

ARTICLE

Drive-By Monitoring of Bridge Support Rotational Stiffness Using Vehicle-Derived Operational Deflection Shape Features

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ABSTRACT: This study proposes an acceleration-based drive-by monitoring framework for extracting bridge operational deflection shape information from vehicle responses alone. A transfer function formulation is developed to reconstruct contact-point bridge accelerations directly from simulated multi-degree-of-freedom vehicle acceleration measurements, followed by band-pass filtering around the first natural frequency and Hilbert transform envelope extraction to obtain spatial amplitude distributions along the bridge span. The framework is evaluated using a coupled vehicle bridge interaction model under both idealised (zero road profile) and realistic (ISO Class A and Class B) conditions, considering healthy and bearing-damaged scenarios across a range of vehicle speeds. The reconstructed responses accurately capture the dominant bridge dynamics and spatial modal behaviour, with the extracted Hilbert transform amplitude envelopes providing smooth operational deflection shape like features that are highly sensitive to reductions in bearing rotational stiffness. Increasing vehicle speed and road roughness reduce damage sensitivity by decreasing spatial resolution and introducing additional variability, yet the damaged bearing condition remains distinguishable across all investigated scenarios. The framework also exhibits good robustness to measurement noise, with extracted spatial features remaining largely unaffected even under low signal-to-noise ratio conditions. Overall, the proposed approach offers a physically consistent and scalable means of indirect bridge monitoring, enabling the extraction of spatially informative structural features from vehicle-only measurements and supporting the development of fleet-based structural health monitoring systems.

KEYWORDS: Drive-by monitoring; operational deflection shape; vehicle bridge interaction; structural health monitoring; bearing damage; Hilbert transform

1 Introduction

Bridges are fundamental components of transport infrastructure, forming critical links that support the safe and efficient movement of people and goods [1,2]. Their performance directly influences economic activity, network resilience, and public safety [3,4]. In recent years, bridge structures have been subjected to increasingly demanding conditions due to rising traffic loads and the effects of climate change, with factors such as temperature fluctuations, flooding, and extreme weather events accelerating the deterioration of structural components. Among these, bridge bearings are particularly vulnerable [5–7], as they play a key role in accommodating movements and transferring loads between the superstructure and substructure. Damage or degradation of bearings can significantly alter the global stiffness and dynamic characteristics of a bridge [8,9], making early detection essential for preventing further deterioration and ensuring long-term serviceability.

Traditionally, bridge condition assessment has relied heavily on visual inspection [10–12]. Although widely used in practice, this approach is inherently limited by its subjective nature, dependence on inspector experience, and restriction to surface-level observations. Hidden defects or early-stage damage, such as gradual stiffness loss in bearings, may therefore go undetected until more severe structural issues arise. To address these shortcomings, vibration-based structural health monitoring (SHM) techniques have been developed [13,14], which utilise measured dynamic responses to infer structural condition [15]. These methods offer improved sensitivity to damage and enable more quantitative assessment than visual inspection. However, their implementation typically requires extensive sensor installations, long-term monitoring infrastructure, and ongoing maintenance, resulting in high costs and logistical demands that make network-scale deployment, particularly across large bridge inventories, difficult to sustain.

In response to these limitations, drive-by monitoring has attracted considerable research interest [16–18]. These methods use instrumented vehicles as mobile sensing platforms to capture bridge responses indirectly during normal crossings, eliminating the need for permanent structural instrumentation [19–21]. By exploiting vehicle bridge interaction (VBI), drive-by techniques offer a cost-effective and scalable alternative for bridge monitoring. A growing body of work has demonstrated the feasibility of extracting bridge dynamic properties, including natural frequencies and damping ratios, from vehicle responses [22–26]. Nevertheless, vehicle signals are influenced not only by the bridge but also by vehicle dynamics, tyre–road interaction, axle configuration, and road roughness, all of which introduce uncertainty and can obscure structural contributions, making reliable damage-sensitive feature extraction challenging [27].

Despite substantial progress in drive-by monitoring, its application to specific structural components, particularly bridge bearings, remains limited. Most existing studies focus on global dynamic indicators such as natural frequencies or statistical response measures, which may lack the sensitivity needed to detect boundary condition changes associated with bearing degradation. There is a limited number of studies that extract spatially informative features directly reflective of structural behaviour in a physically meaningful way. Operational deflection shape (ODS), which describes the spatial deformation pattern of a structure under dynamic excitation [28,29], offer a promising direction in this regard, but conventional ODS estimation requires direct measurements on the structure, limiting its applicability within drive-by frameworks.

To address these challenges, this study proposes an acceleration-based drive-by monitoring framework for extracting vehicle-derived ODS-like features for bridge condition assessment. A transfer function (TF) based formulation is developed to reconstruct contact-point bridge accelerations directly from vehicle axle measurements, without requiring displacement estimation or direct structural instrumentation. The reconstructed signals are subsequently processed through band-pass filtering and Hilbert transform (HT) envelope extraction to obtain smooth spatial amplitude distributions along the bridge span, which serve as physically interpretable proxies for bridge ODS and are sensitive to boundary condition changes such as bearing stiffness reduction.

The novelty of this work lies not in the TF reconstruction itself, which has been established in prior studies, but in its integration with HT envelope extraction to form a vehicle-derived ODS framework for indirect bridge monitoring. Unlike conventional drive-by approaches that primarily yield global modal properties or statistical indicators, the proposed framework recovers spatially informative features from reconstructed contact-point responses, enabling the investigation of support rotational stiffness degradation through changes in spatial response distributions. The framework is evaluated using a coupled VBI model under both idealised and realistic conditions, with systematic investigation of the effects of bearing degradation, vehicle speed, signal noise, and road profile roughness. By combining physics-based signal

reconstruction with spatial feature extraction, this work aims to bridge the gap between drive-by monitoring and component-level damage detection, contributing towards scalable and reliable bridge SHM strategies.

2 Numerical Modelling Framework

2.1 Bridge and Vehicle Dynamic Models

The bridge is modelled as an Euler-Bernoulli beam with a span of 20 m, discretised into 20 finite elements of equal length, as shown in Fig. 1. Each node possesses two degrees of freedom: vertical displacement and rotation. The global mass and stiffness matrices are assembled using standard beam element formulations based on the geometric and material properties summarised in Table 1. Structural damping is neglected in this study. This assumption was adopted to isolate the influence of bearing stiffness on the dynamic response. The support boundary conditions are represented using rotational springs rather than assuming ideal pinned or fixed supports, thereby allowing a continuous transition between these boundary-condition extremes. This formulation provides a convenient and physically interpretable means of modelling changes in bearing rotational stiffness. In the healthy condition, the rotational spring stiffness at both the left and right supports is taken as 100×10^8 N·m/rad. Bearing degradation is subsequently simulated through controlled reductions in support rotational stiffness. Further details of the bridge modelling approach adopted in this study can be found in Li [30].

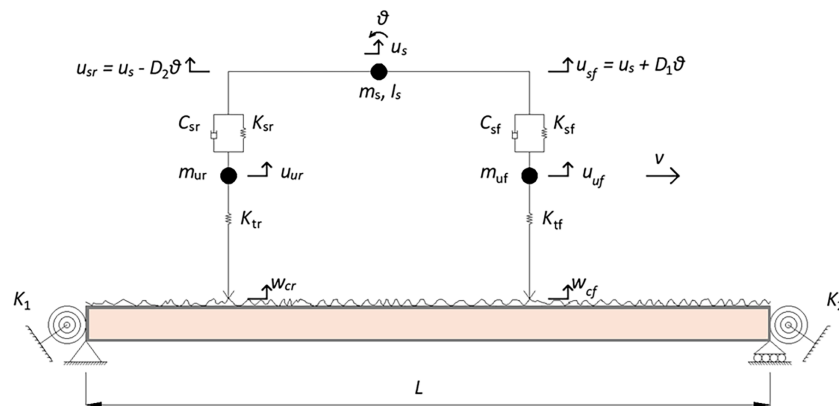


Figure 1: Schematic of the VBI model.

Table 1: Bridge model parameters used in the VBI simulations.

