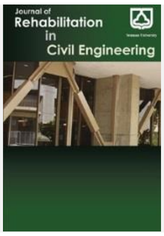

Journal of Rehabilitation in Civil Engineering

Journal homepage: https://civiljournal.semnan.ac.ir/

Bridge Deck Modal Parameters Identification Using Traffic Loads

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ARTICLE INFO

Article history:
Received: 06 August 2024
Revised: 15 December 2024
Accepted: 06 January 2025

Keywords:
Modal identification;
Traffic load;
Frequency domain Decomposition;
Random decrement;
Empirical mode decomposition.

ABSTRACT

Structural Health Monitoring (SHM) has gained significant importance in recent decades, with various methods developed to detect structural damage. Many non-destructive damage detection techniques are based on vibration response analysis, where changes in modal parameters provide insights into the condition of the structure. For long-term monitoring, utilizing operational loads as the source of vibration is more practical. This paper presents a methodology that processes the forced vibration response of a bridge deck subjected to traffic loading for modal parameter identification. Specifically, the free vibration response is estimated using the Random Decrement (RD) technique combined with Empirical Mode Decomposition (EMD). The natural frequencies and mode shapes are extracted using Frequency Domain Decomposition (FDD). To validate the proposed approach, numerical models of 2D and 3D bridge decks are employed, considering various loading scenarios and the effects of load path and speed. The results indicate that the proposed method is effective for modal identification under real traffic loads, with improved accuracy observed when more complex load patterns, closer to actual conditions, are used. Additionally, the proximity of degrees of freedom to the load path enhances the precision of the results. Quantitative comparisons of modal frequencies and mode shapes validate the robustness of the methodology.

E-ISSN: 2345-4423

How to cite this article: Talebi, M. , Tabrizian, Z. and Ghodrati Amiri, G. (2025). Bridge Deck Modal Parameters Identification Using Traffic Loads. Journal of Rehabilitation in Civil Engineering, 13(3), 215-230. https://doi.org/10.22075/jrce.2025.34969.2157

1. Introduction

Bridges serve as essential components of transportation networks, and their structural integrity is vital for ensuring both public safety and the efficient movement of goods and people. Recently, Structural Health Monitoring (SHM) systems have become increasingly important for assessing and preserving the functionality of highway bridges. SHM techniques can broadly be classified into signal-based and model-based methods, which use the structural responses to dynamic forces as the basis for health monitoring [1–3]. These structural responses, which include key modal parameters like natural frequencies, mode shapes, and damping ratios, provide valuable information for damage detection, condition evaluation, and updating finite element models [4–8].

Modal parameter identification can be accomplished using two primary techniques: Traditional Modal Analysis (TMA) and Operational Modal Analysis (OMA) [9–12]. TMA relies on controlled structural excitation (e.g., dynamic force) and measures the structure's response in terms of acceleration, displacement, or velocity. On the other hand, OMA uses ambient vibrations caused by environmental factors such as traffic, wind, and earthquakes, thus eliminating the need for externally controlled forces [9–11,13,14]. While OMA is often preferred for practical applications in the field, challenges such as weak excitation and noise interference can complicate the accurate estimation of modal parameters. Nevertheless, ongoing research has led to significant advancements in improving the robustness and precision of these techniques for bridges[15].

As most modal identification techniques depend on free vibration data, it is important to separate free vibration responses from forced vibrations. The Random Decrement (RD) method has been widely adopted for isolating these free vibrations, especially when ambient excitation is present [15–17]. Initially developed to estimate damping in aerospace structures, the RD method has been adapted for multi-degree-of-freedom systems in civil engineering [12]. Additionally, to better manage non-stationary signals, advanced signal processing techniques such as Empirical Mode Decomposition (EMD) and time-frequency analysis have been explored in recent studies. EMD is particularly effective for decomposing complex non-stationary signals into Intrinsic Mode Functions (IMFs), which can then be analyzed to estimate modal parameters [12,16,18].

This paper proposes a novel approach that integrates RD with EMD to extract free vibration responses from non-stationary ambient data. Specifically, the data are first decomposed into IMFs using EMD, and then the RD technique is applied to these IMFs to extract the free vibration response. This combined method enhances the accuracy of modal parameter estimation and proves to be highly effective for health monitoring of bridge structures.

The paper is organized as follows: Section 2 discusses the Frequency-Domain Decomposition (FDD) technique used to identify modal frequencies and mode shapes. Section 3 introduces the RD-EMD method for estimating free vibration responses. Section 4 presents a hybrid approach that combines FDD and RD-EMD for modal parameter identification. Finally, Section 5 validates the proposed approach through numerical simulations of 2D and 3D bridge deck models.

