. The difference in bridge frequencies between normal and post-flood conditions was used to assess bridge safety. However, their findings indicated that the results were sensitive to road surface roughness, vehicle speed, and expansion joints of the bridge. Similarly, simulations by Keenahan et al. [158] showed that frequency changes in vehicle accelerations due to bridge damage were not always recognizable due to influencing factors such as temperature variations, environmental noise, and vehicle properties. Recently, the development of CP response analysis has significantly improved the precision and efficiency of bridge modal parameter identification, thereby enhancing frequency-based damage detection. In 2021, Corbally and Malekjafarian [47] investigated bridge frequencies identified from CP response and confirmed that these modal frequencies could serve as reliable indicators for bridge damage detection. Their findings were further validated through experimental studies [218]. However, traditional frequency-based methods lack the ability to provide time- or position-specific information about bridge damage. For indirect BHM, since a moving vehicle traverses the entire bridge, researchers aim to determine not only the presence of damage but also its location. In 2017, OBrien et al. [171] proposed using EMD to decompose vehicle accelerations, leveraging the vehicle speed pseudo-frequency component to localize bridge damage. In 2024, Shi et al. [379] presented a frequency identification method for damaged heavy-haul railway bridges using bogie acceleration data. A multi-domain analysis isolated the bridge's first-order modal frequency from vehicle and track frequencies, utilizing the Hilbert–Huang transform to precisely locate energy points indicative of bridge health.

In 2018, Zhang et al. [380] discovered that the vehicle's driving component was highly sensitive to bridge damage. They proposed detecting and localizing bridge damage by identifying the instantaneous amplitude squared (IAS) of the driving component, calculated using the HT of the CP response. Their results, as shown in Fig. 28, demonstrated that bridge stiffness loss could be effectively detected and localized. This concept was further explored by Yang et al. [381], who considered the effects of discontinuity amplification, environmental noise, vehicle damping, and bridge damping. Their research extended to detecting damage in rail and railway track support components [382,383]. Additionally, Shi et al. [75] proposed a method for detecting track modulus and rail damage using CP response from a multi-DOF test vehicle, utilizing the IAS of the driving component as a DI. The effectiveness of IAS for bridge damage detection was later validated through laboratory experiments by Liu et al. [384]. In 2019, Zhang et al. [385] employed the periodic frequency shift of the VBI system as a DI and successfully identified damage in railway track supports. Their study also observed that the proposed method performed better at lower vehicle speeds. In 2020, Yang et al. [386] successfully identified track modulus using the first rail frequency extracted from CP response between the train and rail. They recommended



(a) Damages at 1/3, 1/2 and 2/3 span (b) Damages at 14/30, 15/30 and 16/30 span

Fig. 28. IAS results of the beam with damages in [380].

optimal vehicle speeds and found that track damping negatively affected identification accuracy. While their study focused on railway tracks rather than bridges, their findings provided valuable insights for BHM. In 2021, Zhang et al. [244] treated the vehicle as a moving mass on the bridge and developed a solution for the frequencies of the mass-plate interaction system using Rayleigh's method. They found that when the mass traversed an intact bridge, the deck frequency remained unchanged. However, when local damage was present, significant frequency shifts were observed. In 2023, Lei et al. [220] derived the residual CP bridge deflection of two axles and applied WT to analyze singularities in the residual CP bridge deflection response for damage localization. Their numerical simulations demonstrated the effectiveness of the proposed method. Later, Li et al. [216] proposed an indirect method for detecting, localizing, and quantifying bridge damage using vehicle-scanned bridge frequencies. They updated the bridge's numerical model based on indirectly identified frequencies and introduced a novel MAC-based objective function to enhance the robustness of damage identification. Their results showed that bridge damage could be accurately detected even when considering ongoing traffic. In 2024, Sitton et al. [257] combined changes in indirectly extracted bridge frequencies with a novel point cloud methodology to identify critical damage scenarios and estimate remaining bridge life. They analyzed two bridge types and three specific damage scenarios numerically. They mapped changes in bridge frequencies to potential damage scenarios and performed fatigue analysis to estimate the remaining fatigue life of the bridge. In the same year, Chen et al. [145] proposed using time-varying bridge frequencies to detect bridge bearing disengagement. They observed that when the bridge was intact, its instantaneous frequency curve exhibited a periodic pattern, whereas a disrupted periodic pattern appeared if the bridge bearing was separated. Numerical and experimental results validated the effectiveness of the proposed damage detection approach.

Since road roughness can significantly affect the identification of bridge frequencies, an alternative approach for bridge damage detection involves using frequencies identified by parked vehicles at different positions. In 2014, Chang et al. [387] discovered that parked vehicles could induce variability in bridge frequencies, emphasizing the need to account for their influence in BHM analyses. In 2018, He and Ren [236] conducted a comprehensive study on the frequency variability caused by parked vehicles, providing a reference for bridge model updating. Their findings indicated that when wheel stiffness was sufficiently large, the vehicle could be approximated as a mass on the bridge. Both numerical simulations and laboratory experiments confirmed the effectiveness of this approach using indirectly identified bridge frequencies. In 2021, Cao et al. [388] introduced the concept of the frequency change rate to localize bridge damage using parked vehicles. Damage severity was estimated through a pre-established FE model that correlated the frequency-parameter change rate with damage severity. Their results demonstrated that the proposed method could accurately locate and quantify bridge damage with high precision.

A more comprehensive approach to bridge damage detection involves combining multiple modal parameters, such as frequencies and mode shapes. In 2012, Zhang et al. [242] introduced a new damage index based on extracted Modal Order Shape Smoothness (MOSS) values. A laboratory experiment using vehicles equipped with tapping devices on a plate/bridge setup demonstrated that impact damage locations could be accurately identified. In 2013, Zhang et al. [263] applied the concept of ODS in bridge damage detection, using tapping devices mounted on a passing vehicle. Their study found that the curvature of ODS was highly sensitive to local damage, and its accuracy improved significantly with pre-filtering techniques. In 2014, Oshima et al. [265] utilized multiple single-axle carts and heavy trucks to extract bridge mode shapes for damage detection. Their results showed that immobilization of bridge supports and stiffness loss at the bridge center could be effectively identified by comparing the extracted mode shapes with baseline measurements. In 2018, He et al. [272] introduced the use of regional mode shape curvature (RMSC) instead of traditional mode shape curvature change for localizing bridge damage using mode shapes derived from vehicle accelerations. Numerical simulations validated the effectiveness of this approach. When road roughness was considered, the study found that using two connected vehicles helped eliminate its influence. This idea was later extended to quantify damage by establishing a relationship between damage severity and RMSCs obtained from an un-updated FE model [273]. In 2020, Yang et al. [84] proposed estimating

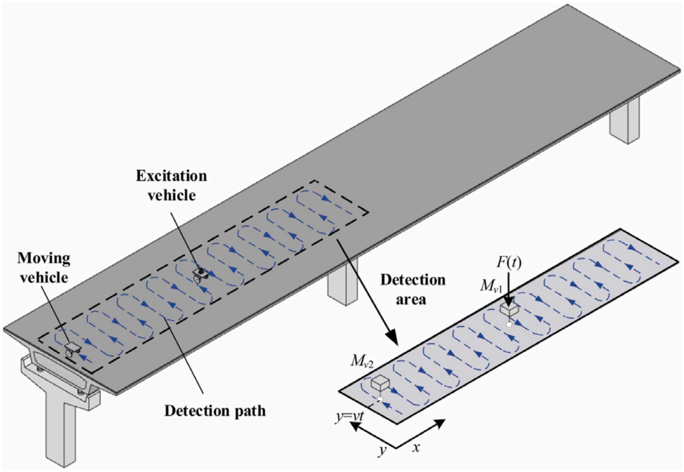


Fig. 29. Schematic diagram of the deck damage detection of box girder bridges in [281].

bridge bending stiffness using the direct stiffness calculation (DSC) method, which utilized identified modal frequencies and mode shapes. To mitigate the inverse effects of road roughness, they conducted two separate runs with different tractor–trailer systems (using the same tractor). Their study demonstrated a practical and feasible approach for the regular monitoring and structural health assessment of beam-like bridge decks. Similarly, in 2022, Yang et al. [271] applied the DSC technique using two trailers to obtain the bridge's fundamental frequency and mode shape for element stiffness evaluation. Their results confirmed the effectiveness of this method in assessing structural integrity.

In 2021, Tan et al. [275] proposed detecting bridge damage using reformulated MOSS values identified from the amplitude of the HT. The MOSS values, considering bridge damping before and after damage, were used as DIs. Both numerical simulations and laboratory experiments demonstrated that stiffness loss could be effectively detected. Additionally, as the damage level increased, the indicator values also increased, providing a means for estimating damage severity. In 2022, Zhang et al. [280] introduced the stationary excitation extraction mode method, which involved a stationary excitation vehicle supplying energy to the bridge while a moving vehicle served as a bridge signal receiver. Simulations of the VBI system in ANSYS verified that this approach could detect and localize bridge damage, particularly hinge joint damage. Their findings suggested that second-order mode shapes should be used to ensure the validity of the detection method. Later, Zhang et al. [281] proposed utilizing the indirectly extracted curvature mode shape difference for bridge damage detection. The schematic diagram of deck damage detection was shown in Fig. 29. Their study showed that this DI was particularly effective in detecting vertical cracks located at the middle of the bridge's width. Also, Yang and He [114] used flexural mode shapes scanned by a 2-DOF single-axle test vehicle and proposed extracting uniform translational response computed for each wheel. Their results demonstrated that uniform translational response curvatures could effectively identify damage locations on plate-type bridges. In the same year, Corbally and Malekjafarian [277] introduced a novel DI based on changes observed in the ODSR. Numerical simulations and laboratory experiments confirmed that ODSR could clearly detect increasing levels of bridge damage. Furthermore, Yang et al. [304] extracted the bridge's fundamental mode shapes using two movable vehicles to evaluate element stiffness, enabling the identification of local stiffness loss. Yang and Wang [276] further investigated mode shape-based damage detection, demonstrating that damage locations could be directly identified through kinks in the extracted mode shape. Their study also suggested that higher mode shapes were more sensitive to damage, even in cases of low damage severity.