Parameter	Symbol	Value	Unit
Bridge span length	L	20	m
Element length	L_e	1	m
Number of elements	N_e	20	–
Material density	ρ	2500	kg/m ³
Elastic modulus	E	35	GPa
Bridge width	B	15	m
Span-to-depth ratio	L/d	20	–
Bridge depth	d	1	m
Sampling frequency	f_s	250	Hz

(Continued)

Table 1 (continued)

Parameter	Symbol	Value	Unit
Time step	Δt	0.004	s
Structural damping ratio	ξ	0	–

The vehicle is modelled as a two-axle half-car system with four degrees of freedom, comprising the vertical displacement of the sprung mass, pitch rotation of the vehicle body, and the vertical displacements of the front and rear unsprung masses. The suspension and tyre systems are represented using linear springs and dashpots, while the coupling between translational and rotational motions is governed by the axle locations relative to the vehicle's centre of gravity. The resulting four acceleration responses form the input to the TF-based contact-point reconstruction framework. The vehicle parameters used in this study are summarised in Table 2 and are adopted from previous studies [31].

Table 2: Vehicle model parameters used in the VBI simulations.

Parameter	Symbol	Mean Value	Unit
Axle spacing	L_a	4.75	m
Sprung mass	m_s	16,200	kg
Front unsprung mass	m_{uf}	700	kg
Rear unsprung mass	m_{ur}	1100	kg
Pitch inertia	I_s	93,457	kg·m ²
Front suspension stiffness	k_{sf}	400	kN/m
Rear suspension stiffness	k_{sr}	1000	kN/m
Front suspension damping	c_{sf}	10	kN·s/m
Rear suspension damping	c_{sr}	20	kN·s/m
Front tyre stiffness	k_{tf}	1750	kN/m
Rear tyre stiffness	k_{tr}	3500	kN/m
Front tyre damping	c_{tf}	72	kN·s/m
Rear tyre damping	c_{tr}	72	kN·s/m

2.2 Coupled Vehicle-Bridge Interaction Formulation

The coupled VBI system is formulated in the time domain as:

$$M(t) \ddot{u}(t) + C(t) \dot{u}(t) + K(t) u(t) = F(t) \quad (1)$$

where $M(t)$, $C(t)$, and $K(t)$ denote the global mass, damping, and stiffness matrices of the coupled system, respectively; $u(t)$ is the displacement vector; and $F(t)$ represents the external forces arising from tyre-road interaction. The system matrices are time-dependent due to the moving contact points between the vehicle and the bridge. The vehicle subsystem is expressed as:

$$M_v \ddot{u}_v + C_v \dot{u}_v + K_v u_v = F_v \quad (2)$$

while the bridge subsystem is written as:

$$M_b \ddot{u}_b + C_b \dot{u}_b + K_b u_b = F_b \quad (3)$$

The coupling between the vehicle and bridge is introduced through a moving force distribution matrix, which maps the axle forces to the corresponding bridge degrees of freedom according to the instantaneous wheel positions. The coupled vehicle–bridge interaction equations are solved using the Newmark- β time integration method with parameters $\gamma = 0.5$ and $\beta = 0.25$, corresponding to the unconditionally stable average acceleration scheme. Further details of the VBI formulation adopted in this study can be found in previous studies [32].

2.3 Road Surface Profile Generation

Road excitation is incorporated through the tyre-road contact interface and modelled using a spectral representation based on the road roughness power spectral density (PSD). The road roughness PSD is defined as:

$$G_d(n) = G_d(n_0) \left(\frac{n}{n_0} \right)^{-w} \quad (4)$$

where $G_d(n)$ is the displacement PSD at spatial frequency n , $G_d(n_0)$ is the reference PSD value at spatial frequency n_0 , and w is the waviness exponent. The reference PSD is defined according to ISO road classification as:

$$G_d(n_0) = 2^k \times 10^{-6} \quad (5)$$

where k denotes the road class index (A–G). In this study, $k = 4$ and $k = 5$ were adopted to generate standard ISO Class A and Class B road profiles, corresponding to reference PSD values of $16 \times 10^{-6} \text{ m}^3$ and $32 \times 10^{-6} \text{ m}^3$, respectively. Road profiles are generated as a superposition of harmonic components with random phase angles, ensuring a stochastic yet controlled representation of surface roughness. A fixed random seed is used to ensure consistency across simulations. The generated spatial profile is converted into time-domain input using the vehicle speed:

$$r(t) = r(vt) \quad (6)$$

with the corresponding velocity and acceleration inputs obtained through differentiation. Spline interpolation is employed to evaluate the road input at the moving axle locations. An idealised zero-profile case is also considered to isolate the structural response:

$$r(x) = 0 \quad (7)$$

Simulations include approach and departure lengths to ensure stable vehicle dynamics before and after bridge crossing. Multiple constant vehicle speeds are considered to investigate their influence on response characteristics and feature extraction. Further details on ISO-based road profile generation can be found in the relevant standards [33] and previous studies [34].

Fig. 2 illustrates an example of a generated Class A road profile used in the simulations, showing the spatial variation of surface elevation along the vehicle path. The profile exhibits smooth stochastic variations, with elevation amplitudes ranging approximately between -0.02 and 0.02 m , consistent with a low-roughness road surface.

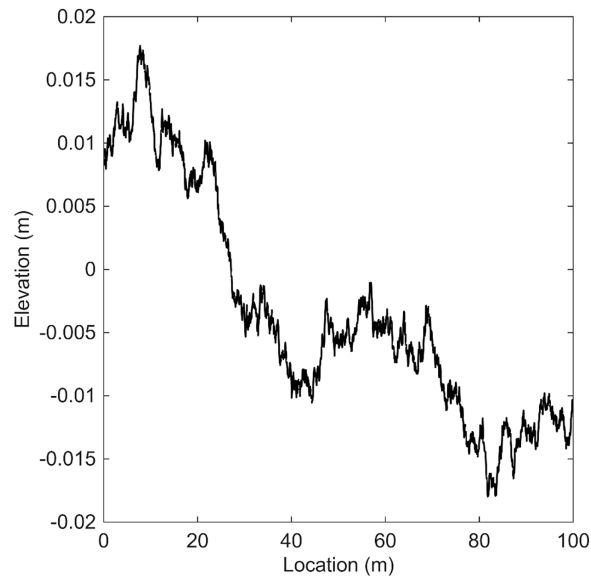


Figure 2: Example of a class A road profile with elevation variations of approximately ± 0.02 m.

2.4 Bearing Deterioration Modelling

Bearing deterioration is modelled through variations in rotational stiffness at the bridge supports. Two rotational springs are introduced at the left and right supports, modifying the global stiffness matrix as:

$$K' = K + K_{rot} \quad (8)$$

here, K is the original stiffness matrix of the bridge model, while K' is the updated stiffness matrix including the contribution of the boundary rotational springs. The matrix K_{rot} is defined by the rotational stiffness values of the left and right supports, K_L and K_R , respectively. The support stiffness values, K_L and K_R , are varied independently over a defined range to simulate both symmetric and asymmetric degradation scenarios. Reduced stiffness represents deteriorated bearing conditions, while higher stiffness corresponds to healthy supports. This formulation enables the investigation of boundary condition changes without introducing local stiffness reductions within the span, thereby isolating the influence of support degradation on the global dynamic response of the bridge.

Fig. 3 illustrates the variation of the first natural frequency as a function of the left and right bearing rotational stiffness. A clear increasing trend is observed, with the fundamental frequency rising from approximately 4.3 Hz at low stiffness values (near 0 N·m/rad) to about 6.4 Hz at high stiffness values (up to 10×10^9 N·m/rad). Lower stiffness values, representing deteriorated bearings, result in reduced natural frequencies, while higher stiffness values correspond to stiffer boundary conditions and increased frequencies. The smooth gradient indicates a consistent sensitivity of the fundamental mode to both symmetric and asymmetric variations in support stiffness.