2. Frequency domain decomposition approach

Frequency Domain Decomposition (FDD) is a technique used for identifying the modal parameters of a structure from its response to broadband excitation. It is an extension of the classic frequency domain approach, often referred to as the Basic Frequency Domain (BFD) method or the Peak-Picking (PP) technique. In the PP approach, the Frequency Response Function (FRF) of a system exhibits distinct peaks at the system's natural frequencies. These peaks represent the resonance frequencies of the structure, which correspond to its dominant modal frequencies. By analyzing the imaginary component of the FRF at each modal frequency, ω_i, the corresponding mode shape, ϕ_i, can be extracted for the ith mode of the structure [19,20].

2.1. Theoretical background of FDD

When a structure is subjected to ambient vibrations, the relationship between unknown input *X(t)* and measured responses *Y(t)* can be expressed as:

$$G_{XX}(j\omega) = \overline{H}(j\omega)G_{YY}(j\omega)H(j\omega)^T \tag{1}$$

Where $G_{XX}(j\omega)$ is the $r\times r$ Power Spectral Density (PSD) matrix of the inputs and $G_{YY}(j\omega)$ is the $m\times m$ PSD matrix of the responses. In this equation, r and m represent the number of inputs and outputs, respectively, $H(j\omega)$ is the $m \times r$ Frequency Response Function (FRF) matrix, Also, "¯" and superscript "T" denote a complex conjugate and transpose, respectively [19,21]. The FRF matrix can be expressed in partial fraction form as:

$$H(j\omega) = \sum_{k=1}^{n}\left(\frac{R_k}{j\omega-\lambda_k} + \frac{\overline{R}_k}{j\omega-\overline{\lambda}_k}\right) \tag{2}$$

where n is the number of modes, λ_k is the pole, $R_k = \phi_k {\gamma_k}^T$ is the residue, and ϕ_k and γ_k^T are the mode shape vector and modal participation vector, respectively [19,22].

2.2. FDD identification algorithm

The FDD method is an output-only modal extraction approach, which allows for the identification of closely spaced modes by decomposing the spectral density matrix into a set of single degree of freedom (SDOF) systems. This procedure is performed by estimating the output Power Spectral Density (PSD) matrix $G_{YY}(j\omega_i)$ for each discrete frequency $\omega=\omega_i$. The PSD matrix is calculated from an array of frequency response functions (FRFs) using the Fast Fourier Transform (FFT) from each degree of freedom (DOF), as [21,23]:

$$G_{YY}(j\omega_i) = \{F_Y(j\omega_i)\}\{F_Y^*(j\omega_i)\}^T \tag{3}$$

where $\{F_Y(j\omega_i)\}$ is an array of complex FFT values for each DOF at frequency ω_i and $\{F_Y^*(j\omega_i)\}^T$ is the complex conjugate transpose of that array. By applying Singular Value Decomposition (SVD) to the PSD matrix, singular values and singular vectors can be extracted from the PSD matrix as:

$$G_{yy}(j\omega_i) = U_i S_i U_i^H \tag{4}$$

where $u_i=[u_{i1}, u_{i2}, \dots, u_{im}]$ is a matrix containing m singular $m\times 1$ vectors u_{ij}, S_i is a diagonal matrix holding scalar singular values S_{ij} and U_i^H is the Hermitian transpose of U_i. If a SVD is performed near a modal peak, the first singular vector u_1, can be interpreted as an estimate of corresponding mode shape ϕ_i [23].

A reference point should be selected to determine the dominated frequencies and estimating the scaled mode shapes. This should be placed such that all modes contribute to the response. Typically, a point that is neither at a nodal nor peak deflection would be ideal for this purpose[24]. If the rth measuring point is chosen as the reference point, the kth component of the ith real mode shape can be calculated as:

$$\phi_{ki} = \frac{u_{ik}(k) \times u_{ik}(r)}{\left(u_{ik}(r)\right)^2} \quad (5)$$

where $u_{i1}(k)$ is the kth component of vector u_{i1} and ϕ_{ki} is the kth component of the ith mode shape. Since FDD is based on the structural free vibration response, the forced vibration response of structures under loading must first be converted into a free vibration response using the Random Decrement (RD) technique.

