Rapid influence line identification for bridges using dynamic responses induced by two passages of a two-axle vehicle

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ABSTRACT: Due to the dynamic fluctuations caused by vehicle-bridge interaction and road roughness, the influence line (IL) cannot be obtained directly from bridge responses. This paper proposes a rapid method for identifying bridge IL using bridge dynamic responses. Initially, analytical solutions for the IL of a simply supported bridge are presented. To address dynamic fluctuations, empirical mode decomposition is utilized to decompose bridge responses into intrinsic mode functions to approximate quasi-static response. Subsequently, the equations based on residual bridge responses induced by forward and reverse passages, which can automatically remove the scale error of IMFs, are introduced to calculate the bridge's IL at discrete points. Furthermore, cubic spline interpolation, with boundary conditions, is used to obtain the complete IL. Numerical simulations, incorporating a two-axle vehicle and a simply supported bridge, are conducted to verify the effectiveness of the proposed method. Results show a close match between identified IL and analytical results.

1 INTRODUCTION

Bridge structures have played a crucial role in enhancing the efficiency of transportation. Nevertheless, recent studies have highlighted issues related to the degradation and aging of existing bridge systems (Li et al., 2023b, 2024b), raising concerns about potential threats to transportational safety. The bridge influence line (IL), considered a fundamental characteristic, serves as a valuable source of information regarding a bridge's health, load-carrying capacity, and weigh-in-motion system. This aspect has garnered significant attention from scholars (Zheng et al., 2022). The quasi-static nature of IL contributes to its high signal-tonoise ratios. Furthermore, the determination of IL typically involves only one sensor at the measurement point, making the assessment of bridge conditions more economically viable.

The structural IL is closely associated with the quasi-static response resulting from moving loads. When a unit of concentrated force moves along the structure, the response at a specific measurement point, encompassing displacements, strains, and rotation angles, can be defined as the IL at that point. In the context of bridges, IL identification can be categorized into two methods: static loading and vehicle loading (Deng et al., 2023). In the former, the bridge is divided into elements, and a known concentrated force is sequentially applied to all nodes. The discrete ILs at all nodes can then be obtained by normalizing the bridge's quasi-static response with the force value. While intuitive, this method can be labor-intensive and time-consuming in practical engineering applications. The latter method, the vehicle loading approach, is more commonly employed due to its

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efficiency and convenience. Responses at specific points on the bridge due to the passage of a calibration vehicle are collected to identify corresponding ILs. Calibration vehicle parameters, such as axle weights, distance, and counts, are typically measured meticulously before the field test. Following the extraction of ILs from bridge responses, the bridge's condition can be assessed based on visual observations, IL variations, or direct stiffness estimation (Ge et al., 2023). However, during the vehicle's passage, the response recorded by the bridge is influenced by vehicle-bridge interaction (VBI) rather than static moving loads, especially when considering road roughness (Li et al., 2024a; Xu et al., 2024). This introduces challenges to the identification of ILs for bridges when utilizing vehicle loading method.

In the last decades, considerable efforts have been devoted to identifying ILs from bridge responses. Recognizing that bridge response can be constructed by the superposition of multiple weighted bridge ILs, Hirchan and Chajes (2005) proposed a method in 2005 to identify ILs by superposing weighted bridge responses, utilizing two passages of vehicles with different axle weights. In 2006, OBrien et al. (2006) introduced a least squares method for extracting bridge ILs from measured responses of a bridge due to multiple-axle vehicular passages. However, due to VBI effects and environmental noise, the extracted ILs may deviate from the real one. In an attempt to address sensitivity to perturbations, Ieng (2015) proposed a Maximum Likelihood Estimation (MLE)-based algorithm in 2015, and the effectiveness of this method was verified on the Millau Viaduct with weigh-in-motion devices. Additionally, the author suggested fusing IL identification results from multiple calibration vehicles to enhance accuracy. Assuming constant vehicle axle loadings and invariant speed, Chen et al. (2015) established the relationship between the vehicle loading matrix, IL vector, and bridge response vector in 2015. However, dynamic fluctuations can easily influence bridge responses. To mitigate this issue, Tikhonov regularization was applied to penalize influence coefficients, and a moving average filter was employed to suppress bridge response fluctuations (Chen et al., 2016). In 2017, Wang et al. (2017) proposed a fitting algorithm using piecewise polynomials and harmonic sinusoids based on theoretical solutions of bridge ILs under different boundary conditions and observations of bridge vibrations. They found that the bridge's dynamic responses could be separated into dynamic fluctuation and quasi-static parts. The method was then verified by numerical simulations including different types of bridges, and the superior capability was observed compared to the direct inverse calculation method. These studies underscore the importance of removing dynamic fluctuations to prevent errors in bridge IL identification. Additionally, addressing the ill-posed inverse problem for the vehicle loading matrix in direct inverse calculation methods can be crucial. Recently, it has been found that empirical mode decomposition (EMD) can be an effective tool for extracting the quasi-static part from the bridge's dynamic responses (Zheng et al., 2020). However, this study did not include the effects of road roughness, which was demonstrated significant in the VBI process and typically was not ignorable in engineering applications (Lan et al., 2023, 2024; Xu et al., 2023). EMD can decompose signals without any prior knowledge of the signal as well as the VBI system and therefore can be potential for automatic quasi-static extraction from the bridge's dynamic responses. Furthermore, existing methods typically require complex computations, which may be difficult for engineers to apply in practical applications. Therefore, a relatively easy-to-operate and robust solution is imperative.