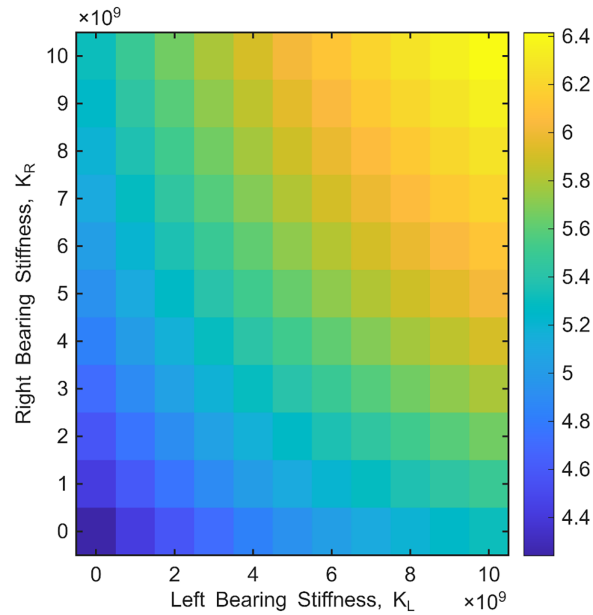


Figure 3: First natural frequency f_1 as a function of left and right bearing rotational stiffness (K_L , K_R) showing an increasing trend with stiffness ($0-10 \times 10^9$ N-m/rad).

3 Methodology

3.1 Vehicle-Derived Contact-Point Acceleration Reconstruction

It should be noted that the present study is based entirely on numerical simulations. The input acceleration signals are obtained from virtual sensors located at the front and rear axles of the vehicle within the coupled VBI model. These vehicle acceleration responses are treated as the only available measurements and serve as inputs to the TF-based reconstruction framework. The reconstructed contact-point responses are subsequently processed using filtering and HT-based envelope extraction to derive vehicle-based ODS-like features for structural condition assessment. The proposed approach reconstructs contact-point bridge responses using only vehicle-borne measurements through a frequency-domain formulation of the half-car model, eliminating the need for direct bridge instrumentation. Starting from the governing equations of the four-degree-of-freedom half-car model, the system is transformed into the frequency domain and expressed in matrix form as:

$$A(\omega)U(\omega) = B(\omega) \quad (9)$$

where A is the frequency-dependent dynamic stiffness matrix, U is the vector of vehicle responses, and B represents the input due to tyre-road interaction. By isolating the first two rows of the system (associated with the sprung mass displacement and pitch rotation) and noting that the corresponding input terms are zero, the body responses can be expressed in terms of the unsprung mass displacements:

$$\{U_s, \Theta\} = A_{ss}^{-1} \cdot A_{su} \cdot \{U_{uf}, U_{ur}\} \quad (10)$$

where A_{ss} and A_{su} are submatrices of the global system matrix. Substituting these expressions into the remaining equations, the contact-point displacements at the front and rear axles (W_{cf} , W_{cr}) can be written in terms of the unsprung mass responses. This results in explicit TF relationships linking the contact-point response to the measured vehicle dynamics:

$$W_c(\omega) = H(\omega) U_u(\omega) \quad (11)$$

where $H(\omega)$ represents the frequency-dependent TF incorporating vehicle mass, suspension, and tyre properties. The corresponding contact-point accelerations are obtained by multiplying by $-(\omega^2)$ in the frequency domain, and the time-domain signals are recovered using inverse Fourier transformation. Hermitian symmetry is enforced to ensure real-valued signals, and a low-pass filter is applied to suppress high-frequency numerical artefacts. Detailed procedures for reconstructing the contact-point response can be found in previous studies [35]. The reconstructed contact-point response contains both bridge-induced and road-induced components. To isolate the bridge contribution, the road-induced component is estimated and removed, yielding a bridge-only contact-point acceleration signal for subsequent analysis.

Fig. 4 compares the reference and TF reconstructed contact-point bridge accelerations along the bridge span for both the front and rear axles. The responses exhibit a clear spatial modulation, with maximum amplitudes occurring near mid-span (approximately 8–12 m) and diminishing towards the supports, consistent with the expected behaviour of the fundamental bridge mode. For the front axle (Fig. 4a), the reference acceleration reaches peak values of approximately $\pm 3 \times 10^{-3} \text{ m/s}^2$, while the TF-reconstructed signal closely follows the overall amplitude envelope, with slightly reduced peak magnitudes (around $\pm 2.5 \times 10^{-3} \text{ m/s}^2$). The reconstructed signal captures the dominant oscillatory pattern and spatial variation, although minor discrepancies are observed in the high-frequency content and local peak amplitudes. A similar trend is observed for the rear axle (Fig. 4b), where the reconstructed response reproduces the general amplitude distribution and phase characteristics of the reference signal. Peak amplitudes are again on the order of $\pm 3 \times 10^{-3} \text{ m/s}^2$ for the reference signal, with the reconstructed signal showing a slightly smoother profile and reduced high-frequency fluctuations. This smoothing effect is attributed to the TF formulation and numerical reconstruction process, which tend to attenuate higher-frequency components. Overall, the TF-based reconstruction demonstrates good agreement with the reference solution in capturing the global dynamic behaviour and spatial envelope of the contact-point acceleration. However, the presence of high-frequency noise and local discrepancies highlights the need for subsequent signal processing (e.g., band-pass filtering and envelope extraction) to enhance the robustness of feature extraction for damage identification.

Fig. 5 presents the comparison between the reference and TF-reconstructed contact-point bridge accelerations after applying a band-pass filter centred on the first natural frequency $f_1 = 4.24 \text{ Hz}$. The filtering is performed over a frequency range of $[3.94, 4.54] \text{ Hz}$, corresponding to a bandwidth of $\pm 0.30 \text{ Hz}$, ensuring effective isolation of the dominant bridge vibration mode. Compared to the unfiltered results (Fig. 4), the signals exhibit a significantly smoother and more coherent oscillatory response, with high-frequency noise and non-structural components effectively suppressed. The filtered signals clearly highlight the fundamental modal behaviour of the bridge. For the front axle (Fig. 5a), the response shows a well-defined spatial modulation, with peak amplitudes occurring near mid-span (approximately 8–12 m). The reference signal reaches amplitudes of approximately ± 2.3 to $\pm 2.5 \times 10^{-3} \text{ m/s}^2$, and the TF-reconstructed signal closely matches both the amplitude and phase of the reference response across the entire span. The agreement is significantly improved relative to the unfiltered case, particularly in terms of peak alignment and reduction of high-frequency fluctuations. A similar trend is observed for the rear axle (Fig. 5b), where the reconstructed signal accurately captures the dominant modal response and spatial distribution. The amplitude remains symmetric about mid-span, with peak values in the range of ± 2.0 to $\pm 2.5 \times 10^{-3} \text{ m/s}^2$. Minor discrepancies are limited to small local variations, indicating that the dominant structural component has been effectively isolated. Overall, the band-pass filtering centred at 4.24 Hz plays a critical role in

enhancing the quality of the reconstructed signals by isolating the fundamental mode and removing non-structural contributions. This significantly improves the agreement between reference and reconstructed responses and provides a robust basis for subsequent envelope extraction and spatial feature analysis.

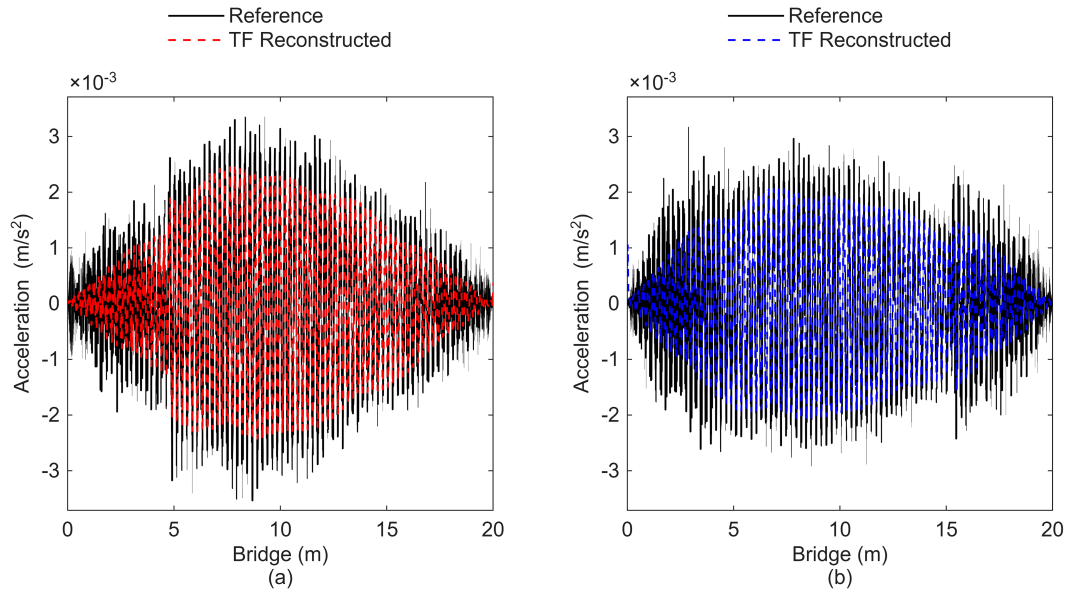


Figure 4: Comparison between reference and TF reconstructed contact-point bridge accelerations without band-pass filtering: (a) front axle; (b) rear axle.