3. Random decrement method

In the previous section, it was assumed that modal parameters could only be estimated under stationary or white noise excitations. However, ambient vibrations from sources such as earthquakes, wind, and traffic are inherently non-stationary. Therefore, methods capable of estimating modal parameters from non-stationary ambient excitation are needed. In this section, the Random Decrement (RD) method is introduced. This method estimates modal parameters from non-stationary excitation by utilizing response signatures evaluated at a fixed time point under specific triggering conditions.

The RD signature is a sequence of response records that are extracted by segmenting the structure's dynamic response at specific triggering points (often referred to as "windows"). These segments are then averaged to reduce the effect of noise and irregularities, leaving a signature that resembles the free vibration response of the system. This signature captures the underlying dynamics of the structure, providing valuable information about its modal characteristics, such as natural frequencies and damping. By applying this technique to non-stationary data, the RD method enables accurate modal parameter estimation in real-world conditions where excitation sources are unpredictable and variable.

3.1. RD signature and autocorrelation relationship in stationary gaussian random vibration

The Random Decrement (RD) technique is based on the assumption that the structural dynamic response is a superposition of two components: (1) the vibration caused by initial displacement or velocity conditions and (2) the vibration due to random excitation (often caused by ambient forces like wind, traffic, or earthquakes) [25,26]. For a structure subjected to random excitation, the equation of motion in terms of displacement $X(t)$, velocity $\dot{X}(t)$, and acceleration $\ddot{X}(t)$ is expressed as[27]:

$$M\ddot{X}(t) + C\dot{X}(t) + KX(t) = F(t) \quad (6)$$

where M, C, and K represent the mass, damping, and stiffness matrices, and $F(t)$ is the external excitation force.

The RD signature is obtained by averaging time segments of a time history in which certain triggering conditions are satisfied. These time segments are selected such that they are synchronized with the occurrence of similar response patterns, often referred to as "trigger points." Once these segments are isolated, they are averaged to produce a signal that resembles the free vibration response of the system, effectively filtering out the effects of random excitation [16,25,26].

$$\overline{X}(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t+\tau) \tag{7}$$

The autocorrelation function $R_X(\tau)$ is used to assess the correlation between the structure's response at two different time points, t_1 and t_2:

$$R_X(t_1, t_2) = E[X(t_1), X(t_2)] \tag{8}$$

This function is crucial for understanding how the response at one time is related to that at another, especially in random vibration conditions. When the RD signature is derived from the autocorrelation, it becomes a weighted sum of these correlations, conditioned by the initial state of the structure [16,25,28].

The key idea is to filter out the random excitation through the relationship between the RD signature and the autocorrelation of the response. For stationary Gaussian random vibrations, the probability distribution of the response *X(t)* is Gaussian, and the RD signature can be related to the autocorrelation as [25,26]:

$$D(X_0)(\tau) = \frac{R_X(\tau)}{R_X(0)} \tag{9}$$

where X_0 is the initial displacement and τ represents the time lag between the response points. This relationship shows how the RD signature at a particular time interval is influenced by the autocorrelation function and the initial response of the system.

The RD method's effectiveness is further improved by choosing appropriate triggering conditions, such as level crossings or positive points, which ensure that the response segments used for averaging are statistically relevant and reflect the underlying modal behavior.

For practical implementation, triggering conditions are often used to isolate segments of the time history. Common triggering conditions include [25]:

Level Crossing: $T_X^L(t) = \{X(t) = a\}$ (10)

Positive Point: $T_X^P(t) = \{a_1 \le X(t) \le a_2\}$ (11)

Local Extermum: $T_X^E(t) = \{a_1 \le X(t) \le a_2, \dot{X}(t) = 0\}$ (12)

Zero Crossing: $T_X^Z(t) = \{X(t) = a, \dot{X}(t) \ge 0\}$ (13)

Among these, the positive point condition is the most versatile, as it allows for flexible control over the number of triggering points by adjusting the levels.

3.2. RD signature of a non-stationary random vibration

Building on the RD method's foundations established in Sections 3.1, this section focuses on its application to non-stationary vibration signals. The key challenge in analyzing non-stationary responses lies in capturing their transient and evolving characteristics, which conventional methods designed for stationary signals may fail to address [16,18]:

To overcome this, the Empirical Mode Decomposition (EMD) is employed as a preprocessing step. EMD decomposes the non-stationary response into a finite number of Intrinsic Mode Functions (IMFs), each representing oscillatory components with distinct frequency ranges. This process ensures that the non-stationary data is transformed into quasi-stationary components suitable for RD analysis. The resulting RD signatures for these IMFs reflect the underlying structural dynamics, enabling modal parameter identification [16,28].