In practice, one of the most common types of damage affecting bridge structures is pier scouring, especially considering climate change challenges in the future. Research has shown that scouring effects can be more prominently detected through vehicle response [210,334]. In 2016, OBrien and Malekjafarian [287] employed high-resolution mode shapes identified using a modified STFDD method to detect bridge damage, which was simulated as regional stiffness loss. Numerical simulation results demonstrated that both the presence and location of the damage could be identified, with the influence of noise effectively reduced using a moving average filter. The proposed method was later applied specifically to detect bridge pier scouring by modeling it as the removal of springs from the central pier piled foundation [288]. The approach was further validated through laboratory experiments [289], confirming its suitability for detecting scour-related damage in bridge structures.

Apart from natural frequencies and mode shapes, other dynamic fingerprints can be integrated with them to improve the localization and quantification of bridge damage. In 2014, Li and Au [389] proposed a damage identification method based on vehicle vibrations. Their approach involved extracting bridge frequencies using EMD and determining damage locations using a modal strain energy-based method. The identified potential damage locations were then refined using a genetic algorithm to estimate the stiffness of each bridge element. The following year, the method was extended to account for the influence of road roughness [390], further enhancing its applicability in real-world conditions. In 2019, Takahashi and Yamamoto [391] introduced a bridge damage detection method based on the continuous spatial singular mode angle (SSMA), an index with high sensitivity to local damage. Unlike the existing approach, which provided a single SSMA value per run [392], their proposed method preserved the spatiotemporal characteristics of the original signal, improving its ability to detect and localize damage accurately.

Damage detection based on indirectly measured bridge dynamic information can be regarded as a downstream task following the identification of the bridge's modal parameters. Typically, the accuracy of damage detection relies heavily on the precision of these modal parameters. Studies utilizing indirectly obtained bridge modal parameters serve as a foundation for further exploration using advanced techniques, improving the robustness and effectiveness of BHM methods.

6.3. Data-driven methods

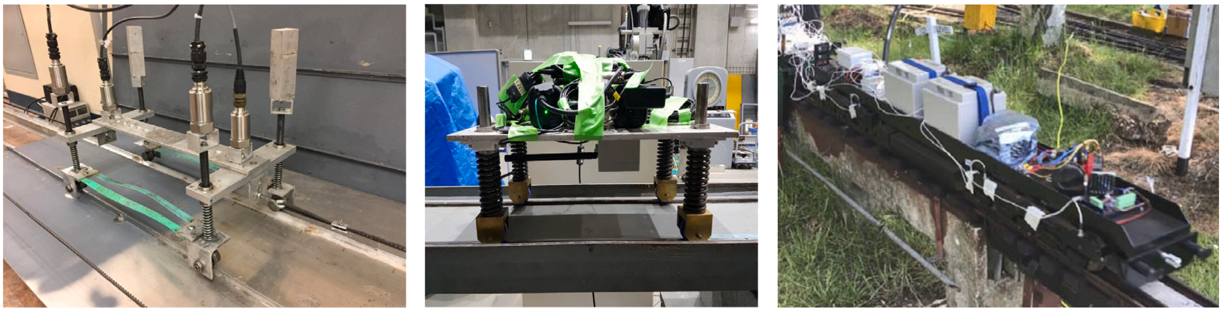
6.3.1. Supervised/semi-supervised learning

With advancements in computer science [26,393,394], AI techniques, including ML and DL approaches, have seen significant growth in the field of BHM. State-of-the-art methods such as CNNs [395], recurrent neural networks (RNNs) [396], and transformer models [397] have been explored for structural health assessment. AI techniques offer the advantage of automatic feature extraction without manual intervention, making them both time-efficient and accurate. However, studies applying ML/DL techniques to BHM remain relatively limited. Souza et al. [398] reviewed existing ML applications in indirect bridge inspection, highlighting their potential and challenges. In the following sections, existing studies in this area will be introduced.

Generally, ML/DL techniques in BHM can be classified into two main categories: (1) supervised/semi-supervised learning and (2) unsupervised learning. Supervised and semi-supervised learning methods typically require labeled data for training, while unsupervised learning can identify critical features directly from the data without labeled data.

For indirect BHM using vehicle response, researchers initially explored supervised and semi-supervised learning methods. In 2014, Lederman et al. [399] attempted to classify bridge damage severity and location using vehicle accelerations. Damage was simulated by different mass sizes and positions on the bridge. By integrating PCA with kernel regression, their approach successfully predicted both damage severity and location. Also in 2014, Chen et al. [400] extended this classification framework to a semi-supervised approach, employing an adaptive graph filter to classify unlabeled and previously unseen signals for indirect BHM. In the same year, Cerda et al. [401] used support vector machines (SVMs) to classify different bridge damage conditions based on vehicle accelerations in a laboratory setup. When considering four levels of severity, their results showed that frequency-based features provided classification accuracy comparable to or even better than those extracted directly from bridge response. However, their findings also indicated that high vehicle speeds could reduce classification accuracy. In 2019, Locke et al. [402] trained a CNN to classify different levels of bridge damage severity while incorporating environmental temperature, vehicle speeds, and weights into the training process. Their results demonstrated that using only low-frequency response peaks (3–10 Hz) could achieve classification accuracy above 80%. In 2020, Liu et al. [403] proposed that all frequency-domain vehicle response contained useful information for damage detection. They applied a stacked auto-encoder (SAE) model to reduce input dimensions, feeding the low-dimensional hidden state into a semi-supervised model with limited labeled data. Their method successfully detected a mass increase as small as 0.1% in a laboratory setup shown in Fig. 30(a). In 2022, Mokalled et al. [404] introduced a Bayesian estimation technique that combined numerical models with field data from a real bridge to detect and classify bridge damage. Their results showed that the approach accurately identified damage presence, location, and severity in many cases. However, sensitivity to measurement noise and vehicle velocity was noted as a limitation. Cheema et al. [405] proposed using Uniform Manifold Approximation and Projection (UMAP) for dimensionality reduction, followed by Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) to determine the number of clusters. Their study demonstrated that this data pipeline could reliably differentiate multiple bridge conditions based on vehicle vibration data in a laboratory VBI system shown in Fig. 30(b). Pre-trained models were shown to accelerate training convergence. In the same year, Hajializadeh [406,407] developed a transfer learning framework for drive-by bridge monitoring. A pre-trained GoogLeNet CNN model was used to transfer learned weights, while raw train-borne accelerations in a laboratory experiment shown in Fig. 30(c) served as DSFs. High classification accuracy was achieved, even when testing with only 30% of the dataset, which included both healthy and damaged bridge cases. In the following year, Hajializadeh [408] extended this work by incorporating a 2D CNN for classifying different damage scenarios under various speeds, rail irregularities, and operational noise conditions. The model was trained using the cross-correlation of accelerations from the first and second bogies as input. Numerical simulations of 2100 runs confirmed the trained model's ability to accurately predict damage severity and location.

In 2023, Lan et al. [409] proposed an optimized AdaBoost-linear SVM to classify the bridge in different health states using the vehicle's raw accelerations. Compared to existing algorithms, the proposed method can improve the accuracy by 5% to 16.7%. In the same year, Lan et al. [410] proposed a time-domain signal process technique to address raw vehicle-borne accelerations, and results showed that the classification accuracy was boosted by 12.2–15.0% with different ML techniques. Also, Abdu et al. [411] utilized a gradient boost regressor to forecast the pier settlement of a bridge in the same year. The authors employed train accelerations in their prediction model. Their simulation, which employed a CRH380 A high-speed train, indicated that more than 70% of the predicted error was less than 0.5 mm, and the highest error recorded was 1.5 mm. In 2023, Li et al. [412] employed Mel-Frequency Cepstral Coefficients (MFCCs) and SVM to detect the bridge's damage using vehicle response. It was found that not only the low-frequency but also high-frequency response of the vehicle contained the bridge's damage information and could contribute to indirect BHM. Also, the authors found that MFCCs were efficient to decrease the dimensionality of the original frequency response of the passing vehicle. In 2024, Li et al. [413] employed two types of CNNs for footbridge damage detection using shared scooter vibrations collected by smartphones. It was observed that 2D CNNs using TFRs of scooters performed better than the 1D CNNs using the scooter's frequency spectrum as the DSFs were time-varying in the scooter's vibrations. Yin et al. [414] proposed a bridge damage identification method using Long Short-Term Memory (LSTM) network and the vehicle's CP response. A novel bridge DI, namely



(a) VBI model in [403] (b) VBI model in [405] (c) Train-railway-bridge interaction model in [406]

Fig. 30. Several VBI models used in supervised/semi-supervised learning studies.

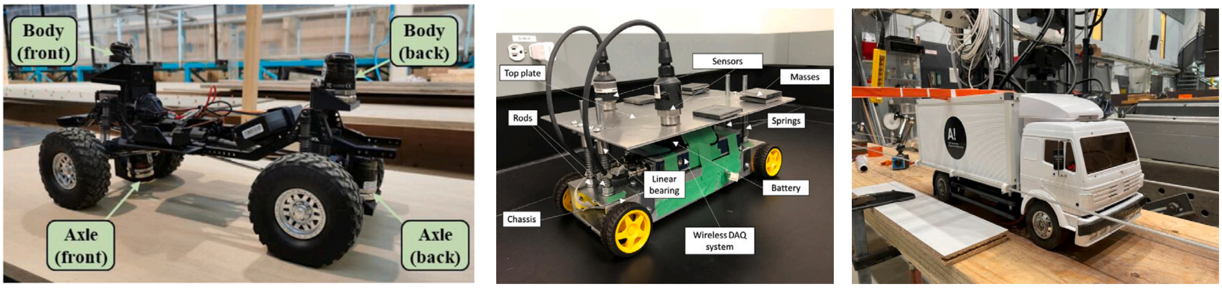
Euclidean Distance Damage Index (EDDI), was developed, which utilized the difference between the actual and predicted values of the CP response. In their simulations when road roughness was considered, EDDI was calculated to be less than 0.12 for a healthy bridge but higher than 0.65 if the bridge was damaged. To avoid the dependence on labeled data when the supervised learning was used, Corbally and Malekjafarian [52] proposed using a calibrated model to generate labeled data of damaged cases and train the CNNs using numerically simulated data. Then, the trained model was utilized to classify the type, location, and severity of bridge damage. Experimental results showed that the proposed framework could well detect existence of the damage and could correctly classified the damage severity and locations in most cases. Similarly, Wang et al. [415] explored the detection of multiple breathing cracks in plate-like bridges. The DI, contact-point displacement variations (CPDV), was calculated from vehicle acceleration data. The dataset using CPDV generated by FE method was utilized to train the CatBoost-based ML model. Then, the CPDV of the actual bridge was utilized to feed into the trained model, and the locations and severity of the damage were predicted. The effectiveness, applicability, and feasibility of this method were verified by laboratory experiments using a model car and an aluminum bridge.