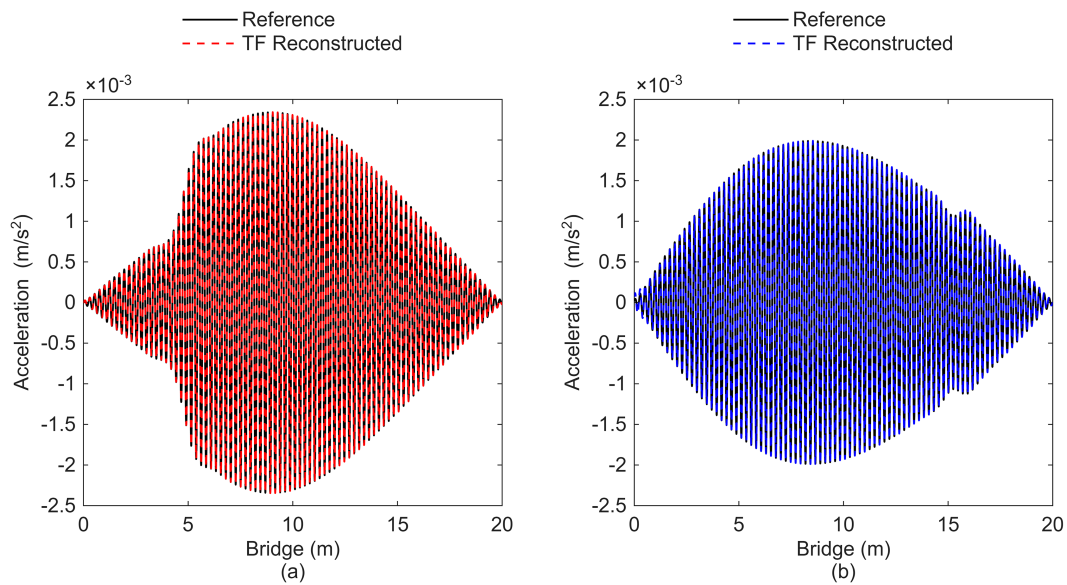


Figure 5: Comparison between reference and TF reconstructed contact-point bridge accelerations after band-pass filtering around the first natural frequency: (a) front axle; (b) rear axle.

3.2 Spatial Feature Extraction and Damage Quantification

To extract structural information from vehicle-derived signals, a unified signal processing framework is applied to the reconstructed contact-point bridge accelerations. Following time-domain simulation, the contact-point responses beneath each axle are first obtained using the TF-based reconstruction approach, which enables estimation of bridge response using vehicle acceleration measurements only. The reconstructed signals are restricted to the time intervals during which each axle is located on the bridge span and are mapped spatially according to the corresponding axle positions. Prior to feature extraction, the signals are mean-removed and band-pass filtered around the dominant bridge modal frequency to isolate the primary structural vibration component while suppressing noise and non-structural contributions. The HT is then applied to the filtered signals to construct the analytic signal [36,37]:

$$z(t) = x(t) + i\mathcal{H}[x(t)] \quad (12)$$

where $x(t)$ is the band-pass-filtered signal and $\mathcal{H}[\cdot]$ denotes the HT. The corresponding amplitude envelope is computed as:

$$A(t) = |z(t)| \quad (13)$$

This envelope represents the instantaneous amplitude of the structural response and provides a smooth, mode-dominated description of the bridge dynamics. As the vehicle traverses the bridge, the time-domain response is transformed into the spatial domain using the relationship:

$$x = vt \quad (14)$$

where x is the spatial coordinate along the bridge and v is the vehicle speed. The extracted amplitude envelopes from the front and rear axles are therefore expressed as functions of bridge position rather than time. To ensure consistency, both responses are interpolated onto a common spatial grid, and a combined spatial response is obtained by averaging the front and rear axle envelopes. This process improves robustness and reduces axle-dependent variability. The resulting spatial amplitude distributions serve as vehicle-derived proxies for the ODS of the bridge. Changes in structural boundary conditions, particularly bearing stiffness degradation, influence both the magnitude and spatial distribution of these ODS-like features. By comparing spatial amplitude distributions under different conditions, damage-sensitive indicators can be identified, where variations in amplitude level and spatial pattern provide insight into changes in support stiffness and overall structural behaviour.

Fig. 6 presents the comparison between the reference and TF-reconstructed HT envelopes of the band-pass filtered contact-point bridge accelerations. The envelopes provide a smooth representation of the spatial variation of the structural response and serve as a proxy for the ODS of the bridge. For the front axle (Fig. 6a), the HT envelope exhibits a clear modal shape, with amplitude increasing from near zero at the supports to a peak of approximately $2.3 \times 10^{-3} \text{ m/s}^2$ at mid-span (around 8–10 m), before decreasing symmetrically towards the opposite support. The TF-reconstructed envelope is nearly indistinguishable from the reference, with a Modal Assurance Criterion (MAC) value of 0.999992, indicating almost perfect agreement in spatial distribution. A similar trend is observed for the rear axle (Fig. 6b), where the envelope also follows the expected fundamental mode shape, with peak amplitudes around $2.0 \times 10^{-3} \text{ m/s}^2$ near mid-span. Minor local deviations are visible around 14–16 m; however, the overall spatial pattern and amplitude distribution are accurately captured, as reflected by the high MAC value of 0.999941. Compared to the acceleration signals (Fig. 5), the HT envelopes provide a significantly smoother and more robust representation of the structural response, effectively removing oscillatory behaviour while preserving spatial characteristics. This highlights

the effectiveness of the combined band-pass filtering and HT in extracting mode-dominant features from the reconstructed signals. Overall, the results demonstrate that the proposed TF-based reconstruction method, when combined with appropriate signal processing, can accurately recover spatial response characteristics of the bridge using vehicle-only measurements. The near-unity MAC values confirm that the method is capable of reliably reproducing ODS-like features, providing a strong basis for damage detection through changes in spatial amplitude distributions.

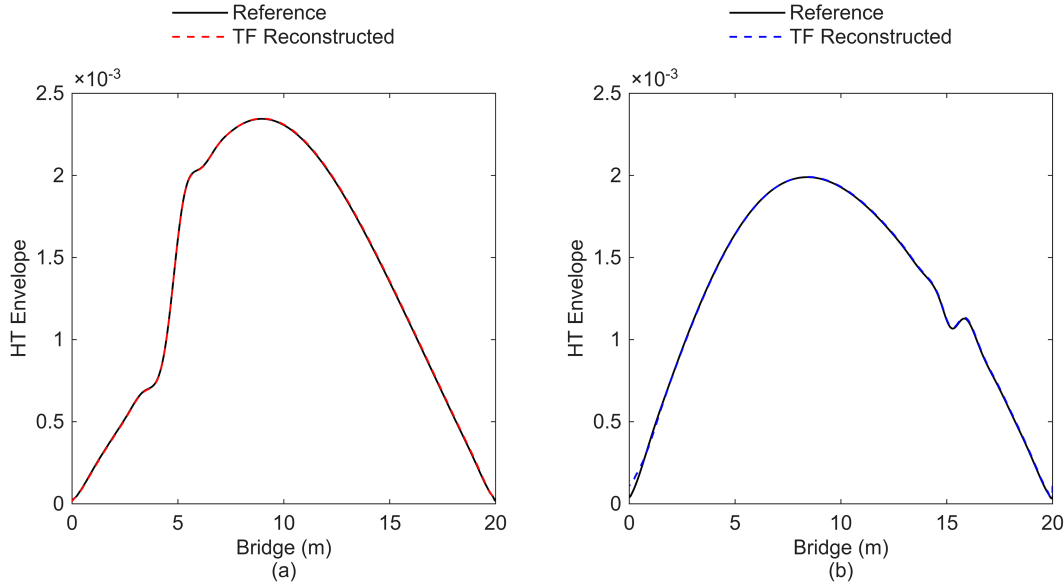


Figure 6: Comparison between reference and TF reconstructed HT envelopes of the band-pass filtered contact-point bridge accelerations. (a) Front axle response; (b) rear axle response.