The EMD process iteratively sifts the original response signal *X(t)*, isolating components by identifying local extrema and calculating their envelopes. These envelopes are averaged to produce a residual, progressively yielding IMFs. Each IMF captures a specific frequency range, from the highest oscillations in the first IMF to slower trends in subsequent IMFs. The final residual represents the long-term trend or monotonic component of the response.

Once the IMFs are extracted, those with frequencies matching the structure's expected response are selected, combined, and subjected to RD analysis. By reconstructing the signal from these IMFs, an accurate representation of the structure's free vibration is obtained.

The EMD-based RD method allows for direct application to non-stationary signals without requiring predefined basis functions, making it ideal for ambient vibration data. However, care must be taken to mitigate end effects, where boundary distortions may impact the accuracy of the IMFs. Advanced techniques, such as mirror extensions, can be applied to reduce such errors.

The reconstructed signal *X(t),* composed of selected IMFs, can then be expressed as [29–31]:

$$X(t) = \sum_{j=1}^{n}\left(C_j + r_n\right) \tag{14}$$

where C_j represents the selected IMFs, and rn is the residual. To confirm the relevance of chosen IMFs, their frequency content is analyzed using evolutionary spectra. The evolutionary spectrum analysis is an additional step that helps assess how well the selected IMFs represent the frequencies of interest in the signal over time. By examining the spectral density of both the IMFs and the original signal through a moving window, we ensure that the IMFs are relevant and align with the structural dynamics we're trying to capture. This ensures the reconstructed signal accurately represents the structure's dynamic behavior [16,28].

The combination of EMD and RD offers an innovative approach to analyzing non-stationary responses, bridging the gap between theoretical techniques and real-world applications in structural dynamics.

4. Modal identification using ERF method

The modal parameters of a structure, such as natural frequencies and mode shapes, are critical for Structural Health Monitoring (SHM). This study introduces a new method, the ERF method, to identify structural modal parameters by processing the structural response to operational loads. The ERF method follows three main steps:

- **EMD (Empirical Mode Decomposition):** This step converts the non-stationary forced vibration response of the structure into a quasi-stationary signal, effectively reducing noise and isolating the dominant structural response, much like a filtering process. This enhances the clarity of the signal for subsequent analysis.

- **RD (Random Decrement):** The quasi-stationary signal obtained from EMD is then transformed into a free vibration response. This step bridges the gap between operational response data and modal identification techniques traditionally applied to free vibration data.
- **FDD (Frequency Domain Decomposition):** Finally, the free vibration response is analyzed using the FDD technique to estimate key modal parameters, including the structure's natural frequencies and mode shapes.

By transforming the non-stationary response into a quasi-stationary free vibration signal, the ERF method enables the application of free vibration-based identification techniques, which typically yield more accurate results. Moreover, the EMD step plays a crucial role in filtering out noise, ensuring that the extracted modal parameters accurately represent the structural dynamics. Fig. 1 provides a schematic representation of this process, illustrating the conversion of an operational forced response into a form suitable for accurate modal parameter estimation.