This paper proposes a rapid bridge IL identification approach using bridge dynamic responses during two passages of a two-axle vehicle. Firstly, the analytical IL of a simply supported bridge is introduced. Then, after the bridge's dynamic responses due to VBI and road roughness in the forward and reverse passages are obtained, the EMD is employed to eliminate the fluctuation part in the signal and extract the approximate quasi-static responses of the bridge. Third, equations based on residual bridge responses for bridge IL identification are further derived, which can automatically eliminate the scale error caused by the EMD and avoid the calculation of the inverse of the vehicle loading matrix. The discrete IL points can further be obtained. Finally, by combining the boundary conditions, the cubic spline interpolation is utilized to obtain the entire bridge IL. Numerical simulations including a two-axle vehicle and a simply supported bridge are performed to verify the proposed method, and different influence factors, such as vehicle gravity center positions, vehicle speeds, measurement points, road roughness classes, and environmental noises are examined. It is worth noting that in this study, the bridge's displacement IL is the object of our investigations. The remainder of this paper is organized as follows. Section 2 introduces the theoretical foundations for

bridge IL identification using its dynamic responses under two passages. Section 3 presents numerical simulations including two case studies to verify the proposed method. Finally, this paper is concluded in Section 4.

2 THEORETICAL FOUNDATION

In this section, the analytical solutions for the influence line of a simply supported beam are first introduced, which serves as the ground truth for verifying the IL identification in this work. Then, theories for identifying the IL using two passages of a two-axle vehicle are introduced.

2.1 Theoretical influence line

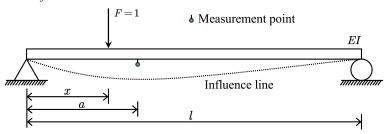


Figure 1. Analytical influence line.

As is defined, the influence line denotes the responses of one position under the moving quasistatic unit force. In this work, the identification of displacement IL for bridges is investigated. As shown in Figure 1, when the unit force is applied at x, then the bridge's static response at the measurement point can be obtained accordingly. The analytical solutions for the displacement IL of a simply supported beam are piecewise, as shown in Equation. (1),

$$f(x) = \begin{cases} \frac{(a-l)x^3 + (a^3 - 3la^2 + 2l^2a)x}{6lEI} & (0 \le x < a) \\ \frac{ax^3 - 3lax^2 + (2l^2a + a^3)x - la^3}{6lEI} & (a \le x \le 1) \end{cases}$$
 (1)

where l represents the span length of the bridge; E means Young's modulus; I is the moment of inertia of its cross-section. Assuming that the left end of the bridge is the origin of the x-axis, we utilize a to denote the distance between the measurement point and the origin. x is the position of the moving unit force. After the above parameters are determined, the bridge's IL can be analytically calculated, as illustrated by the dotted line in Figure 1.

2.2 Proposed influence line identification method

In practical engineering, applying a moving concentrated force to a bridge can be inherently challenging. Consequently, acquiring ILs directly can be challenging. Prior research has proposed using load tests for the identification of bridge ILs, where heavy vehicles are commonly employed to apply moving forces (Deng et al., 2023). However, it has been confirmed that the passage of vehicles induces dynamic VBI rather than quasi-static responses. Additionally, calibration vehicles often feature multiple axles with varying weights, making direct utilization of the obtained bridge responses impractical. This section introduces the IL identification method proposed in this work.