To quantify changes in the extracted ODS-like features resulting from bearing degradation, a normalized Euclidean distance based damage indicator is defined as [38]:

$$DI = \frac{\sqrt{\sum_{i=1}^N (ODS_{D,i} - ODS_{H,i})^2}}{\sqrt{\sum_{i=1}^N ODS_{H,i}^2}} \quad (15)$$

where $ODS_{H,i}$ and $ODS_{D,i}$ are the healthy and damaged ODS amplitudes at spatial location i , respectively, and N is the number of spatial sampling points. Larger values of damage indicator correspond to greater changes in the ODS-like feature relative to the healthy condition, indicating increased sensitivity to bearing stiffness reduction.

4 Results

4.1 Baseline Assessment under Idealised Conditions

To establish a baseline, simulations were first conducted under idealised conditions using a deterministic vehicle model, a zero road profile, and a constant speed of 1 m/s. Three symmetric bearing conditions were considered: healthy (H: $K_L = K_R = 100 \times 10^8$ N·m/rad), damaged case 1 (D1: $K_L = K_R = 50 \times 10^8$ N·m/rad), and damaged case 2 (D2: $K_L = K_R = 0$ N·m/rad). This configuration isolates the structural contribution and enables the accuracy of the TF reconstruction to be evaluated without the influence of road-induced disturbances. Fig. 7 compares the band-pass-filtered reference and TF-reconstructed contact-point bridge accelerations for the front and rear axles. Overall, the TF-reconstructed responses show excellent agreement with the reference signals across all bearing conditions, demonstrating that the proposed reconstruction method successfully captures the dominant bridge vibration component. As the bearing rotational stiffness decreases from H to D2, the acceleration amplitude increases significantly. For the healthy case, the response remains within approximately $\pm 6 \times 10^{-4}$ m/s², while D1 increases to approximately $\pm 1.5 \times 10^{-3}$ m/s² and D2 reaches approximately $\pm 3 \times 10^{-3}$ m/s². This behaviour indicates that reduced bearing restraint leads to increased bridge vibration response. Consistent trends are observed for both the front and rear axles, although minor local differences are present due to axle spacing and vehicle dynamic effects. The largest responses generally occur near the mid-span region, consistent with excitation of the dominant bridge mode. While small discrepancies between the reference and TF-reconstructed signals can be observed in some cases, these are negligible relative to the overall amplitude variations associated with bearing stiffness reduction. Overall, the results under ideal conditions demonstrate that the TF reconstruction can accurately recover contact-point bridge accelerations for different bearing states. More importantly, the clear increase in response amplitude with decreasing support stiffness confirms that the reconstructed responses contain damage-sensitive information suitable for subsequent HT envelope extraction and ODS-like feature analysis.

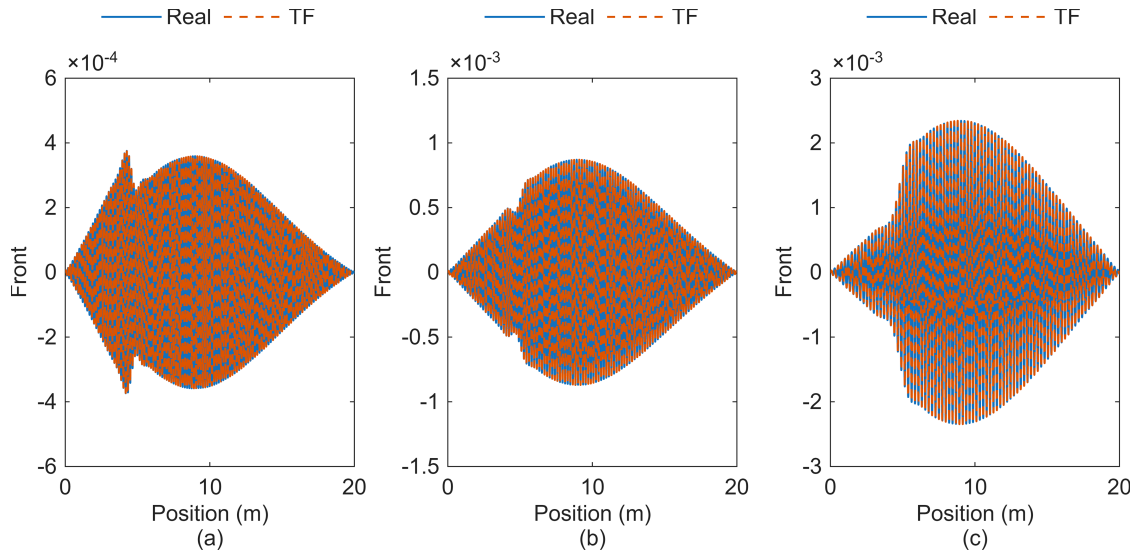


Figure 7: (Continued)

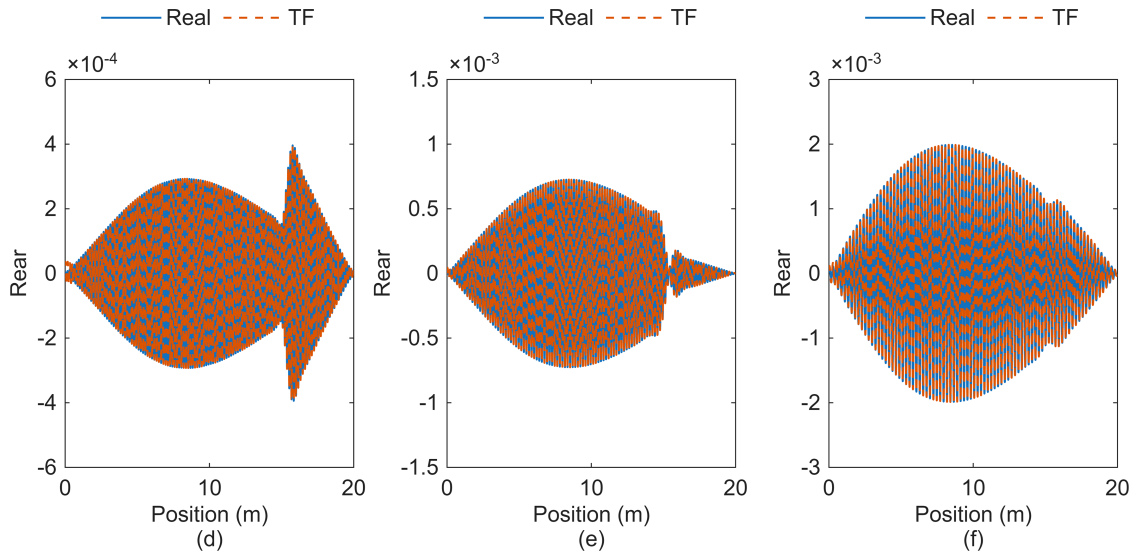


Figure 7: Band-pass-filtered reference and TF-reconstructed contact-point bridge accelerations at 1 m/s under symmetric bearing conditions, (a–c) correspond to the front axle for the H, D1, and D2 scenarios, respectively, while (d–f) correspond to the rear axle for the H, D1, and D2 scenarios, respectively.

Fig. 8 shows the unnormalized HT amplitude curves extracted from the TF-reconstructed contact-point accelerations at 1 m/s. Compared with the filtered acceleration responses in Fig. 7, the HT envelopes provide a smoother spatial representation of the bridge response and make the effect of bearing stiffness reduction more evident. For the front axle (Fig. 8a), the peak HT amplitude increases from approximately $0.35 \times 10^{-3} \text{ m/s}^2$ in the healthy case to about $0.85 \times 10^{-3} \text{ m/s}^2$ for D1 and $2.3 \times 10^{-3} \text{ m/s}^2$ for D2. A similar trend is observed for the rear axle (Fig. 8b), where the peak amplitude increases from around $0.3 \times 10^{-3} \text{ m/s}^2$ to approximately $0.7 \times 10^{-3} \text{ m/s}^2$ and $2.0 \times 10^{-3} \text{ m/s}^2$ for D1 and D2, respectively. To quantify the deviation from the healthy-state response, an ODS-based damage indicator was introduced based on the normalized Euclidean distance between the healthy and damaged HT envelopes. For the front axle, the damage indicator increases from 1.33 for D1 to 5.23 for D2, while for the rear axle the corresponding values increase from 1.34 to 5.29. The substantial increase in damage indicator with increasing bearing stiffness degradation demonstrates that the extracted HT envelopes are highly sensitive to support condition changes. Although some local irregularities are observed near approximately 5 m in the front-axle response and 15–16 m in the rear-axle response, likely due to axle-position effects and local dynamic interaction, the overall spatial response pattern remains clearly distinguishable between the healthy and damaged cases. Overall, the HT amplitude curves provide a clear ODS-like feature for identifying support stiffness changes, while the proposed damage indicator enables quantitative assessment of bearing degradation severity.