Supervised and semi-supervised learning methods using vehicle response for indirect BHM can assist researchers in identifying essential DSFs within vehicle vibrations and provide insights into how damage detection is achieved. However, in real-world engineering applications, labeled data for damaged scenarios are rare and often challenging to obtain. This limitation significantly hinders the advancement and practical implementation of these methods.

6.3.2. Unsupervised learning

While supervised learning methods can achieve high performance in bridge damage detection, acquiring labeled data in real-world engineering applications remains a significant challenge. For a specific bridge, damage patterns can be highly variable, making it difficult to train models based on precise simulations [416]. In contrast, unsupervised learning relies solely on the data itself without requiring labeled samples, making it a promising approach for extracting DSFs from vehicle response. In 2019, Malekjafarian et al. [417] applied Artificial Neural Networks (ANNs) to detect bridge damage using vehicle accelerations. Their study introduced two ANN models: (1) the first model used vehicle positions and speeds as input features while labeling the vehicle's acceleration data; (2) the second model used vehicle frequencies and speeds as input features while labeling the frequency response. During training, only vibration data from a healthy bridge were used, and DIs were derived from the errors between predicted and true signals. The results demonstrated that both the severity and location of bridge damage could be identified. Corbally and Malekjafarian [48] later extended these ANN models by incorporating the effects of temperature variations to improve the identification of cracks in the bridge deck and potential changes in support conditions. Despite the presence of high vehicle speeds and poor road roughness, CP response enhanced the model's ability to monitor bridge behavior. Their approach was also validated for railway track damage detection [73]. In 2024, Corbally and Malekjafarian [418] compared the performance of using vehicle frequency spectrum and ODSR, combined with vehicle speeds, for ANN training. Their findings using a model car (see Fig. 31(a)) indicated that both FFT-based frequency features and ODSR could effectively detect rotational restraint changes caused by the seizing of bridge bearings, demonstrating the applicability of ANN-based unsupervised learning in BHM.

In 2019, Mei et al. [419] introduced the use of MFCCs for the first time in indirect BHM. They proposed a modified transformation method between the Hertz and Mel scales specifically tailored for bridge engineering applications. In a laboratory setup including a robot car shown in Fig. 31(b), by combining MFCCs with PCA, they extracted and compared the statistical characteristics of transformed features from multiple vehicle runs, enabling bridge damage detection and severity estimation. Additionally, Mei and Gül [420] employed Kullback–Leibler divergence to quantify the distribution of DSFs extracted via MFCCs across different vehicle runs. Both numerical simulations and laboratory experiments validated the effectiveness of this method in detecting bridge damage and assessing its severity. Notably, this approach was also demonstrated to be efficient when implemented on smartphones, accelerating the integration of smart city technologies for bridge monitoring [421]. Souza et al. [422] later adopted the framework proposed by Mei et al. to explore the application of MFCCs for monitoring high-speed railway bridges, further extending its applicability to different structural conditions. In 2024, Talebi-Kalaleh and Mei [423] proposed an innovative approach that integrated compressed sensing into a crowdsensing framework to enable high-frequency data collection and transmission. After extracting features using MFCCs and PCA for dimensionality reduction, they calculated damage indices by measuring the distance



(a) Vehicle model in [52, 418] (b) Vehicle model in [419] (c) Vehicle model in [425]

Fig. 31. Several vehicle models used in unsupervised learning studies.

between probability density functions using the Wasserstein distance metric. Also in 2024, Shirzad-Ghaleroudkhani and Gül [424] introduced a crowdsensing-based bridge damage detection method utilizing smartphone accelerations. They proposed an inverse filter-based monitoring approach to suppress operational effects, followed by MFCC analysis to compute an abnormality index for damage detection. Their laboratory experiments confirmed the effectiveness of the proposed method in detecting two different damage levels at various bridge locations.

Another widely used unsupervised ML technique for BHM is the autoencoder (AE). AEs typically reconstruct input data through an encoder–decoder architecture with a bottleneck in the middle. The reconstruction errors are then used as DIs for bridge damage detection. In 2021, Sarwar and Cantero [66] first applied a deep AE to extract mean absolute error values as DIs from vehicle time-domain accelerations. Their results demonstrated that damage could be detected, and its severity could be estimated based on the distribution of reconstruction errors. In 2023, Li et al. [425] proposed using a deep AE for real-time bridge monitoring based on short-time vehicle response. Their study with a model car (see Fig. 31(c)) found that even short-time vehicle vibrations contain valuable damage-sensitive information about the bridge. The proposed method achieved an overall damage detection success rate of 86.2% across different damage scenarios. Later that year, Li et al. [426] introduced the assumption-accuracy method, which assessed bridge health conditions based on damage classification accuracy. Their findings showed that when MFCCs were used as input features, classification accuracy increased significantly when the bridge was damaged but remained low when the bridge was intact. Calderon Hurtado et al. [427] explored the use of an adversarial AE for BHM using vehicle accelerations. The adversarial AE model consisted of two components: (1) an encoder–decoder structure that mapped input data into a latent space and reconstructed it, and (2) a discriminator trained to estimate the probability of each sample belonging to a predefined prior distribution. Their study demonstrated that the AAE approach outperformed traditional PCA, AE, and DAE methods in both damage identification and severity assessment. In 2024, Hurtado et al. [28] introduced a fully unsupervised computer vision-based methodology for indirect BHM using drive-by inspection. Their approach employed empirical Fourier decomposition to analyze the filtered residual CP response of a two-axle vehicle, extracting IMFs as DSFs. The wavelet synchrosqueezed transform was then applied to these features for bridge damage assessment. Two types of AEs, convolutional variational AEs and convolutional adversarial AEs, were used to define DIs, and both numerical simulations and experiments confirmed their effectiveness. Fernandes et al. [76] utilized deep AEs with different sensor placement strategies to detect bridge scour damage based on train bogie vibrations. They introduced a Kullback–Leibler divergence-based damage index to determine the number of vehicle-crossing events required for damage detection. The accuracy of their approach was assessed using receiver operating characteristic curves. Numerical results demonstrated that scour damage at levels as low as 5% and 10% could be reliably detected when sensors were placed on the front and rear bogies. Additionally, de Souza [77] employed Log-Mel spectrogram features extracted from vehicle accelerations, combined with sparse AEs, to calculate statistical distribution-based DIs for bridges. A 3D vehicle–track–bridge interaction system was developed to validate the proposed approach. Their study demonstrated that, even when considering multiple damage scenarios, vehicle speeds, environmental noise, and track irregularities, the method remained robust in detecting and characterizing bridge damage.

Apart from AE-based methods, other advanced unsupervised techniques have been developed in recent years for BHM. In 2022, Liu et al. [428] introduced the Hierarchical Multi-task Unsupervised Domain (HierMUD) approach to transfer a damage diagnosis model from one bridge to another without requiring labeled data for the new bridge. Their framework jointly optimized hierarchical feature extractors, damage predictors, and domain classifiers in an adversarial manner, extracting features that were both task-informative and domain-invariant. Experiments with three vehicles crossing two bridges demonstrated that the framework outperformed baseline methods and had lower prediction variance. The proposed approach achieved an average accuracy of 95% for damage detection, 93% for damage localization, and a mean absolute error of 0.172 kg for damage quantification (simulated using additional masses). Similarly, Ghiasi et al. [429] applied the concept of unsupervised domain adaptation for railway track monitoring using train vibrations. Their approach leveraged labeled dynamic-based features from one bridge while using data from an unknown bridge to improve generalization. The results showed that their framework increased anomaly detection accuracy by 14% compared to traditional unsupervised learning methods. In 2024, Ghiasi et al. [27] proposed an AI-based framework for railway track geometrical defect detection using train vibrations and a one-class SVM. They first extracted the most relevant feature subset from train time-domain data and then employed a one-class SVM to assess and identify track geometrical defects by detecting deviations from historical behavior. Field measurements validated the proposed method. Although this study focused on track monitoring, it provided valuable insights applicable to indirect BHM. Additionally, Alamdari [430] formulated BHM as an unsupervised semantic segmentation problem to identify structural damage. Their approach applied automatic feature learning using the matrix profile concept to conduct an all-pair similarity search within time-series data. Numerical simulations considered uncertainties such as road roughness and variations in vehicle properties. The study found that the location of the change point always coincided with the minimum point of the corrected arc crossings profile, highlighting a new perspective for unsupervised damage detection.

To better illustrate the methods utilized in existing studies, Table 5 categorizes the classifications, utilized features, techniques, and validation approaches employed in these studies. The review of data-driven methods highlights the significant rise in the application of ML/DL techniques for indirect BHM in recent years, demonstrating the immense potential of data-driven approaches in this field. In 2024, Cantero et al. [431] contributed to this progress by developing a benchmark dataset for validating various data-driven methods. This dataset serves as a standardized reference, facilitating the comparison and evaluation of different ML/DL approaches for indirect BHM, ultimately enhancing their reliability and applicability in real-world scenarios.

6.3.3. Physics-driven learning

The above have introduced current developments using supervised, semi-supervised, and unsupervised learning techniques. However, these methods typically require a large volume of data in the training phase, which might not be available in practical engineering. Therefore, the concept of using physics-informed machine learning is proposed, which integrates the strengths of both physics-based modeling and data-driven machine learning [432]. It can improve generalization, interpretability, and robustness in structural monitoring. In addition, it can reduce reliance on large labeled datasets, handle uncertainty, and enhance accuracy under sparse or variable conditions, making it highly suitable for damage detection and long-term bridge health monitoring. Such physics-informed learning techniques have been gradually employed in bridge health monitoring based on the vehicle–bridge system [433]. In the field of indirect BHM, researchers have been attracted by such advantages of physics-informed learning, which has great potential to explore.