2.2.1 Brief on structural responses induced by vehicle-bridge interaction

When utilizing a vehicle as the excitation source, it becomes essential to consider the effects of vehicle-bridge interaction in the bridge's responses, rather than simply treating the vehicle's axle weights as moving forces. In this study, a two-axle vehicle is employed for bridge IL identification, as illustrated in Figure 2. The vehicle exhibits four degrees of freedom (DOFs), denoted by red arrows: body bounces z_v , body pitching θ_v , front and rear wheel bounces z_{w1}

and z_{w2} . It possesses a body mass m_v , a body moment of inertia I_v , and two-wheel masses m_{w1} and m_{w2} . Also, it features the individual suspension system with stiffness k_{s1} , k_{s2} and damping c_{s1} , c_{s2} , along with the wheel stiffness k_{w1} , k_{w2} and damping c_{w1} , c_{w2} . The vehicle body's center of gravity is determined by d_1 and d_2 , with the axle distance being $d = d_1 + d_2$. When the vehicle is stationary on the bridge, the weights of front and rear axles can be calculated using Equation. (2). However, during the vehicle's passing process, due to the influence of VBI responses and road roughness. P_1 and P_2 will change, causing dynamic bridge responses.

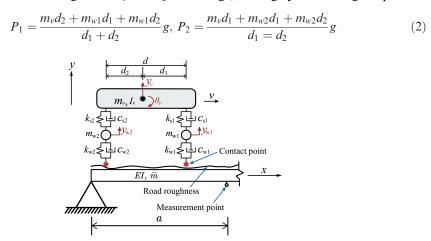


Figure 2. Vehicle-bridge interaction model.

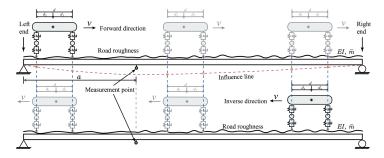


Figure 3. Two passages of the vehicle.

2.2.2 Approximation of quasi-static deflections using EMD decomposition

Typically, the displacement obtained at the measurement point due to VBI is dynamic. In this study, EMD is employed to eliminate the dynamic fluctuation in the acquired displacement. Through EMD, the original bridge deflections under the vehicle's loads can be decomposed into several intrinsic mode functions (IMFs). In this investigation, the quasi-static part of the bridge's displacement exhibits a sinusoidal function as the main trend, while the dynamic part is primarily locally distributed. To accurately capture the quasi-static part, a high maximum number of IMFs is set to fully decompose the signal.

In this work, the vehicle is assumed to pass the bridge at a constant speed in both forward and reverse directions, as shown in Figure 3. Denoting the bridge's deflection when the vehicle is moving forward as $R^f(t)$ and when moving in reverse as $R^r(t)$, EMD is applied to decompose the deflection at the measurement point, and the appropriate IMF is selected. This procedure is represented by Equation. (3).

$$R_{IMF}^{i}(t) = EMD(R^{i}(t)), i = f, r.$$
(3)

After the above operation using EMD, the bridge's dynamic response can be partially eliminated, and the approximated quasi-static deflection can be acquired for later analysis.

2.2.3 Influence line identification

To be uniform with the representation of IL, the independent variable t in Equation. (3) was replaced by the axle's position x on the bridge. Assuming that the vehicle's quasi-static deflection at the measurement point can be approximately obtained in the forward and reverse direction passages by Equation. (3). For $\hat{R}^f_{IMF}(x)$, we can directly replace t in $R^f_{IMF}(t)$ by x = vt. However, for $\hat{R}^r_{IMF}(x)$, the response must be flipped to align the positions of axles, see Equation. (4),

$$\begin{cases} \hat{R}_{IMF}^{f}(x)\underline{x = vt}R_{IMF}^{f}(t) \\ \hat{R}_{IMF}^{r}(x)\underline{x = vt}\operatorname{Flip}\left(R_{IMF}^{f}(t)\right) \end{cases}$$

$$(4)$$

where Flip means flipping the time sequence. As mentioned, assuming the known weights of the moving vehicle's front and rear axles are P_1 and P_2 , respectively, we can obtain the representations of bridge responses in forward and reverse directions, as shown in Equations. (5) and (6).

$$P_2 f(x) + P_1 f(x+d) = \hat{R}^f_{IMF}(x)$$
 (5)

$$P_1 f(x) + P_1 f(x+d) = \hat{R}_{IMF}^r(x)$$
(6)