4.2 Effect of Vehicle Speed on Feature Quality and Damage Sensitivity

The influence of vehicle speed was investigated using a deterministic vehicle model and a zero road profile over a range of speeds representative of practical operating conditions. At low speed (1 m/s, Fig. 8), the HT amplitude envelopes are smooth and well-defined due to the dense spatial sampling of the bridge response. Clear separation between the healthy and damaged cases is observed for both axles, with the damage indicator increasing from 1.33 to 5.23 for the front axle and from 1.34 to 5.29 for the rear axle between D1 and D2. These large values indicate strong sensitivity to bearing stiffness degradation under near quasi-static conditions. At 15 m/s (Fig. 9), the overall envelope shape remains similar, although local fluctuations

become more evident due to increased dynamic interaction and reduced sampling density. The damage indicator remains capable of distinguishing the damage cases, increasing from 0.084 to 0.183 for the front axle and from 0.171 to 0.233 for the rear axle. At 25 m/s (Fig. 10), the envelopes exhibit greater variability while maintaining a clear separation from the healthy condition. The damage indicators increase to 1.05 and 1.38 for the front axle and 0.85 and 0.64 for the rear axle for D1 and D2, respectively, indicating substantial deviations from the healthy-state response despite the increased dynamic effects. At 35 m/s (Fig. 11), the envelopes become more oscillatory and less smooth, reflecting the shorter vehicle–bridge interaction time and reduced spatial resolution. Nevertheless, the damage indicators remain elevated, with values of 0.19 and 0.59 for the front axle and 0.17 and 0.78 for the rear axle for D1 and D2, respectively. Although the damage indicator does not increase monotonically with damage severity at every speed and axle location, the damaged cases remain consistently distinguishable from the healthy condition. Overall, the HT-based features remain sensitive to bearing degradation across all investigated speeds. Although increasing speed generally introduces additional variability and reduces the smoothness of the extracted envelopes, the damage indicator consistently differentiates the damaged cases from the healthy condition. These results, as presented in Table 3 suggest that vehicle-derived ODS-like features provide damage-sensitive information over a broad range of operating speeds, although the level of sensitivity depends on the interaction between vehicle dynamics and bridge response.

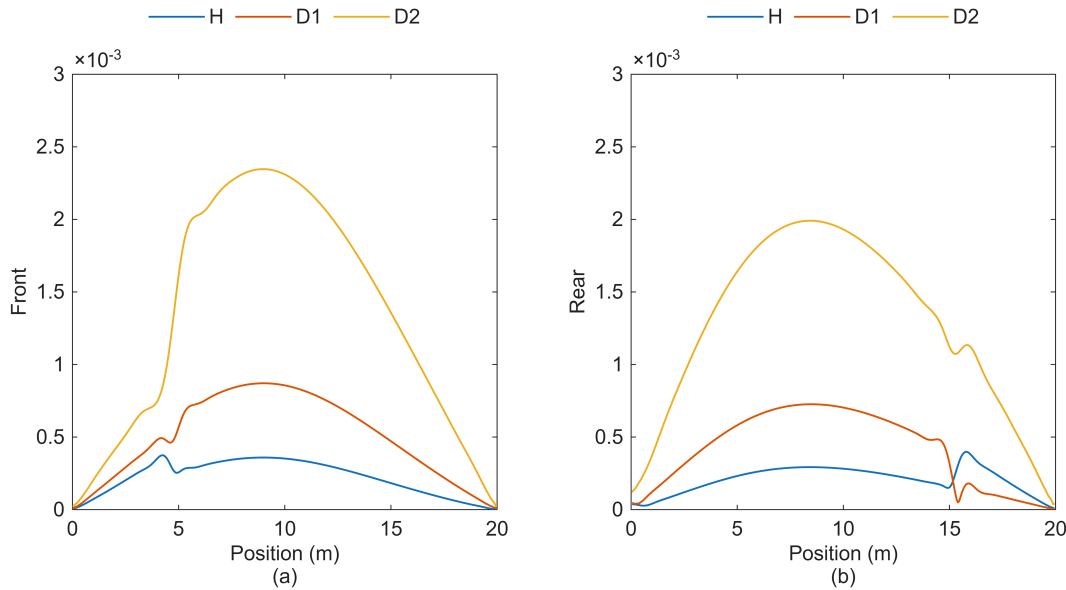


Figure 8: Unnormalized HT amplitude curves from TF-reconstructed responses at 1 m/s under symmetric bearing conditions: H, D1, and D2. (a) Front axle; (b) rear axle.

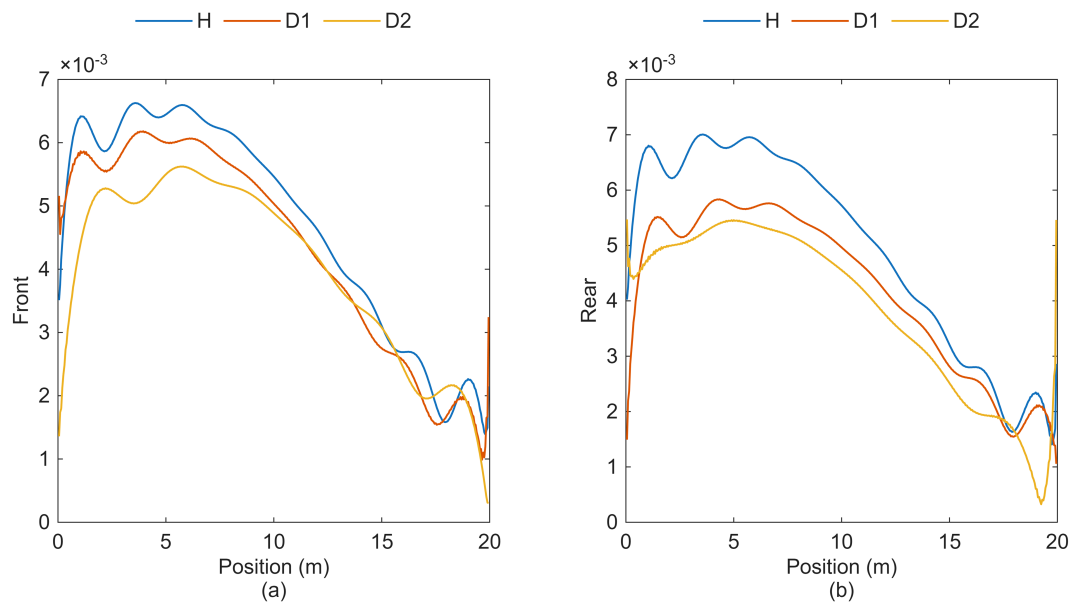


Figure 9: HT amplitude curves at 15 m/s for H, D1, and D2. (a) Front axle; (b) rear axle.