In 2023, Lan et al. [51] proposed a physics-guided framework for indirect bridge health monitoring using vehicle acceleration data. By embedding physical principles into data processing, the method constructed damage and location indices based on differences and coherence in vehicle response between healthy and damaged bridge states. These indices showed strong correlations with damage severity and remained robust under variations in vehicle and road conditions. The framework employed a semi-supervised model with minimal data requirements, avoiding black-box learning. Experimental validation demonstrated effective damage detection, localization, and quantification, outperforming traditional feature extraction methods such as PCA and Isomap. In 2024, Erduran and Gonen [434] proposed a damage index that established a physical connection between vehicle accelerations and the instantaneous curvature (IC) of the bridge. This analytical relationship provided a direct and effective means of detecting and localizing bridge damage, even when multiple adverse factors were considered in numerical simulations. Recently, Zhou et al. [435] developed a physics-constrained generative adversarial network for probabilistic road surface roughness estimation using vehicle response. Their approach involved two steps: (1) a physics-informed GAN combined bridge vibration deflection and surface roughness information extracted from vehicle accelerations; and (2) a feed-forward network isolated the bridge surface roughness from the combined data. Laboratory experiments validated the effectiveness of the method, successfully detecting artificial barriers on bridge surfaces and achieving a mean relative error of 3.33% in height estimation.

These advancements have shown that physics-informed learning methods have excellent performance in capturing structural dynamic characteristics, enhancing early damage detection capability, and improving long-term bridge monitoring robustness. As research continues, the fusion of physics-informed learning with technologies, e.g., digital twins and IoT sensing systems, is expected to further improve scalability and applicability in practical engineering.

From the above introduction to data-driven methods for bridge damage detection, we can see that these methods have a significant advantage in indirect BHM. They can facilitate solving problems related to simultaneous passage of multiple vehicles, in-deterministic traffic distributions, and the time-dependent nature of the VBI system.

When considering the simultaneous passage of multiple vehicles on a bridge, data-driven methods can inherently account for the effects of ongoing traffic. Similar to modal parameter extraction scenarios, ongoing traffic can enhance bridge vibrations, allowing more structural information to be transferred to the sensing vehicles. However, in real-world applications, traffic patterns vary over time, which may obscure damage-induced changes in the bridge response. To address this, a large volume of training data is needed to improve the generalization capability of the model. Employing large volumes of vehicle data can also help with minimizing the influence of indeterministic traffic distribution at different times a day or year, as the data-driven models can automatically learn different distributions of ongoing traffic.

Furthermore, in engineering applications, as the traffic distribution is typically in-deterministic, instead of relying on absolute values, distributions, confidence intervals, or changes in variance can be used to detect damage under random traffic. A typical example is Ref. [436] in which the uncertainty of indirectly identified frequencies is evaluated. These statistical indicators are often more meaningful in real-world engineering settings and help engineers make informed decisions.

As introduced in Section 5.1.1, the VBI system is a time-dependent dynamic system. Once there is more traffic on the bridge, such effects will be amplified. However, data-driven methods can well consider these effects. ML models trained on vehicle response data can learn and represent the time-dependent behavior of the bridge automatically. Nevertheless, such methods typically demand large and diverse datasets for training. Varying traffic can further increase the diversity of operating conditions that must be captured. Collecting such comprehensive datasets remains a major practical challenge for real-world implementation.

Table 5
Data-driven damage detection using vehicle response.

Validation	Algorithm	Refs.	Features used for model training	Techniques
Simulations	Supervised	[48]	CP frequency response, temperature, speeds	ANN
	Supervised	[73]	Energies of accelerations	ANN
	Supervised	[402]	Frequency response	CNN
	Supervised	[411]	Accelerations	Gradient boost regressor
	Supervised	[417]	Vehicle positions, frequencies, speeds	ANN
	Unsupervised	[66]	Accelerations	CNN, LSTM, DAE
	Unsupervised	[404]	Accelerations	Bayesian estimation
	Unsupervised	[414]	CP response	LSTM
	Unsupervised	[422]	Frequency response	MFCCs
	Unsupervised	[76]	Accelerations	DAE
	Unsupervised	[77]	Frequency response	MFCCs, Sparse AE
Lab Experiments	Supervised	[52]	Frequency response	CNN
	Supervised	[401]	Frequency response	SVM
	Supervised	[406,407]	TFRs	CNN
	Supervised	[408]	Cross-correlation of accelerations	CNN
	Supervised	[409]	Accelerations	AdaBoost-linear SVM
	Supervised	[412]	Frequency response	MFCCs, SVM
	Supervised	[415]	Residual CP displacements	CatBoost
	Supervised	[418]	Frequency response, ODSR, speeds	ANN
	Semi-supervised	[400]	Accelerations	PCA, adaptive graph filtering
	Semi-supervised	[403]	Frequency response	SAE
	Unsupervised	[28]	TFRs	Convolutional variational AEs
	Unsupervised	[405]	Frequency response	UMAP, HDBSCAN
	Unsupervised	[419–421,423]	Frequency response	MFCCs, PCA
	Unsupervised	[424]	Frequency response	MFCCs, inverse filter
	Unsupervised	[425]	Frequency response	DAE
	Unsupervised	[426]	Frequency response	Logistic regression
	Unsupervised	[427]	Residual frequency response between axles	AAE
	Unsupervised	[428]	TFRs	HierMUD
	Unsupervised	[430]	Accelerations	Automatic feature learning
Field tests	Supervised	[413]	Frequency response	Explainable CNN
	Unsupervised	[27]	Accelerations	One-class SVM
	Unsupervised	[429]	Accelerations	Domain adaptation, KNN

As discussed in Section 5.1.2, long-term bridge monitoring using vehicle response is subject to uncertainties in vehicle parameters at different time periods. When applying data-driven methods, such uncertainties, such as temperature-dependent or wear-induced changes in tire and suspension properties, should be incorporated during the training phase. Otherwise, significant variations in vehicle characteristics over time may hinder the model's ability to distinguish between structural damage and shifts in vehicle dynamics, as data-driven models are often highly sensitive to such changes.

7. Affiliated investigations for indirect bridge health monitoring

The previous sections have introduced VBI models and various methods for indirect BHM using vehicle response. It is evident that the primary challenges in extracting bridge information from vehicle response stem from the influence of road roughness and vehicle properties. These two factors significantly contribute to vehicle vibrations, making it essential to mitigate their effects for accurate indirect BHM [256]. To address this issue, several studies have explored the estimation of road roughness and track irregularities, as well as vehicle parameter identification. These aspects are crucial for accurately computing CP response from vehicle vibrations. While such studies do not directly focus on indirect BHM, they have played an essential role in advancing the field by improving data quality and analysis accuracy. These efforts are categorized as affiliated investigations, and the following sections provide a summary of key contributions in three areas: road roughness estimation, railway track monitoring, and vehicle parameter identification.

7.1. Road roughness estimation

In indirect BHM, accurate road roughness estimation plays a crucial role in facilitating the extraction of bridge-related information [107,437]. Several studies have explored methods to estimate road roughness using vehicle response, aiming to reduce its interference in bridge damage detection. In 2008, González et al. [438] proposed an approach that utilized prior knowledge of the vehicle transfer function, which depended only on vehicle parameters. This function was obtained by dividing the PSD of accelerations measured over a known profile by the PSD of that profile. Numerical simulations using a half-car model demonstrated that the estimated PSD of road roughness closely matched the actual roughness profile. In 2019, Zhan and Au [439] introduced a method for estimating road roughness based on response from a vehicle running multiple times over a bridge with different additional masses. They tested three different models, spring–mass, spring–damper–mass, and half-vehicle models, and evaluated the feasibility of their method through FE modeling. Their results confirmed that road roughness could be estimated effectively across various vehicle configurations. In 2020, Keenahan [440] developed a novel method to estimate road roughness by analyzing vehicle accelerations. Their approach combined a direct integration algorithm with the Cross Entropy (CE) optimization method. Additionally, they introduced a vehicle fleet monitoring concept, which enabled road profile estimation without prior knowledge of vehicle properties. Numerical simulations demonstrated that the estimated roughness profile closely matched the ground truth. In the same year, Yang et al. [441] proposed an effective procedure for identifying road surface roughness using two connected test vehicles passing over a bridge. They introduced a static correlation formula to relate the dynamic deflections of the two vehicles' contact points on the bridge through displacement influence lines. With this relation, a road roughness estimation formula was derived. Their method was validated using various vehicle properties and simple/three-span continuous beam models, showing excellent agreement between back-calculated and assumed roughness profiles. However, their results indicated that heavy and high-speed vehicles were not ideal for this estimation approach.

In 2024, Li et al. [442] introduced a method for estimating bridge surface roughness using a single-axle, dual-wheeled 3D test vehicle equipped with an augmented KF. Accelerometers were mounted atop the axle near the wheels to capture vertical and rocking vibrations. In the developed augmented KF, bridge surface roughness was treated as the only unknown variable in the state-space formulation, while the observation vector was restructured by integrating accelerations recorded from both wheels and their derivative displacements. Field tests using a self-made vehicle demonstrated that the estimated bridge surface roughness closely matched the actual conditions.

7.2. Railway track monitoring

Apart from bridges, railway track conditions can also be assessed using vehicle or train response. Traditionally, railway track monitoring has relied on track quality instruments [443], which are time-consuming and labor-intensive. Recent studies have explored alternative methods using train-borne accelerations and vehicle-track interaction models for more efficient and automated track health monitoring. In 2011, Molodova et al. [444] found that short track defects, such as squats, welds with poor finishing quality, insulated joints, and rail corrugation, could be identified through axle box accelerations (ABA). In 2015, Li et al. [445] improved the detection of rail squats using ABA by: (1) incorporating longitudinal ABA to capture more damage-sensitive information, (2) using multiple sensors, noise-reduction techniques, and repeated measurements to enhance detection accuracy, and (3) applying signal-processing techniques to minimize disturbances caused by wheel defects. In 2016, Molodova et al. [446] further utilized ABA for monitoring the health condition of insulated rail joints. Their study identified frequency bands in the ABA power spectrum as the most relevant DIs. The proposed method achieved an 84% success rate in detecting IRJ defects across two validated tracks. In the same year, Quirke et al. [447] proposed a method for detecting track stiffness variations by analyzing vehicle accelerations from vehicle–track dynamic interactions. They applied the CE optimization method to determine the track stiffness values that best replicated the measured vertical accelerations of a carriage bogie. In 2017, Lederman et al. [448] introduced a new track monitoring technique that leveraged the sparsity inherent in train vibration data. Their approach used the expectation–maximization algorithm to iteratively estimate track irregularities and train system properties. In each step, they applied orthogonal matching pursuit to find a sparse approximation of the track irregularities. While their study did not explicitly focus on damage detection, they suggested that this method could be adapted for that purpose. Later in 2017, the same authors [449] proposed a data fusion method for track monitoring using multiple trains. Their two-step approach first minimized position offset errors through data alignment, then fused data using an adaptive KF that weighted data points based on their estimated reliability. Their results showed that fusing data from multiple trains enhanced the ability to detect track changes. In 2019, Rapp et al. [450] extended the application of ABA for detecting localized track irregularities, specifically targeting mud spots, further demonstrating the utility of ABA in railway track condition assessment.