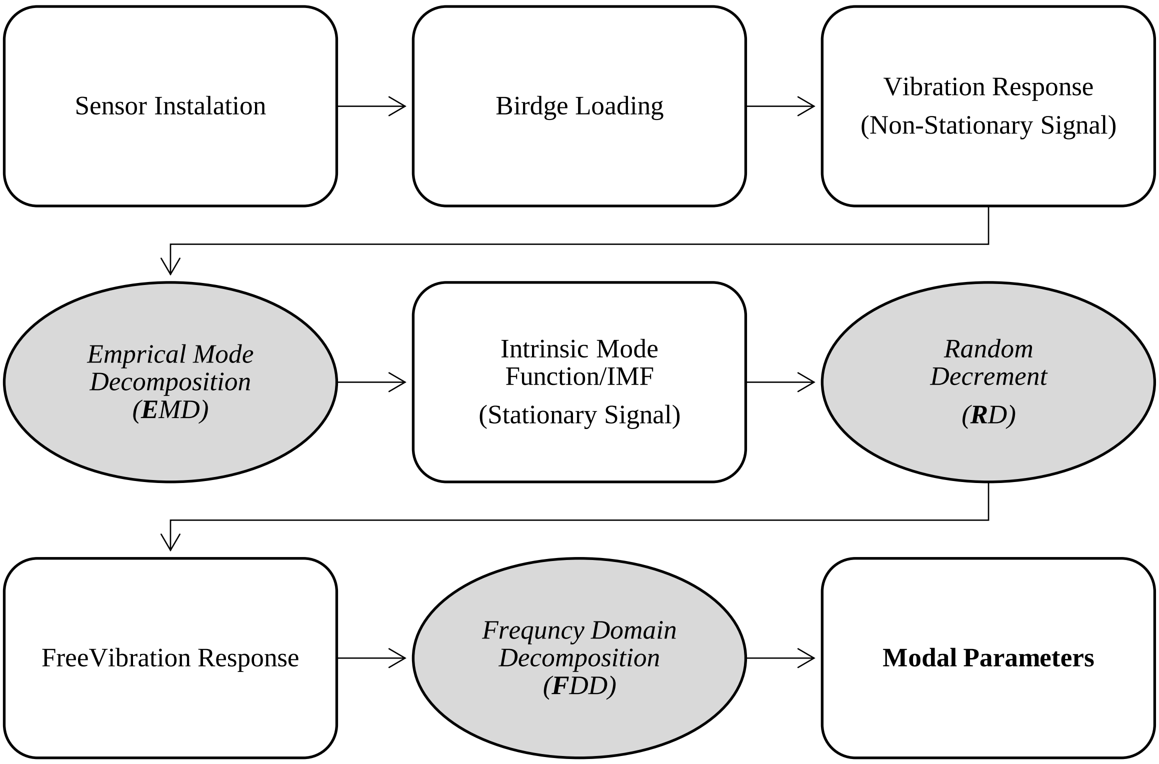
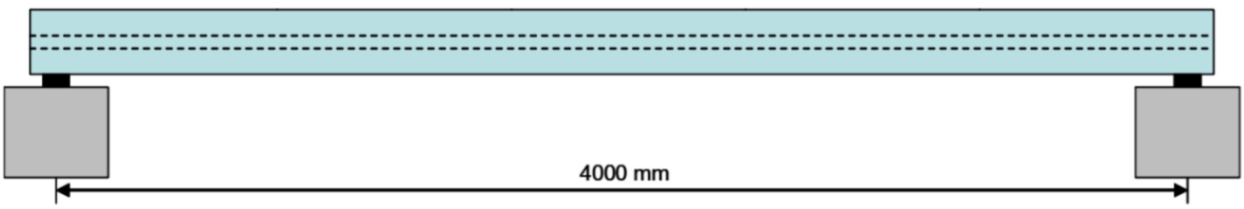


Fig. 1. ERF Method for Modal Identification.

5. Evaluating modal identification techniques for bridge decks

This section outlines the validation of the proposed modal identification method through both 2D and 3D numerical models of bridge deck. The 2D model is a simply supported beam with an INP80 cross-section, 4100 mm in length, and a free span of 4000 mm. The beam is supported by a hinge at one end and a roller at the other, as described in [32]. The model Geometry and its loading arrangement are shown on Fig. 2. Also in natural frequencies and mode shapes are given in Fig. 3.



a) Steel beam in 2D model [32]

b) Loading arrangement in 2D model

Fig. 2. 2D beam model.