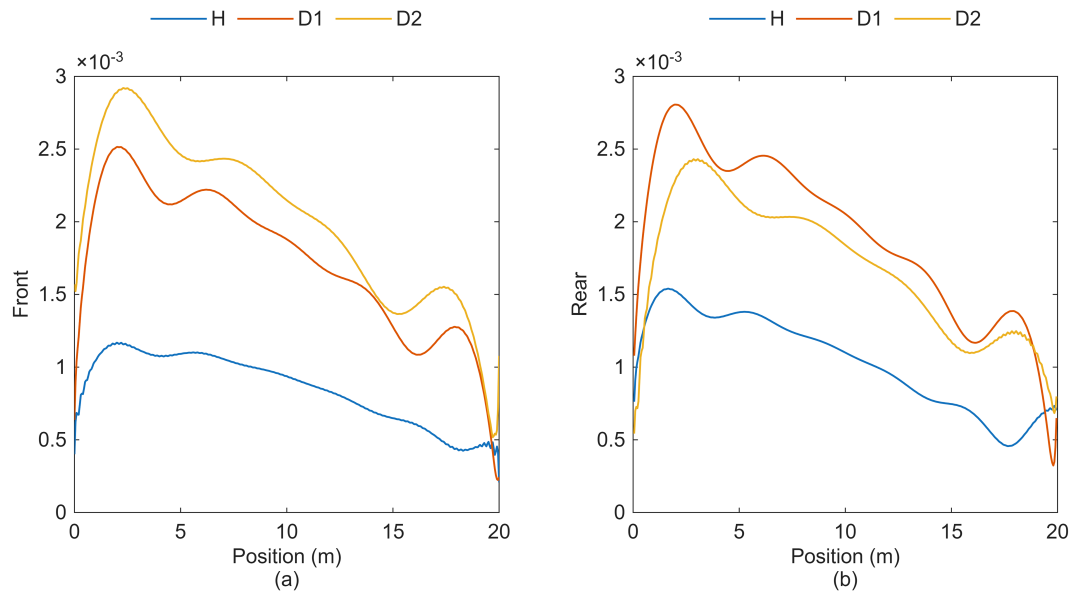


Figure 10: HT amplitude curves at 25 m/s for H, D1, and D2. (a) Front axle; (b) rear axle.

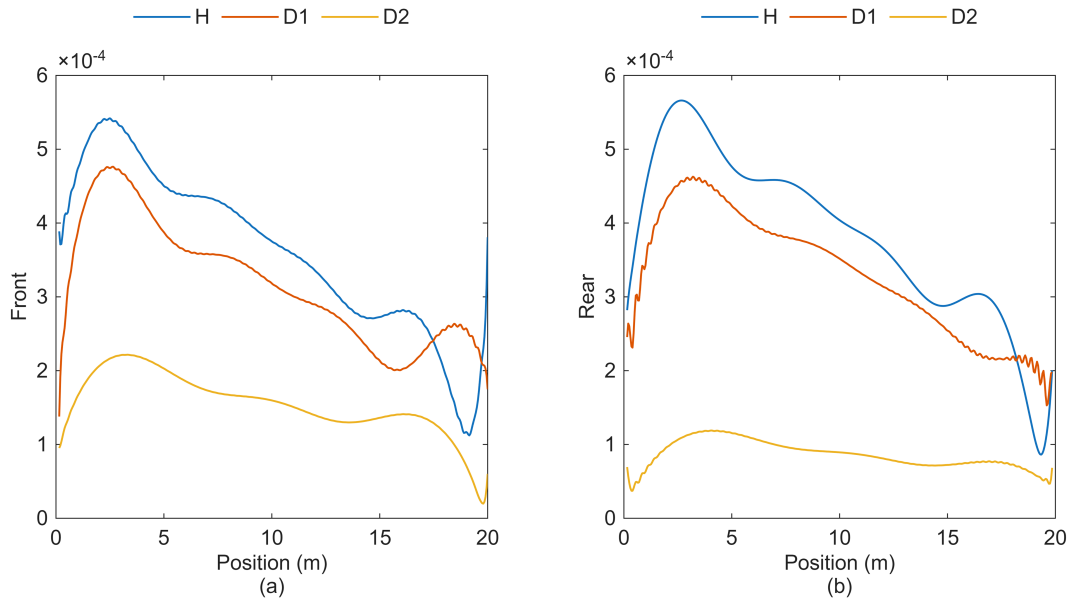


Figure 11: HT amplitude curves at 35 m/s for H, D1, and D2. (a) Front axle; (b) rear axle.

Table 3: Damage indicator values obtained from the HT amplitude envelopes.

Speed (m/s)	Front D1	Front D2	Rear D1	Rear D2
1	1.33	5.23	1.34	5.29
15	0.084	0.183	0.171	0.233
25	1.051	1.383	0.845	0.635
35	0.186	0.585	0.172	0.784

4.3 Robustness of Extracted Features to Measurement Noise

To evaluate the robustness of the proposed framework to measurement uncertainty, Gaussian white noise [39] was added to the vehicle acceleration measurements prior to the TF reconstruction process. A vehicle speed of 25 m/s was adopted, and three noise levels were considered: no noise, 10 dB signal to noise ratio (SNR), and 5 dB SNR. Fig. 12 compares the HT amplitude curves obtained under different noise conditions. For both the front axle (Fig. 12a) and rear axle (Fig. 12b), the curves remain almost unchanged as the noise level increases, with only minor amplitude differences observed. The overall envelope shape and peak locations are well preserved, indicating that the extracted ODS-like features are relatively insensitive to the considered noise levels. To quantify the effect of noise, a damage indicator was calculated as the normalized Euclidean distance between the noisy and no-noise HT amplitude curves. The results are summarised in Table 4. For the front axle, the indicator values are 0.0136 and 0.0110 for the 10 and 5 dB SNR cases, respectively, while the corresponding rear-axle values are 0.0181 and 0.0298. All values remain below 0.03, indicating that the influence of measurement noise is relatively small. Overall, the results demonstrate that the proposed TF-based reconstruction and HT processing framework exhibits good robustness to measurement noise, with the key spatial characteristics remaining largely unaffected even under the 5 dB SNR condition.

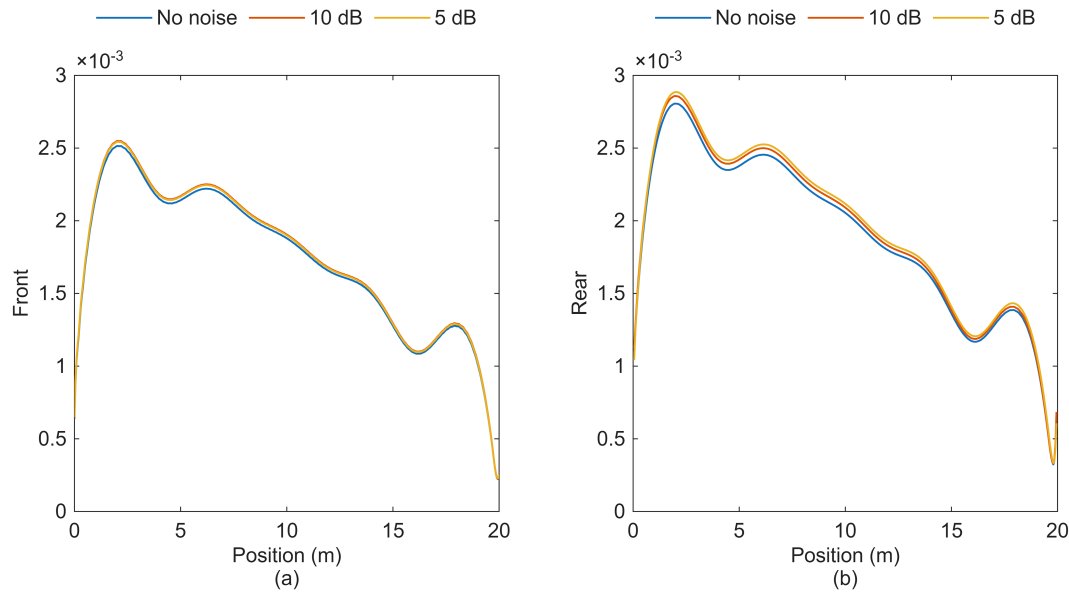


Figure 12: HT amplitude curves at 25 m/s under different signal noise levels: no noise, 10 dB SNR, and 5 dB SNR. (a) Front axle; (b) rear axle.

Table 4: Noise sensitivity indicator values obtained from the HT amplitude envelopes under different signal noise levels.