Similar to road roughness estimation, track irregularity estimation is crucial for indirect BHM when applied to railway bridges. Unlike road vehicles, trains passing over the same railway track multiple times experience consistent track irregularities, offering greater potential for robust monitoring techniques. Traditional measurements of track irregularities rely on laser displacement sensors [451,452], which provide high accuracy but are expensive to implement on a large scale. To address this, several studies have explored alternative techniques for estimating track irregularities from train response. In 2007, Weston et al. [453,454] installed accelerometers on the left and right axle boxes of trains to estimate short-wavelength irregularities. Their experiments on a mainline vehicle demonstrated the effectiveness of their approach in detecting both vertical and lateral irregularities. The method was validated for a wide range of vehicle speeds, including speeds as low as 1 m/s. In 2010, Mori et al. [455] developed a portable track condition monitoring system that could be easily installed on in-service trains to estimate track irregularities. Their approach utilized train body roll angles to differentiate between different levels of irregularities, providing a practical and cost-effective alternative to traditional laser-based methods. These early studies have successfully demonstrated the feasibility of estimating track irregularities from train vibrations, paving the way for further advancements in railway infrastructure monitoring using indirect sensing techniques.

Over the last decade, the use of KF for track irregularity estimation has been widely studied and proven effective. In 2014, Tsunashima et al. [456] first proposed using KF to estimate track irregularities based on car-body motions. Their approach demonstrated the feasibility of using train dynamic response for track condition monitoring. Building on this work, Xiao et al. [457] developed a KF-based method for estimating track irregularities while considering VBI effects. The KF was used to optimally estimate the state vector of the VBI system, allowing for improved identification of track irregularities. Their results showed that incorporating VBI effects led to superior performance compared to traditional methods. Further advancing this approach, Xiao et al. [146] proposed a method to simultaneously identify track irregularities and railway bridge frequencies. They established a state-space model with unknown input condensation for a time-dependent VBI system and introduced an extended KF algorithm with an adaptive procedure to accelerate estimation convergence. Numerical simulations confirmed the effectiveness of the method for both single-span and multi-span railway bridges. In 2022, Xiao et al. [458] extended this approach into a probabilistic framework, introducing a recursive Bayesian KF algorithm to quantify uncertainty in the identification of track irregularities and bridge natural frequencies. Their numerical studies, conducted on two high-speed railway bridges with a train model, validated the effectiveness and accuracy of the recursive Bayesian KF method. However, this method required prior knowledge of vehicle parameters (mass, damping, and stiffness), which could limit its practical applicability. In 2017, Odashima et al. [459] proposed an alternative approach utilizing inverse dynamics to estimate track irregularities from car-body accelerations. Their method expressed track geometry as a random walk model, incorporating it into a state equation for inverse analysis using KF. Numerical simulations and full-scale tests demonstrated that the algorithm achieved acceptable estimation accuracy, making it a viable solution for real-world railway track monitoring. These studies highlight the growing role of Kalman filtering and Bayesian estimation in track irregularity detection, providing robust and efficient methodologies for indirect railway health monitoring.

In 2019, DeRosa et al. [460] developed and evaluated model-based methods to identify geometric track irregularities using acceleration data from onboard vehicles traveling along the track. They proposed one frequency-domain-based method and two time-domain-based methods. Their findings indicated that both the frequency-domain method and the KF-based approach were largely unaffected by noise and could reconstruct track irregularities with high accuracy. In 2020, Niu et al. [461] introduced a track irregularity assessment method based on transfer functions and measured carriage-body accelerations. They constructed an autoregressive with exogenous input model and a state-space model using system identification techniques to establish the transfer relationship between track irregularities and carriage-body accelerations. Their analysis revealed that the distributions of track irregularities and carriage-body accelerations did not completely overlap. In 2021, Munoz et al. [462,463] proposed a model-based approach using multiple sensors mounted on a track recording vehicle to estimate lateral and vertical track irregularities. The method leveraged KF techniques for high efficiency and was experimentally validated on a scaled 90 m track. The experimental results demonstrated track irregularity estimation errors of less than 0.7 mm. In 2023, Stoura et al. [72] developed a mobile sensing framework for estimating track irregularities using onboard monitoring. Accelerometers were installed on in-service trains to capture vibration data. The approach combined reduced-order vehicle models with Bayesian inference for joint input-state estimation, with prior updating of vehicle parameters using an unscented KF. The method was validated using field test data from the Swiss Federal Railways network. In 2024, Guo et al. [464] introduced a novel approach incorporating measurement system-based attitude calculation and a model-based unknown input observer estimator. This method recorded the dynamic response of multiple sensors installed on the vehicle and bogie. Vertical and lateral acceleration signals from the vehicle and bogies were integrated into displacements, and a state-space representation of the vehicle suspension model was constructed for inverse dynamic analysis to estimate track irregularities. Laboratory experiments achieved vertical errors of 0.05 mm and lateral errors ranging from 0.5 to 1 mm.

Apart from KF techniques, alternative approaches have been explored for track irregularity estimation. In 2016, Wei et al. [465] proposed using train bogie and car body accelerations processed through a DC filter and a low-pass filter to estimate track irregularities. The track alignments were obtained by double integrating the processed signals. Field tests conducted on Shanghai Metro Line 1 demonstrated the feasibility of this method. Also in 2016, OBrien et al. [466] analyzed bogie vertical accelerations and train angular velocities to determine longitudinal track irregularities. The CE optimization technique was employed to identify track irregularities by fitting the generated vehicle response to real dynamic response of a railway carriage bogie. The proposed approach was verified using a numerical model consisting of a 2D vehicle model and a three-layer track model. Building on this work, in 2017, OBrien et al. [467] developed a method to estimate the longitudinal track profile from measured vehicle inertial response. Accelerometers and gyrometers were installed on a train to record vertical accelerations and angular velocities. The CE optimization technique was then used to derive the track longitudinal profile, with results showing good agreement between the inferred and surveyed profiles. More recently, in 2023, Carrigan and Talbot [468] employed a transfer function in the frequency domain to derive rail roughness spectra from axle-box vibrations. Two key factors: variations in track support stiffness along the track and vibration coupling between wheels, were thoroughly considered. Numerical results indicated that the proposed method effectively accounted for train speed variability. Hao et al. [469] proposed a DL-based approach for track geometry estimation using practical data. Their AM–CNN–GRU model integrates an attention mechanism, a CNN, and a gated recurrent unit. By mapping the train's vertical and lateral accelerations to two vertical track irregularities, they trained a DL model capable of predicting track irregularities under complex influencing factors. Similarly, Pires et al. [470] introduced a data-driven method for estimating geometric track irregularities from railway vehicle data using ML techniques. They found that a deep neural network achieved the best performance, with a root mean squared error (RMSE) of 0.556 ± 0.025 mm. In the same year, Cai et al. [471] proposed using a Bayesian-optimized improved bidirectional long short-term memory neural network model (BO-BiLSTM) for point estimation of track irregularities, using vehicle vertical and lateral accelerations as input. Their method achieved estimation errors approximately 50% lower than those of RNNs. Additionally, they introduced an interval estimation model that combined BO-BiLSTM with Gaussian process regression, ensuring that over 90% of measured values fell within the estimated interval while effectively balancing estimation reliability and uncertainty. In 2024, Zhang et al. [472] refined the signal processing of train vibration sensors, emphasizing the precise placement of sensors on the bogie for more accurate track profile estimation. They found that microelectromechanical system accelerometers installed on the bogie provided the best compromise between proximity to the source and resistance to impulsive noise.

7.3. Vehicle parameter identification

To derive CP response, which have been shown to outperform the vehicle's original accelerations, vehicle parameters are typically assumed to be known. In 2017, Wang et al. [127] used sensors installed on a passing vehicle to identify both its parameters and road roughness. They applied a time-domain method based on Bayesian theory using a particle filter. Numerical results demonstrated that vehicle parameters and road roughness could be estimated with high accuracy and robustness against noise and modeling errors. Field tests using a profiler further validated the effectiveness of the proposed method. In 2019, Shereena and Rao [473] simultaneously identified road roughness and vehicle parameters by coupling an unbiased minimum variance estimator with an optimization scheme. In their study, the unbiased minimum variance estimator allowed for a linear temporal evolution of state variables while incorporating roughness as an unknown input term, thereby eliminating the need for linearization. Several different objective functions were also explored. In 2023, OBrien [338,474] proposed a Bayesian approach for estimating road profiles and vehicle properties using off-bridge data collected from a fleet of passing vehicles, with numerical examples verifying the method's effectiveness. Later, Hu et al. [475] introduced a KF family-based algorithm for simultaneous vehicle parameter identification and road roughness estimation using vehicle response. In this study, the vehicle was modeled as a 3D multibody system, and an internal objective function incorporating vehicle parameters was constructed to match predicted and measured accelerations. A genetic algorithm was employed for optimized solution finding. Field test results showed that road roughness estimates from the proposed method closely aligned with those obtained using a standardized laser International Roughness Index profilometer. In 2022, Zhang et al. [97] proposed a method for estimating vehicle parameters using measured vehicle response. They identified these parameters by analyzing the free response of a vehicle passing over bumps. Subsequently, they derived the vehicle's FRF to wheel contact points from the equations of motion and used this FRF to estimate road roughness. The proposed approach was validated through field tests involving a calibrated vehicle. Later, Zhang et al. [59] further refined this method by incorporating Tikhonov regularization and a shape function technique to update the estimated vehicle FRF. This enhancement helped eliminate singular data caused by the direct computation of the FRF, leading to more stable estimations. Field tests confirmed that the improved method effectively and efficiently identified vehicle parameters.

Since this paper primarily focuses on indirect BHM, only studies conducted by researchers working in this specific direction are reviewed here. For a broader discussion on the estimation of road roughness, track monitoring, and vehicle parameters, several review articles [476–480] have summarized state-of-the-art research and can offer valuable insights to readers.

8. Recent developments and future investigations

8.1. Recent developments

Recently, some key challenges in indirect BHM have emerged, and new approaches have been developed to update state-of-the-art. This section will introduce these developments to provide key insights for researchers.