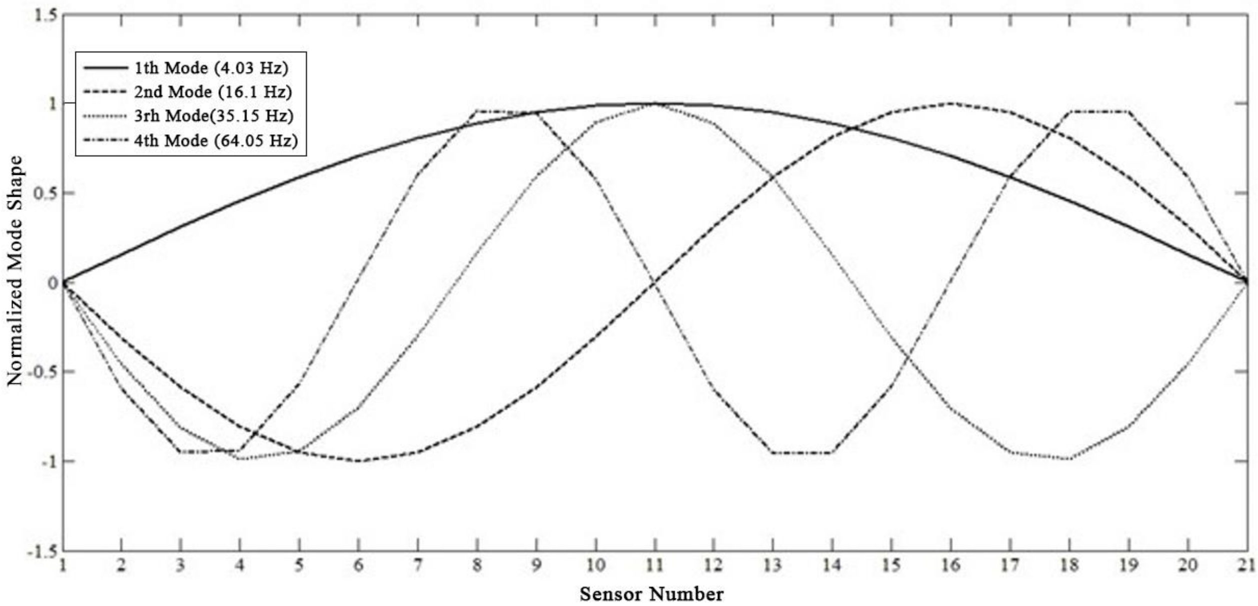


Fig. 3. Mode shapes of 2D model.

Acceleration responses to moving loads are recorded using numerical sensors placed at 200 mm intervals along the beam. The loading scenarios for this model are outlined in Table 1.

Table 1. Loading scenarios of 2D model.

	Loading Scenario	1	2	3	4	5	6	7	8	9
Velocity (m/s)	1st Load (70 N)	0.4	0.3	0.2	0.4	0.3	0.3	0.4	0.3	0.3
	2nd Load (70 N)	-	-	-	0.4	0.3	0.2	0.4	0.3	0.2
	3rd Load (70 N)	-	-	-	-	-	-	0.4	0.3	0.8

The 3D model represents a composite bridge deck, as shown in Fig. 4, where the concrete slab has a thickness of 75 mm at the center and 113 mm at the girders. It is supported by two structural WT girders spaced 1.5 m apart, spanning 6 m. Shear studs are applied to ensure full composite action, and straps are used at 5-meter intervals to prevent lateral buckling of the beams. More details about this model could be found in [33,34]. Fig. 5a provides natural frequencies and mode shapes of 3D Model.