Here, $\hat{R}_{IMF}^f(x)$ and $\hat{R}_{IMF}^r(x)$ can be directly obtained by sensors installed on the bridge and the EMD. In this paper, the deflection at the measurement point is employed, which can be typically measured by linear variable differential transformers, laser displacement sensors, computer vision techniques, and so on. By subtracting Equation. (6) from Equation. (5), we can get

$$f(x) - f(x+d) = \frac{\hat{R}_{IMF}^{r}(x) - \hat{R}_{IMF}^{f}(x)}{P_1 - P_2}.$$
 (7)

Furthermore, for the identification of IL, the boundary conditions are Equation. (8).

$$f(0) = f(l) = 0 (8)$$

Therefore, by substituting Equation. (8) into Equation. (7), we can get $f(d), f(2d), \dots, f(nd)$, in which n means the integer part of l/d. In engineering, the curve obtained by Equation. (3) cannot match the quasi-static response perfectly due to the influence of road roughness and VBI. When the vehicle's axles pass the same road roughness point, the influence of road roughness can also be weakened using Equation. (7). From Equation. (1), it can be known that the IL is a piecewise cubic function of x. After Equation. (8) and f(0), f(d), f(2d), \dots , f(nd) and f(l) are obtained, cubic spline interpolation can be employed to acquire the IL values at other points of the bridge.

3 NUMERICAL SIMULATIONS

3.1 Parameters of the VBI system

In this section, numerical simulations are employed to verify the effectiveness of the proposed method in this paper. Parameters of the vehicle are as follows: body mass $m_v = 542.5$ kg, body moment of inertia of $I_v = 550$ kg · m², wheel masses $m_{w1} = m_{w2} = 40$ kg, suspension stiffness $k_{s1} = k_{s2} = 1 \times 10^4$ N/m, suspension damping $c_{s1} = c_{s2} = 2 \times 10^3$ N · s/m, wheel stiffness $k_{w1} = k_{w2} = 1.5 \times 10^5$ N/m, and wheel damping $c_{w1} = c_{w2} = 430$ N · s/m. The constant parameters are $d_1 = 1.0$ m and $d_2 = 1.87$ m, and thus the axle distance d = 2.87m. When passing the bridge, the vehicle's speed is set as 2m/s.

The finite element (FE) model of the bridge is shown in Figure 4, it has a length $l=30\mathrm{m}$ and flexural stiffness $EI=2.5\times10^{10}\mathrm{N/m^2}$. In dynamic response generation due to the VBI, its mass of unit length is $=6000\mathrm{kg/m}$. The bridge is divided into 10 elements, and each element has a length of 3.0m. Nine displacement sensors, S1~S9, are installed on the intermediate nodes to collect bridge deflections when the vehicle passes the bridge, as shown in Figure 4.

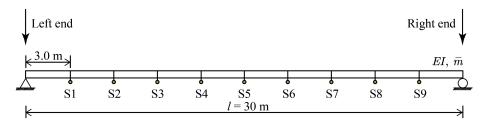


Figure 4. FE model of the bridge and measurement sensors.

During the VBI process, the road roughness plays an important role as it can enhance the amplification of interaction responses (Li et al., 2024c). Also, it can increase dynamic fluctuations of the bridge's response, posing challenges to extracting quasi-static responses from collected signals. In this paper, the road roughness is generated according to ISO 8608 (2016) based on the power spectral density function. Compared to normal road roughness, the pavement of bridges typically is well maintained and therefore can be categorized as very good. In this section, Class A road roughness with $G_d(n_0) = 4 \times 10^{-6}$ m³ is employed. Moreover, in practice, the contact between the vehicle's tire and bridge pavement is an area instead of a point. To eliminate this effect, a moving average filter was utilized to smooth the point-wise road roughness. The length of generated road roughness is 30+2.87+2.87=35.74 m. The vehicle starts to move when its front axle is on the bridge's left end and stops when the rear axle leaves its right end.

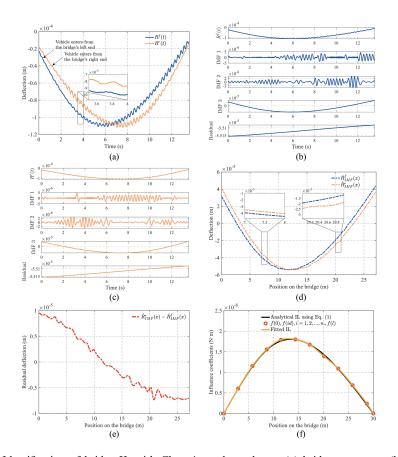


Figure 5. Identification of bridge IL with Class A road roughness: (a) bridge responses, (b) EMD on bridge responses under vehicle's forward passage, (c) EMD on bridge responses under vehicle's reverse passage, (d) approximate quasi-static bridge response using EMD, (e) residual deflection, (f) IL identification.