8.1.1. Bridge modal parameter identification and modal-based damage detection

Stationary sensing vehicles. As one of the important influencing factors, eliminating the effects of road roughness from vehicle response remains challenging. Recent studies have therefore emphasized the use of stationary vehicles in indirect BHM. When a sensing vehicle is temporarily parked on the bridge, the recorded signals exclude road roughness effects and reflect only the interaction between the vehicle and the bridge. Since this method does not interrupt traffic flow, ongoing vehicles and environmental factors such as wind and ambient noise can provide the necessary excitation to induce bridge vibrations. Under such conditions, the stationary vehicle effectively acts as a movable sensor to capture the bridge's response. Recently, Zhang et al. [481] successfully identified both the natural frequencies and damping ratios of a bridge using the response of a stationary vehicle. In their approach, an initial excitation was provided by a passing vehicle, after which the coupled vehicle–bridge system underwent free vibration. Analytical modeling showed that the stationary vehicle's response contained clear bridge modal information. A customized NExT-mLSCE algorithm was applied to extract modal parameters from noisy signals. Numerical and laboratory experiments confirmed that the method could accurately identify multiple mode frequencies and damping ratios. In addition, such a method was found to be robust against variations in vehicle properties, speeds, and measurement noises, without requiring specially designed test vehicles.

Coherence and entropy analysis. As one of the practical methods for bridge modal parameter identification from vehicle response, coherence and entropy analysis-based methods have been continuously developed, especially for the downstream work, such as damage detection. Such an idea is promising as it can robustly identify bridge-related information from vehicle response, even though the appearance of simultaneously ongoing vehicles is shown. For example, AlGadi et al. [436] proposed a model-free spectral filtering framework using vehicle-independent coherence measures to extract bridge modal frequencies from drive-by data. By suppressing road and vehicle noise without explicit vehicle dynamics knowledge, the method identified up to eight frequencies with high precision, as validated by portable sensor measurements and uncertainty analysis. An indirect monitoring system for detecting bridge foundation scour was proposed by Tola et al. [482] using a train-mounted mobile mapping system. By comparing measured stiffness response with numerical models optimized via cross-entropy algorithms, the method successfully detected scour presence by analyzing displacement differences between healthy and damaged states. Liu et al. [483] presented a novel entropy-based method, STW-HMTFPE, for detecting bridge damage from scanning vehicle contact response without a baseline. By analyzing hierarchical multi-scale time–frequency permutation entropy within a sliding window, the method effectively localized single and multiple damages and remained robust against road roughness.

Spatial modes of 3D bridges. Most existing studies have been investigating methods by assuming the bridge as a simply or continuously supported beam. However, in practical engineering, bridges exist in a 3D space, and there are lanes on the pavements. Vehicles may pass different lanes at different times. Therefore, investigating spatial modes and damage is meaningful in the implementation of indirect BHM in practical engineering. Recently, studies have shown the interest of researchers in exploring 3D vehicles and bridges. The research starts from the mode of 2D bridges. In early 2025, Yang et al. [484] utilized 3D visualization to analyze the space–time variation of modal frequencies in a rectangular plate under vehicle loading. Results showed that frequency variation decreased with higher mode orders due to dynamic stiffening, and vehicle–plate coupling significantly affected short-span bridges, necessitating careful consideration in frequency measurement. For 3D bridges, Li et al. [485] proposed using a two-axle vehicle to scan vertical and flexural–torsional frequencies of 3D thin-walled girder bridges. A signal enhancement approach combining Successive Variational Mode Decomposition and window functions effectively mitigated road roughness noise, achieving frequency identification with less than 5% relative error in numerical investigations. Cai et al. [486] utilized residual contact response of a two-axle vehicle to extract vertical and flexural–torsional frequencies of thin-walled box bridges. Analytical and numerical investigations showed that the method effectively removed vehicle frequency masking and was robust to environmental noise, achieving accurate identification under varying operational conditions. In addition, a theoretical framework was developed by Yang et al. [487] to study the effect of higher-order VBI on torsional-flexural frequencies of thin-walled girders. The study concluded that accurate instantaneous frequency calculation required higher vibration modes, especially for girders with closely spaced modes, as vehicles entangle vertical and torsional-flexural frequencies. Moreover, Cheng et al. [488] presented using an instrumental 3D two-axle passing vehicle to identify spatial mode shapes of 3D bridges. They provided theoretical and numerical investigations in this study, and a hybrid signal processing approach combining VMD and CWT was proposed to extract vertical and lateral flexural–torsional frequencies and reconstruct spatial mode shapes despite the appearance of road roughness. Zhou et al. [489] introduced a 3D VBI framework using an 3D two-axle vehicle to measure spatial mode shapes and localize damage in multi-girder bridges. A hybrid algorithm combining residual CP response, CWT, and modal flexibility curvature indicators was proposed to identify bridge information from vehicle response, enabling the detection of spatial damage across longitudinal and lateral girders under moderate road roughness. Furthermore, Yang et al. [490] presented a general theory for using a four-wheel scanning vehicle to identify vertical and torsional modal properties of thin-walled girders. By exploiting spatial correlations between front and rear wheels, the method separated bridge response to determine damping ratios and recover mode shapes free of damping distortion. Recently, Zhou et al. [491] proposed a method for extracting flexural and torsional mode shapes of bridges using a 3D two-axle vehicle, which was validated by analytical and experimental studies. A multi-peak-spectra idealized filter and CWT were used on residual CP response to effectively mitigate vehicle self-vibrations and road roughness effects during modal identification. Zhu et al. [492] presented a method for identifying bridge modal parameters based on tire pressure variations of a two-axle vehicle. By converting pressure changes to CP displacements and using VMD, the approach eliminated road roughness effects and successfully identified frequencies and mode shapes in field tests on a real 3D bridge.

Researchers have also investigated the effectiveness of indirect BHM for non-beam bridges. These bridges can be quite common in real environments, but have not been studied universally. First, Erduran et al. [493] presented an analytical formulation to prove that natural frequencies of any bridge type could be identified from vehicle vibrations, removing the restriction to beam bridges. Validations on a numerical arch bridge and an experimental cable-stayed bridge confirmed the successful extraction of non-sinusoidal mode shapes and frequencies. In addition, Komarizadehasl et al. [494] proposed an innovative drive-through method using vehicle-mounted MEMS sensors to extract bridge eigenfrequencies during a single crossing. Validated on two cable-stayed bridges in Shanghai, the approach fused data from multiple sensors to improve signal-to-noise ratios, offering a cost-effective and non-intrusive solution for large-scale bridge monitoring.

Time–frequency analysis. As introduced in the previous sections, researchers have noticed that heavy vehicles can amplify the vibration amplitudes. However, at the same time, if the vehicles are heavy, they can induce changes in identified bridge modes. These pose challenges to damage detection as the changes induced by vehicles can shadow the changes caused by damage. Therefore, time-frequent analysis becomes necessary and a hot topic in engineering applications of indirect BHM. Moreover, analyzing TFRs can help with the identification of modal shapes and damping ratios. For example, a comparative analysis of Hilbert and Wavelet Transforms was conducted by Yang and Zhang [495] for identifying bridge damping ratios using a two-axle test vehicle. The study derived estimation formulas and demonstrated through parametric studies that the WT offered superior performance, enabling reliable damping estimation using response from only the first two spans. Qiao et al. [496] introduced a method to extract beam bridge mode shapes using residual response between consecutive vehicle contact points. Two denoising techniques based on complete EEMD were proposed. Results showed that the CEEMDAN-IWT method showed superior performance in attenuating noise and ensuring robust modal identification as it employed an improved wavelet thresholding strategy for denoising high-frequency components. Time–frequency analysis also helps with damage detection. Wang et al. [497] detected bridge bearing damage by analyzing the asymmetry of time-varying frequencies extracted from vehicle response. Using SET and Shannon Entropy, the method quantified spatial asymmetry to identify support degradation, demonstrating robustness against noise and roughness in both numerical simulations and model-scale experiments. A multi-SST method was proposed by Gao et al. [498] to extract time-varying characteristics of VBI systems for damage detection. Numerical and experimental results demonstrated that this time–frequency analysis effectively decomposed non-stationary signals, providing sensitive indicators for identifying local structural damage in bridges.

Automation in modal identification. Currently, even though quite many methods for indirect modal parameter identification are proposed, they commonly require manual operations of engineers, e.g., data processing or identification. With the development of AI, automation in engineering has become a new trend, and it should also be considered in indirect BHM. Recently, a fully autonomous modal analysis approach was presented by Golnary et al. [499] to identify bridge natural frequencies using vehicle acceleration data and subspace state-space system identification. With multi-clustering algorithms and QR decomposition, they developed a robust subspace framework that can filter spurious poles from the stabilization diagram, which were caused by road roughness noise. They validated this framework through both numerical simulations and experimental data. This study provides a paradigm for new studies toward automatic modal identification. Investigating multi-vehicle scenarios, Abuodeh and Redmond [500] optimized system identification for bridge networks using supercomputing and automated postprocessing. Findings suggested that heavier, faster leading vehicles aided frequency extraction, and advanced signal processing, like autonomous peak picking VMD, could overcome challenges posed by road roughness and vehicle suspension effects.

Short while ago, Xu et al. [501] provided a comprehensive theoretical and practical overview of the advanced VSM for bridge modal parameter identification. It systematically covered methodologies for extracting bridge dynamic properties using sensing vehicles, addressing key challenges and providing a foundational reference for the field.

8.1.2. Signal processing and data-driven bridge damage detection

New features by signal processing. The key step for damage detection is to identify DSFs from vehicle response. However, extracting key DSFs typically requires detailed analysis and signal processing. Such features can be related to modal parameters. Recently, researchers have developed new methods to identify DSFs directly from vehicle response in the time or frequency domain. For example, Erduran [502] introduced a damage detection framework based on the vehicle's response to static bridge displacements rather than dynamic parameters. A new damage index, calculated from the amplitude difference at the vehicle's natural frequency, was shown to be robust against road roughness and capable of accurately locating damage in various scenarios. Later, Jiang et al. [503] proposed a drive-by damage identification method that used SVMD on vehicle acceleration response to extract IMFs. The difference in these functions served as a damage indicator, successfully identifying single and multiple damages in both simply supported and continuous bridges, despite road roughness interference.

New damage models. In existing studies, researchers typically assume that the damage (such as cracks) cannot recover automatically. However, such a process can be dynamic in engineering applications, especially for bridges. A typical damage of a bridge under traffic flows is called breathing cracks. As a continuous study of Ref. [415], in a recent work, Wang et al. [504] proposed an LSTM-based model to detect breathing cracks in bridges using CPDV derived from vehicle acceleration. CPDV was then employed as the input variable of a long short-term memory neural network to monitor the damage location and degree of the bridge. Numerical simulations and laboratory experiments demonstrated that the method accurately identified damage locations and degrees, showing robustness against road roughness and varying vehicle speeds. This research study opened a new direction for the indirect BHM.