Noise Level (dB)	Front Axle	Rear Axle
0	0	0
10	0.0136	0.0181
5	0.011	0.0298

4.4 Performance under Realistic Road Surface Conditions

To evaluate the robustness of the proposed methodology under more realistic operating conditions, simulations were conducted using ISO Class A and Class B road profiles and compared with the ideal zero-road case at a vehicle speed of 25 m/s for both the healthy (H) and damaged (D1) bearing conditions. Fig. 13 compares the extracted HT amplitude curves under the three road conditions. For both the front axle (Fig. 13a) and rear axle (Fig. 13b), increasing road roughness leads to higher response amplitudes and increased spatial variability. The Class B profile produces the largest amplitudes, while the zero-road case remains the smoothest. Nevertheless, the general shape of the HT envelopes is preserved across all road conditions, indicating that the proposed TF reconstruction and HT processing retain the dominant spatial response characteristics. For all road profiles, the damaged case consistently exhibits higher amplitudes than the corresponding healthy case over most of the bridge span. However, the separation between the healthy and damaged cases decreases as road roughness increases. This trend is reflected in the damage indicator values summarised in Table 5. For the front axle, the indicator decreases from 1.051 under the zero-road condition to 0.794 and 0.673 for the Class A and Class B profiles, respectively. Similarly, for the rear axle, the indicator decreases from 0.845 to 0.336 and 0.207. These reductions indicate that road roughness introduces additional variability into the reconstructed responses and reduces the sensitivity of the extracted HT features to bearing damage. Overall, although increasing road roughness reduces the magnitude of the damage indicator, the damaged bearing condition remains distinguishable for both Class A and Class B profiles, demonstrating that the proposed framework retains robustness under realistic road conditions.

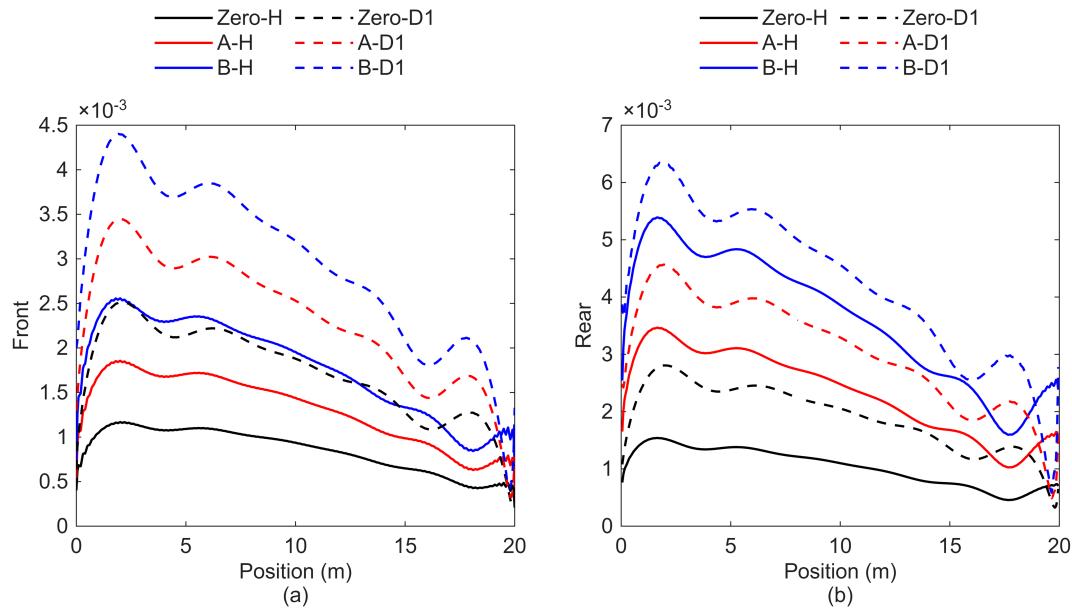


Figure 13: Comparison of HT amplitude curves under zero-road, class A, and class B road profiles at 25 m/s. (a) Front axle; (b) rear axle.

Table 5: Damage indicator values for the healthy and D1 bearing conditions under different road profile roughness levels.

Road Profile	Front DI	Rear DI
Zero Road	1.051	0.845
Class A	0.794	0.336
Class B	0.673	0.207

5 Discussions

The proposed framework combining TF-based contact-point reconstruction with HT envelope extraction provides a practical and physically interpretable approach for extracting vehicle-derived ODS-like features for bridge support condition assessment. The reconstructed contact-point accelerations showed excellent agreement with reference bridge responses across all investigated scenarios, confirming that the dominant bridge-induced dynamics can be reliably recovered from vehicle-only measurements. The resulting HT amplitude envelopes are sensitive to changes in bearing rotational stiffness and offer richer spatial information than conventional drive-by indicators such as modal frequencies or statistical response measures, enabling a more direct representation of structural behaviour.

Under idealised conditions, bearing stiffness degradation produced clear and consistent increases in both ODS amplitude and damage indicator values, indicating that support deterioration influences not only the magnitude of the bridge response but also its spatial distribution. Vehicle speed affected the quality of the extracted features: lower speeds yielded denser spatial sampling and smoother envelopes with clearer separation between healthy and damaged states, while higher speeds introduced greater variability due to reduced vehicle–bridge interaction time and lower spatial resolution. Nevertheless, damage-sensitive trends remained observable across the full range of speeds investigated.

The framework demonstrated good robustness to measurement noise. Even at 5 dB SNR, the extracted HT amplitude envelopes and corresponding damage indicator values remained largely unchanged, suggesting that the combination of TF reconstruction, band-pass filtering, and HT envelope extraction effectively suppresses noise without compromising structural feature quality. Road profile roughness proved more consequential: increasing roughness introduced additional variability into the reconstructed responses and reduced damage indicator sensitivity, reflecting the difficulty of separating road-induced and bridge-induced signal components in practice. That said, the damaged bearing condition remained distinguishable under both ISO Class A and Class B profiles, demonstrating acceptable robustness under realistic operating conditions. Road profile estimation and signal separation therefore remain important priorities for future development.

Several limitations should be acknowledged. The bridge model is an Euler–Bernoulli beam with rotational spring supports, and bearing deterioration is represented solely through reductions in rotational stiffness. While physically interpretable, this idealisation does not capture the full complexity of real bearing behaviour, which may involve friction, uplift, nonlinear effects, material ageing, and temperature dependence. The framework also requires prior knowledge of vehicle dynamic properties and the dominant bridge frequency, and uncertainties in these parameters could affect reconstruction accuracy in practice. More broadly, as noted by the works [40–42], indirect bridge monitoring faces persistent challenges from vehicle variability, environmental and operational effects, and the limitations of output-only system identification, challenges that the road roughness results of this study echo directly. Experimental and field validation, extension to more realistic bridge and bearing models, and the development of robust road-profile compensation strategies remain essential steps before practical deployment in fleet-based monitoring systems.

6 Conclusions

This study presented a drive-by monitoring framework for bridge support condition assessment using vehicle-derived ODS-like features. Contact-point bridge accelerations were reconstructed from vehicle-only measurements via a TF formulation, then processed through band-pass filtering and HT envelope extraction to obtain smooth spatial amplitude distributions along the bridge span. The framework was evaluated using a coupled vehicle-bridge interaction model across a range of bearing damage levels, vehicle speeds, signal noise conditions, and road profile roughness classes. The TF-based reconstruction accurately captured the dominant bridge-induced dynamics, with near-unity MAC values confirming close agreement between reconstructed and reference ODS-like features. The extracted HT amplitude envelopes provided physically interpretable spatial representations of bridge behaviour that were consistently sensitive to reductions in bearing rotational stiffness. The ODS-based damage indicator quantified these changes clearly under idealised conditions, with lower vehicle speeds yielding better spatial resolution and more distinct separation between healthy and damaged states, though damage sensitivity was retained across all speeds tested. The framework showed strong robustness to measurement noise, with only negligible changes in extracted features even at low SNR. Road profile roughness had a greater influence, reducing damage indicator sensitivity under Class A and Class B conditions, though the damaged bearing state remained identifiable in all cases. These results highlight road-induced signal contamination as the principal practical challenge for the approach. Overall, vehicle-derived ODS-like features offer a promising and scalable basis for indirect bridge support monitoring. Future work will prioritise laboratory and field validation, more realistic bridge and bearing models, and the development of road-profile compensation techniques to support deployment in fleet-based SHM systems.

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Conflicts of Interest: The author declares no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

SHM	Structural Health Monitoring
VBI	Vehicle Bridge Interaction
TF	Transfer Function
ODS	Operational Deflection Shape
HT	Hilbert Transform
PSD	Power Spectral Density
MAC	Modal Assurance Criterion
SNR	Signal to Noise Ratio

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