Case study on IL identification

In engineering applications, road roughness has the potential to amplify the responses of the VBI system (Li et al., 2023a). Consequently, the dynamic fluctuation becomes more pronounced, presenting challenges in identifying the quasi-static responses of the bridge. This section initially delves into Class A road roughness. The bridge's responses, collected by S6 in Figure 4 during the two passages of the vehicle, have been plotted in Figure 5a. It is evident that the influence of road roughness magnifies the dynamic fluctuation in the bridge's responses, particularly noticeable in the middle part of the passage.

Figure 5b and 5c present the results of $R^{f}(t)$ and $R^{r}(t)$ using EMD. We can see that EMD continues to capture the approximate quasi-static response of the bridge, with the utilization of IMF 3 in this case. The extracted approximate quasi-static responses are illustrated in Figure 5d. Despite the dynamic components not being entirely eliminated, as evidenced in the zoom-in figure in Figure 5d. The residual deflection during the two vehicle passages is shown in Figure 5e. It is observed that the residual trend, denoted as $[f(x) - f(x+d)](P_1 - P_2)$, is well-tracked.

The results of bridge IL identification using the proposed approach are illustrated in Figure 5f. Notably, the identified IL (represented by the yellow solid line) closely aligns with the analytical one (denoted by the black solid line). This alignment signifies the effectiveness of the proposed method in identifying the bridge's IL, even in the presence of road roughness within the VBI system. To assess the bridge IL identification results using the proposed method, two commonly used criteria, overall relative error (ORE) and peak relative error (PRE), are utilized (Zheng et al., 2019). They can be calculated using Equation. (9) and (10), respectively,

$$ORE = \frac{\|\phi_{\text{analytical}} - \phi_{\text{identified}}\|_{1}}{\|\phi_{\text{identified}}\|_{1}} \times 100\%$$
(9)

$$ORE = \frac{\|\phi_{\text{analytical}} - \phi_{\text{identified}}\|_{1}}{\|\phi_{\text{identified}}\|_{1}} \times 100\%$$

$$PRE = \frac{\|\phi_{\text{analytical}}\|_{\infty} - \|\phi_{\text{identified}}\|_{\infty}}{\|\phi_{\text{identified}}\|_{\infty}} \times 100\%$$
(10)

where $\phi_{\rm analytical}$ means the analytical IL of the bridge, and $\phi_{\rm identified}$ denotes the bridge IL identified from responses collected by sensors installed on the bridge. In this section, when the Class A road roughness is considered, the two criteria can be obtained as 1.17% and 0.73%. It can be seen that relative errors are typically within 5%, which is acceptable in engineering applications (Zheng et al., 2020).

CONCLUSION AND FUTURE WORK

This paper proposes a rapid IL identification approach for bridges using dynamic responses induced by vehicles. Firstly, the analytical solutions for a simply supported bridge are presented. Then, for the removal of the dynamic fluctuations caused by the interaction between the vehicle and bridge, the EMD is utilized to approximate the quasi-static responses of the bridge. Finally, equations based on residual bridge responses under two vehicular passages for IL identification are derived. Numerical simulations including a two-axle vehicle, a simply supported bridge, and road roughness, are performed to verify the proposed method. Several concluding remarks are drawn below.

- 1) The proposed method can rapidly identify the bridge's IL with good precision when Class A road roughness is considered. ORE and PRE values are within 5% and acceptable in engineering.
- 2) EMD can help to remove the fluctuations in bridge responses with no prior knowledge of the vehicle and bridge even if the road roughness is included in the VBI process.

Even though promising results have been obtained in this research, our future studies will explore IL identification using multiple-axle vehicles and the effectiveness of this method through laboratory experiments and field tests. Also, the spatial effects of the vehicle will be investigated, which extends the bridge IL identification to the bridge influence surface identification.