Semi-supervised/unsupervised learning. Due to the development of AI, automatic learning has become a hot topic in SHM. Identifying the key challenges in supervised learning, semi-supervised/unsupervised learning attracted much attention in recent studies, and such a trend is still on the rise. At the beginning of 2025, Tyler et al. [505] introduced a semi-supervised SHM framework using isolation distributional kernels to classify bridge damage from vehicle acceleration data. Validated through simulations and laboratory experiments, the method offered efficient, linear runtime complexity and effectively handled limited datasets while providing accurate severity quantization. As a commonly utilized unsupervised learning algorithm, the autoencoder is still well utilized in recent developments. For instance, Bernardini et al. [506] proposed a damage detection method for steel truss railway bridges using CWT and sparse autoencoders on bogie vertical accelerations. Simulations of a Warren truss bridge demonstrated the method's ability to assess health status effectively using batches of train transits, even under varying speeds and track irregularities. Later, they combined CWT with multiple sparse autoencoders to detect and localize damage in steel truss railway bridges [507]. Investigations using a calibrated FE model revealed that utilizing vertical accelerations from both leading bogies significantly improved localization performance compared to single-signal approaches. By regarding BHM as an unsupervised semantic segmentation, Hamedani et al. [508] proposed using the matrix profile to detect anomalies in bridge acceleration time series collected from passing vehicles. Validated on the Old ADA Bridge in Japan, the method successfully detected damage using limited datasets without requiring prior supervised learning.

Optimal feature selection. For automatic learning methods, the key assignment is to identify the sensitive features in input (e.g., accelerations, frequency spectrum, and so on). If one can successfully locate the features related to bridges, damage detection can become efficient. For locating the optimal features, Corbally et al. [509] proposed a novel anomaly detection method that uses knowledge transfer from a calibrated numerical model to optimize feature selection via the binary slime mould algorithm. By training a one-class SVM on selected features, the framework successfully identifies damage in experimental VBI models, outperforming traditional non-transfer methods. The authors have also evaluated feature engineering approaches for supervised bridge health monitoring using vehicle signals, comparing filter-based and wrapper-based feature selection methods [510]. Results from simulations and experiments demonstrated that wrapper-based selection improved damage classification accuracy by 10%–20%, achieving over 90% performance when combined with bandpass filtering.

Interpretation and capability optimization of learning models. To better understand how DL models are addressing features and generating outputs, researchers have tried to represent the latent outputs of neural networks. For example, using deep learning and knowledge distillation, Peng et al. [511] extracted interpretable DSFs from drive-by measurements using advanced deep learning and knowledge distillation techniques. They analyzed network outputs and theoretical derivations to show that low-frequency driving speed-related components deserve more attention for damage detection than traditional bridge modal vibration components. In addition, when DL techniques are utilized, there are quite a few hyperparameters to modify. Fine-tuning on hyperparameters and network design may be required to achieve the maximum capability of the DL models. Fernandes et al. [512] presented a methodology for classifying multiple early-stage damage types, including cracks, bearing device damage, and scour, in railway bridges using vehicle response. A two-step approach, incorporating min–max normalization preprocessing, dimensionality through piecewise aggregate approximation, and damage-sensitive feature extraction using CNNs. Bayesian optimization was employed to select the CNN architecture. Results indicated high classification accuracy and robustness against environmental and operational variabilities. In addition, Yan et al. [513] integrated the VSM with a parallel CNN to detect bridge damage using fused time-domain and frequency-domain features. Numerical and experimental validations showed the model was insensitive to measurement noise, maintaining low detection errors even under high noise conditions.

8.1.3. Crowdsensing and fleet monitoring

To minimize the cost in health monitoring of the bridge, the crowdsensing techniques employed in indirect BHM. It can be divided into two groups: participatory and opportunistic crowdsensing. Participatory Crowdsensing (PCS) demands active user involvement. Participants must manually run apps, input data, or capture specific observations. It yields high-quality, contextual data but requires incentives to motivate users for the conscious effort involved. Instead, opportunistic crowdsensing is passive and automatic. It collects data continuously in the background using smart device sensors (GPS, etc.) without user input. It is ideal for large-scale, continuous monitoring (like traffic) but must manage high data volume and power consumption. Crowdsensing provides a good strategy to employ response of multiple vehicles on bridges for indirect BHM. Recently, Talebi-kalaleh et al. [514] presented a crowdsensing framework using a sparse network of random vehicles to predict bridge response and identify modal characteristics. By estimating response at virtual fixed nodes and using residual contact-point data, the framework accurately identified modes and predicted response despite high data missing rates and noise. Moreover, Zeng et al. [515] proposed a multibridge inference SHM framework that used drive-by crowdsensing to monitor multiple bridges simultaneously at the network level. By comparing MFCC features and KL Divergence across the network, MISHM identified structural changes with enhanced fault tolerance and scalability for smart city infrastructure.

Another strategy is called fleet monitoring, which involves using the response of a fleet of vehicles to mitigate influence factors, such as road roughness and specific vehicle information. For example, He and Yang [516] proposed a three-step procedure that integrated generalized Kalman filtering and compressive sensing to identify high-resolution bridge mode shapes from multi-vehicle response. The method retrieved CP displacements and reconstructed sparse response matrices, achieving high spatial resolution and effectively removing pavement irregularity effects in numerical demonstrations. In their study, no more than four test vehicles are theoretically needed to reconstruct the vibration component of a mode shape, even though more test vehicles are recommended to enhance the robustness of mode shape reconstruction. Lately, a fleet monitoring approach was developed by Ren et al. [517] to detect bridge damage by calculating bridge influence lines from vehicle accelerations using the inverse Newmark-beta method. Two proposed damage indicators based on the Moving Reference Influence Line effectively detected stiffness loss and mitigated measurement noise through data aggregation from the vehicle fleet.

8.1.4. Robots and smartphones

Robots with wheels can be installed with multiple types of sensors, such as LiDAR, GPS, gyroscope, etc. For monitoring bridges, vibrations can be one of the essential resources to evaluate the condition of the bridge. Since those sensors are installed on the robot instead of the bridge, such methods can be included in the scope of indirect BHM. In 2025, Luleci et al. [518] validated a drive-by monitoring methodology using a mobile robot equipped with sensors, applying frequency-domain filtering with adjacent road data to isolate bridge vibrations. Experiments on a real-world bridge demonstrated precise mode identification, establishing the robot's capability for scalable, local assessments in bridge networks. As an essential part of crowdsensing, vibrations collected by smartphones can contain information related to bridges when they are installed on vehicles. As an illustration, Dabbaghchian et al. [519] introduced a quality metric for crowdsourced smartphone-vehicle trip data to improve bridge modal property estimation. Using a Convolutional Neural Network to filter low-quality trips based on their impact on aggregated mode shapes, the method significantly increased the modal assurance criterion in blind aggregation scenarios. In addition, Peng et al. [520] proposed a method to identify vehicle-road CP response using smartphone sensors with unknown vehicle parameters. By incorporating a physics-informed constraint that front and rear tires experience the same road profile, the optimization model robustly estimated response, improving the feasibility of city-level infrastructure monitoring. Smartphones can be regarded as a replacement for onboard sensors on vehicles.

8.1.5. Railway and track monitoring

Even though the monitoring of railways and tracks is sometimes not directly related to bridges, the developments in this area can provide new insights for indirect BHM when they both utilize the response of passing vehicles (trains specifically for railway). Therefore, such studies are included in this section. There have been advancements both in theories and data-driven methods recently. Wang et al. [521] proposed a method for detecting spatial offsets in high-speed railway bridges by fusing multi-source data from inspection trains. Using Dung Beetle Optimizer-Variational Mode Decomposition and LSTM networks, the approach effectively predicted spatial settlement, with reliability confirmed through numerical models and actual measurement data. Later, Wang et al. [522] introduced a drive-by method for detecting interlayer damage in heavy-haul railway bridges using virtual CP response to reduce irregularity effects. By introducing a Hilbert-transform-based indicator and considering sleeper passing frequency, the method effectively located damage across various speeds and vehicle masses in spatial track–bridge systems. Stoura et al. [523] proposed an indirect monitoring approach to identify railway bridge frequencies using only train acceleration data, which eliminated the need for direct force measurements. The method employed a Bayesian filter to estimate contact forces and subspace identification for modal analysis, showing good agreement with reference values in simulations and field tests. For the development in track monitoring, Ghiasi and Malekjafarian [524] used a data-driven framework to detect railway track maintenance needs from in-service train acceleration data. By extracting time, frequency, and time–frequency features and selecting them via ANOVA, a Cascade Feed-Forward Neural Network classified maintenance activities like tamping and surfacing with 95% accuracy. Later, an unsupervised domain adaptation framework was proposed by Ghiasi et al. [525] for monitoring railway track geometry using high-speed train acceleration data. By employing progressive distribution alignment with label correction, the method transferred diagnostic models between different railway lines without target labels, achieving significantly higher defect detection accuracy than traditional supervised approaches.

8.2. Future investigations

Indirect BHM presents a promising and cost-effective alternative to traditional inspection methods, particularly because it does not require dedicated sensor installation or traffic pauses. Although a substantial number of studies regarding indirect BHM have been conducted in the last years, its practical implementation still faces several unresolved challenges that merit further investigation and development. These challenges involve both methodological limitations and real-world uncertainties that can hinder accurate and reliable damage detection. This section will highlight current challenges and introduce future investigation directions based on discussions.

Influence of the VBI process. A fundamental aspect of indirect BHM is its dependence on the VBI process. Many existing studies rely on heavy vehicles to amplify excitations applied to bridges and improve the detectability of modal parameters. These approaches often assume that the vehicle does not significantly influence the bridge's structural state. In practice, however, heavy vehicles may induce significant time-varying behavior in the VBI system, making it difficult to distinguish between bridge response due to damage and those caused by the presence of the vehicle itself. To address this, future research should explore how different vehicle types, particularly light versus heavy vehicles, affect the fidelity of extracted modal parameters and the sensitivity of damage indicators. When light vehicles are utilized, the bridge may lack fruitful sources of excitations, so its vibration amplitude will decrease. External excitations, such as tap-scanning, using shakers, and fleet monitoring, have great potential in future explorations. Instead, when heavy vehicles are utilized, extracting time-varying modal parameters using time–frequency analysis or employing sensitive data-driven methods may provide new insights for damage detection.