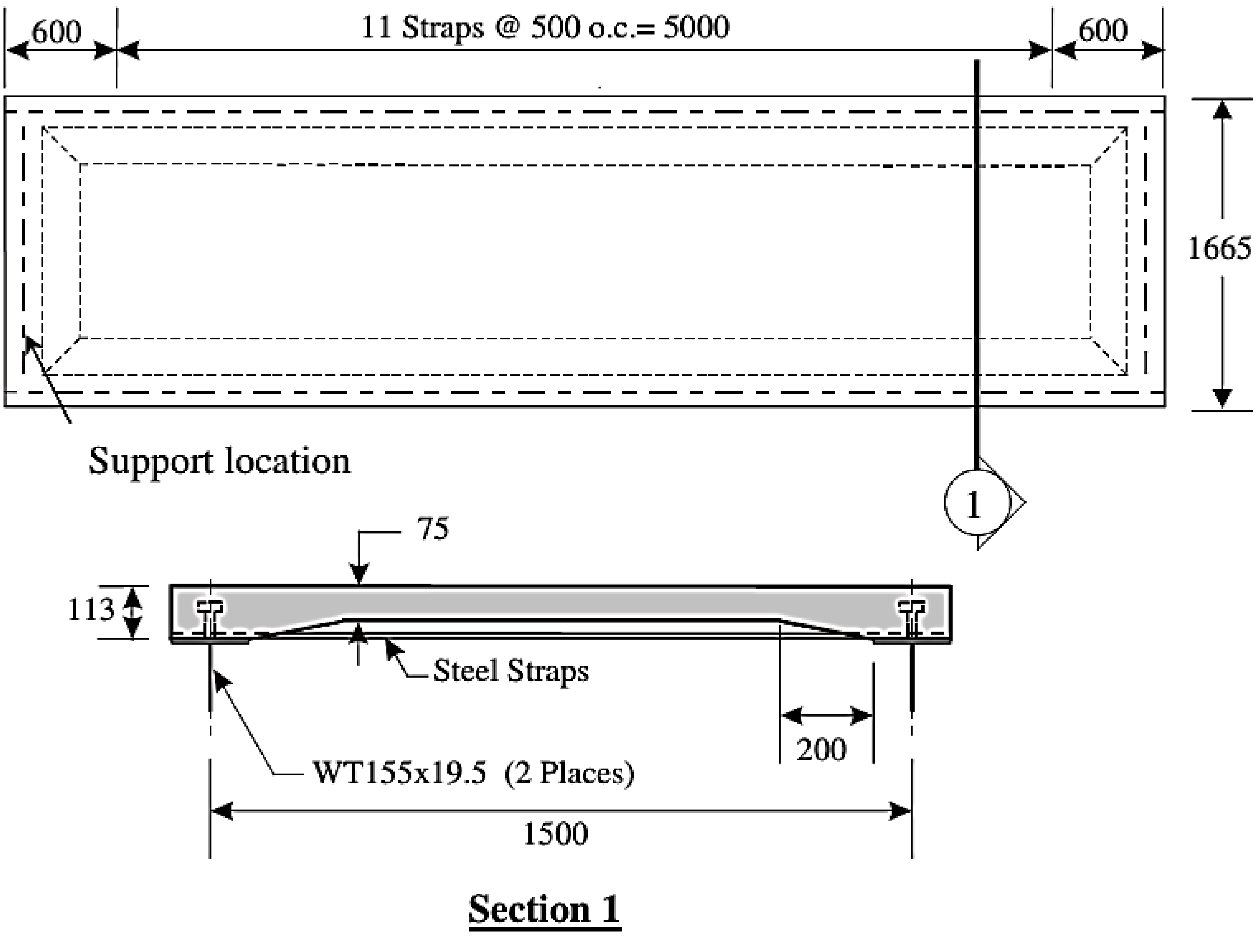
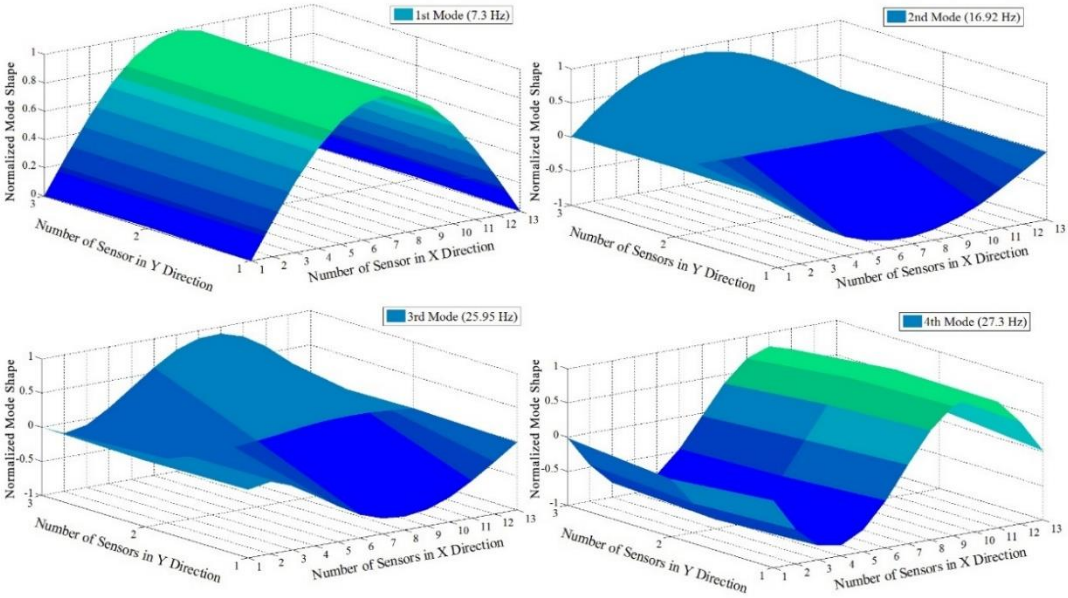


Fig. 4. 3D model of composite bridge [34].