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REFERENCES

- chen, z.-w., zhu, s., xu, y.-l., li, q., cai, q.-l. (2015). Damage Detection in Long Suspension Bridges Using Stress Influence Lines. *Journal of Bridge Engineering* 20(3): 5014013.
- Chen, Z.W., Cai, Q.L., Li, J. (2016). Stress Influence Line Identification of Long Suspension Bridges Installed with Structural Health Monitoring Systems. *International Journal of Structural Stability and Dynamics* 16(4): 1640023.
- Deng, L., Wu, H., He, W., Ling, T., Liu, G. (2023). Genuine Influence Line and Influence Surface Identification from Measured Bridge Response Considering Vehicular Wheel Loads. *Journal of Bridge Engineering* 28(2): 4022145.
- Ge, L., Koo, K.Y., Wang, M., Brownjohn, J., Dan, D. (2023). Bridge damage detection using precise vision-based displacement influence lines and weigh-in-motion devices: Experimental validation. *Engineering Structures* 288: 116185.
- Hirachan, J., Chajes, M. (2005). Experimental influence lines for bridge evaluation. Bridge Structures 1(4): 405–412.
- Ieng, S.-S. (2015). Bridge Influence Line Estimation for Bridge Weigh-in-Motion System. *Journal of Computing in Civil Engineering* 29(1): 6014006.
- ISO 8608, 2016. Mechanical vibration Road surface profiles Reporting of measured data E, 44.
- Lan, Y., Li, Z., Koski, K., Fülöp, L., Tirkkonen, T., Lin, W. (2023). Bridge frequency identification in city bus monitoring: A coherence-PPI algorithm. *Engineering Structures* 296: 116913.
- Lan, Y., Li, Z., Lin, W. (2024). Physics-guided diagnosis framework for bridge health monitoring using raw vehicle accelerations. *Mechanical Systems and Signal Processing* 206: 110899.
- Li, Z., Lan, Y., Lin, W. (2023a). Indirect damage detection for bridges using sensing and temporarily parked vehicles. *Engineering Structures* 291: 116459.
- Li, Z., Lin, W., Zhang, Y. (2023b). Real-time drive-by bridge damage detection using deep auto-encoder. *Structures* 47: 1167–1181.
- Li, Z., Lan, Y., Feng, K., Lin, W. (2024a). Investigation of time-varying frequencies of two-axle vehicles and bridges during interaction using drive-by methods and improved multisynchrosqueezing transform. *Mechanical Systems and Signal Processing* 220: 111677.
- Li, Z., Lan, Y., Lin, W. (2024b). Footbridge damage detection using smartphone-recorded responses of micromobility and convolutional neural networks. *Automation in Construction* 166: 105587.
- Li, Z., Lan, Y., Lin, W. (2024c). Indirect Frequency Identification of Footbridges with Pedestrians Using the Contact-Point Response of Shared Scooters. *Journal of Bridge Engineering* 29(6): 04024036.
- OBrien, E.J., Quilligan, M.J., Karoumi, R. (2006). Calculating an influence line from direct measurements. Proceedings of the Institution of Civil Engineers: *Bridge Engineering* 159(1): 31–34.
- Wang, N.B., He, L.X., Ren, W.X., Huang, T.L. (2017). Extraction of influence line through a fitting method from bridge dynamic response induced by a passing vehicle. *Engineering Structures* 151: 648–664.
- Xu, H., Wang, M.H., Wang, Z.L., Yang, D.S., Liu, Y.H., Yang, Y.B. (2023). Generation of Surface Roughness Profiles for Inclusion in Vehicle-Bridge Interaction Analysis and Test Application. *International Journal of Structural Stability and Dynamics* 23(8): 2350094.
- Xu, H., Liu, Y.H., Chen, J., Yang, D.S., Yang, Y.B. (2024). Novel formula for determining bridge damping ratio from two wheels of a scanning vehicle by wavelet transform. *Mechanical Systems and Signal Processing* 208: 111026.
- Zheng, X., Yang, D.-H., Yi, T.-H., Li, H.-N. (2019). Development of bridge influence line identification methods based on direct measurement data: A comprehensive review and comparison. *Engineering Structures* 198: 109539.
- Zheng, X., Yang, D.H., Yi, T.H., Li, H.N. (2020). Bridge influence line identification from structural dynamic responses induced by a high-speed vehicle. *Structural Control and Health Monitoring* 27(7): 1–10.
- Zheng, X., Yi, T.-H., Zhong, J.-W., Yang, D.-H. (2022). Rapid Evaluation of Load-Carrying Capacity of Long-Span Bridges Using Limited Testing Vehicles. *Journal of Bridge Engineering* 27(4): 04022008.