Consideration of ongoing traffic. Closely related is the challenge of simultaneously ongoing traffic and its dual role in indirect BHM. Studies have shown that ongoing traffic can contribute positively by introducing additional energy into bridge vibrations. However, both moving and stationary vehicles on a bridge can introduce variations in the extracted modal parameters, potentially masking damage-induced changes. Therefore, future research should carefully examine both the positive and negative effects of ongoing traffic to improve the reliability of indirect BHM. It is particularly important to investigate how to separate structural information from traffic-induced variability, especially under congested traffic conditions, which may introduce complex and overlapping vibrations. To reduce the influence of ongoing traffic, one promising solution is to slightly control traffic flows (e.g., allowing 1–2 light vehicles), which can ensure excitation resources for the bridge and will not induce great changes in structural state. As another potential method, indirect BHM can be combined with other techniques, such as computer vision, to learn traffic patterns. Cameras on bridges can be utilized to isolate periods where the sensing vehicle domains the traffic on the bridge, which can reduce the influence of other ongoing traffic.

Practical bridge modeling. As shown in recent developments, researchers start to build more precise bridge models, such as in a 3D space. To make indirect BHM practical, this trend will continue and deserves further investigation in future years. Damage detection for 3D bridges using vehicle response also has great potential to provide new insights for indirect BHM. For damage identification, a technical challenge lies in the treatment of boundary conditions in model-based methods. Real-world supports are often complex and difficult to represent using idealized pinned or fixed assumptions. In recent studies, elastic and viscoelastic boundary models have been introduced to better capture practical support behavior. Despite these efforts, accurately modeling and identifying boundary conditions remains a significant challenge. Future research should focus on developing hybrid modeling strategies, using model updating techniques, and incorporating multiple operating scenarios to refine boundary representations. Addressing this issue will improve the reliability and generalizability of indirect BHM in real bridge applications.

New bridge types. Moreover, existing studies have primarily focused on conventional girder bridges with simplified assumptions. Other bridge types, such as arch, truss, cable-stayed, and suspension bridges, have unique structural dynamics that may interact with vehicle-induced response in fundamentally different ways. Tailored monitoring strategies and modeling approaches are needed to extend indirect BHM to broader types of bridge structures. Moreover, while most studies on indirect BHM focus on road and railway bridges, footbridges, which constitute an essential part of modern transportation networks, deserve equal attention. The increasing use of micro-mobility vehicles, such as bicycles and scooters, and moving human beings with sensors on footbridges presents an opportunity for footbridge health monitoring. Exploring how these lightweight vehicles and pedestrians can contribute to structural assessments is an important direction for future research.

Uncertainty analysis. Incorporating real-world uncertainty remains a critical task in advancing indirect BHM. Environmental influences such as temperature fluctuations, variable loading conditions, and wind effects, along with gradual changes in vehicle properties (e.g., tire stiffness/damping or suspension degradation), can all affect system behavior. Probabilistic modeling and uncertainty quantification should be integrated into the monitoring framework to increase reliability under these diverse conditions. For example, future studies are expected to build in-deterministic models for bridge modal parameters and damage conditions, which are more meaningful for engineers to make decisions on maintenance. Wind-induced effects, in particular, represent an important yet underexplored factor in indirect BHM. Wind can introduce additional excitations through buffeting, vortex shedding, and aerodynamic forces, which may enhance vibration amplitudes but also introduce nonstationary and variable dynamic response. These effects can obscure structural changes, complicating damage detection. Future work may consider modeling aerodynamic forces explicitly and investigating their impact on VBI systems and modal identification accuracy.

Big data for data-driven methods. Meanwhile, the growing adoption of data-driven methods brings both new opportunities and notable limitations. These approaches typically require large datasets for effective training. In addition, for supervised learning, labeled data, especially for damaged structural states, are scarce in practice. Acquiring sufficient training data while minimizing reliance on labeled samples will present significant challenges going forward. For data collection, future studies may consider employing public transportation systems, such as city buses that cross numerous bridges year-round, or collaborating with taxi companies to extract onboard sensor or smartphone data. Combining GPS and acceleration measurements can assist in localizing and monitoring individual bridges. To reduce dependence on labeled data, techniques such as transfer learning, population-based SHM, and the use of synthetic datasets generated from digital twins may help bridge this gap. In addition, semi-supervised/unsupervised learning methods capable of identifying DSFs directly from unlabeled data hold strong potential, particularly for continuous, large-scale monitoring applications.

Advanced sensing using robots, smartphones, and IoT devices for crowdsensing. Advancements in mobile sensing platforms, particularly robots, smartphones, and IoT devices, have introduced practical, low-cost solutions for implementing indirect BHM. Robots can be equipped with a variety of sensors, such as LiDAR, GPS, and gyroscopes, and can provide valuable information about infrastructures, including bridges. Extracting bridge-related information indirectly from robotic data holds great potential for future research. Furthermore, with ongoing hardware developments, edge computing capabilities within robots are becoming feasible and may offer new insights for indirect BHM. At the same time, other smart devices, such as smartphones, wearable sensors (e.g., smartwatches, glasses), and IoT nodes, can capture data relevant to bridge health conditions. Mining meaningful structural information from their routine operating data presents new opportunities for indirect BHM. Moreover, robots and smart devices can collect multimodal data, integrating images, videos, text, and vibration signals using large language models within a unified framework offers promising directions for future developments.

Field tests. Despite the growing interest in indirect BHM, many current methods have been validated only through simulations or controlled laboratory tests. Real-world field deployment introduces additional noise sources, environmental variations, and operational constraints that are difficult to replicate in experimental settings. In addition, several assumptions made in current methods may not hold in practical applications. For instance, even experienced engineers may find it difficult to drive test vehicles in a perfectly straight line, and vehicle speed may fluctuate during bridge crossings. To ensure practical applicability, future research must place greater emphasis on field validation to test the robustness and scalability of proposed methods under realistic conditions (such as variations in driving speed and curved vehicle trajectories).

9. Conclusions

This paper presents a comprehensive review of indirect BHM using vehicle response over the past years. Since the proposal of this method in 2004, numerous studies have been conducted by researchers worldwide. The indirect method offers a significantly more cost-effective alternative to traditional bridge monitoring techniques, as it requires only a few sensors installed on passing vehicles. As a result, interest in this method has grown, particularly in recent years. This review provides an in-depth analysis of various aspects of indirect BHM, including utilized VBI models, bibliometric analysis, advancements in indirect modal parameter identification and damage detection, related investigations leveraging vehicle response, and recent developments. Existing technologies and ongoing challenges are carefully discussed to support researchers in this field. Based on the findings from this survey and the authors' experience, the following concluding remarks are presented:

(1) Over the past three years, there has been a significant increase in journal publications focused on indirect BHM using vehicle response. In particular, studies on CP response between vehicles and bridges, as well as data-driven approaches, have gained considerable momentum and popularity within the scientific community. Beyond fundamental research, such as indirect modal parameter identification, researchers have increasingly shifted their attention toward downstream applications, including bridge damage detection and residual life prediction. This trend highlights the growing interest in advancing indirect BHM methodologies toward more practical and predictive maintenance solutions.

(2) Researchers have extensively investigated various VBI models for indirect BHM. A wide range of vehicle models, including quarter-car, half-car, train, and single-axle configurations, have been thoroughly explored. Additionally, bridge models have evolved from simple line and planar representations to more advanced 3D models. Recent developments have introduced full-car vehicle models and 3D bridge structures, making the simulations more realistic and closely aligned with actual VBI systems in engineering practice.
(3) Many methods have been proposed to extract bridge modal parameters from vehicle response, with a strong emphasis on indirect bridge frequency identification, as it serves as the foundation for determining bridge mode shapes and damping ratios. The effectiveness of indirect bridge modal parameter identification has been robustly validated through numerical simulations, laboratory experiments, and field tests. Frequency changes can trigger an early warning as a first level of structural identification and further combined with local sensing approaches.
(4) One major challenge in extracting bridge modal parameters from vehicle response is the interference caused by the vehicle's own dynamic characteristics. This issue can be significantly mitigated by employing CP response, BPFs, signal processing techniques such as VMD and EMD, as well as modifying vehicle parameters.
(5) Another key obstacle in bridge modal parameter identification from vehicle vibrations is the influence of road roughness. Researchers have explored various strategies to reduce its impact, including leveraging residual response from connected vehicles or multiple vehicle runs, utilizing vehicle resting periods, applying crowdsensing techniques, incorporating ongoing traffic, and introducing active excitations.
(6) The signals collected by passing vehicles, such as accelerations, and displacements, can be used for bridge damage detection. However, these methods typically require a high signal-to-noise ratio and are susceptible to contamination from road roughness, environmental noise, and unstable vehicle parameters in real-world engineering applications. Additionally, indirectly identified bridge modal parameters can serve as indicators of bridge damage, but they may lack sensitivity to local damage.
(7) Advancements have emphasized the use of data-driven approaches for indirect bridge damage detection, demonstrating their effectiveness and sensitivity to local damage. However, supervised and semi-supervised ML techniques often require labeled data from damaged scenarios, which are scarce in engineering practice. In contrast, unsupervised learning can extract meaningful patterns from data without the need for labeled examples. Several numerical and experimental studies have validated the feasibility of indirect damage detection and quantification using these techniques.
(8) Related investigations, such as road roughness estimation, track monitoring, and vehicle parameter identification, play a supportive role in indirect BHM and are considered foundational research. Specifically, accurate road roughness and track irregularity estimation can help mitigate their adverse effects on bridge information extraction, while precise vehicle parameter identification is often essential for deriving reliable CP response.
(9) Recent developments have explored advanced methods for bridge modal parameter identification and damage detection, with particular attention to spatial mode extraction, automation, new damage models, crowdsensing, and the use of robots and smartphones. Given the significant challenges in practical applications, several promising directions for future investigation are proposed.

CRediT authorship contribution statement

Zhenkun Li: Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Formal analysis, Conceptualization. **Weiwei Lin:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Formal analysis, Conceptualization. **Chul-Woo Kim:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Maria Pina Limongelli:** Writing – review & editing, Formal analysis, Conceptualization. **Eleni Chatzi:** Writing – review & editing, Formal analysis, Conceptualization.

Declaration of competing interest

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

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Data availability

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