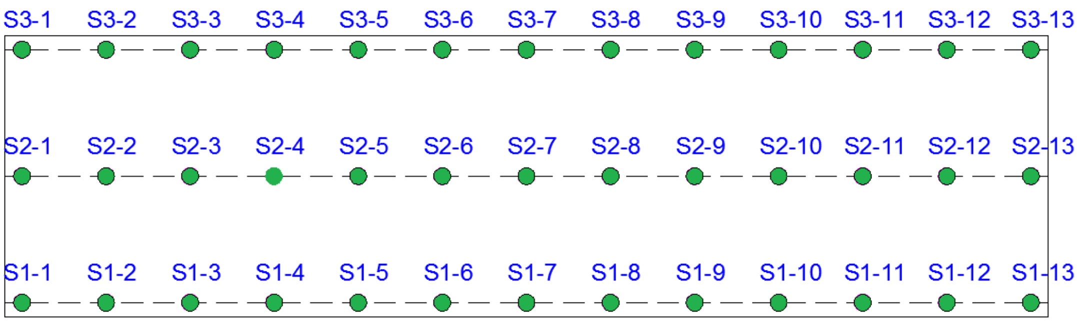
For data acquisition, acceleration sensors are placed along three lines on the bridge, as shown in Fig. 5b. Two load paths are examined to study the effect of load location, and various loading scenarios are considered. The vehicle model for loading is shown in Fig. 5d, with specific loading scenarios provided in Table 2.

Table 2. Loading scenarios for 3D model.

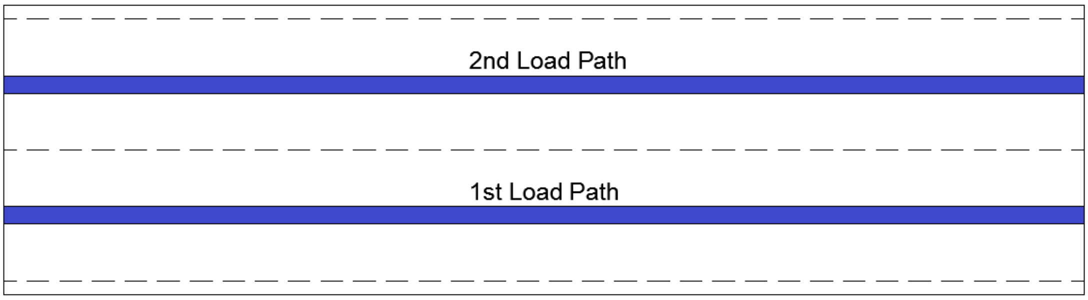
Velocity (m/s)	Load path	Loading scenario		
		1st	2nd	3rd
1st Vehicle (Front Axle 7920 N, Rear Axle 7140 N)	1st	1.8	1.4	1.8
	2nd	-	-	-
2nd Vehicle (Front Axle 7920 N, Rear Axle 7140 N)	1st	0.9	-	0.9
	2nd	-	-1.4	-
3rd Vehicle (Front Axle 7920 N, Rear Axle 7140 N)	1st	-	-	-
	2nd	-	-	-0.9



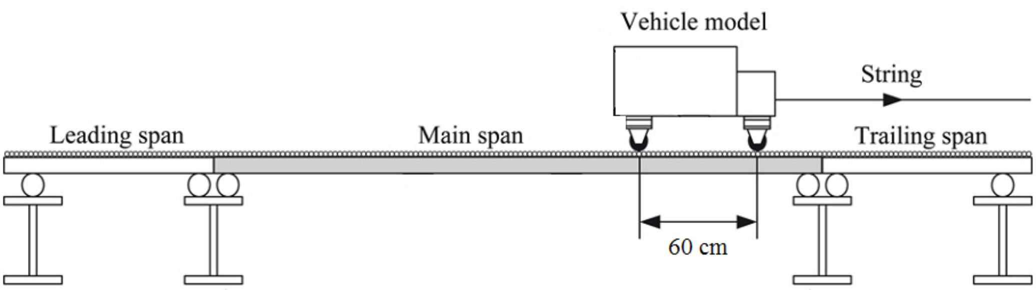
a) Mode shapes and natural frequencies.



b) Sensor locations.



c) Loading path.



d) Vehicle model for loading [35].

Fig. 5. 3D model detail.

From the measured acceleration responses to various loading scenarios in 2D-model, natural frequencies and mode shapes were estimated using the ERF method. The accuracy of the ERF method is influenced by the range of the signal (specifically τ=x% of T), to which the autocorrelation function is applied. As illustrated in Fig. 6, the average Modal Assurance Criterion (MAC) of the first three estimated mode shapes for different values of τ for the final loading scenario reveals that the most accurate results are obtained when 50%≤x≤70%. Table 3 presents the natural frequencies and mode shape similarities for the 2D model, derived using the ERF method under various loading scenarios for τ = 0.6T.

The MAC equation generally calculates the similarity between two mode shapes ϕ_i and ϕ_j as follows [36]:

$$MAC(\phi_i, \phi_j) = \frac{(\phi_i^T,\phi_j)^2}{(\phi_i^T,\phi_i)(\phi_j^T,\phi_j)} \times 100 \tag{15}$$

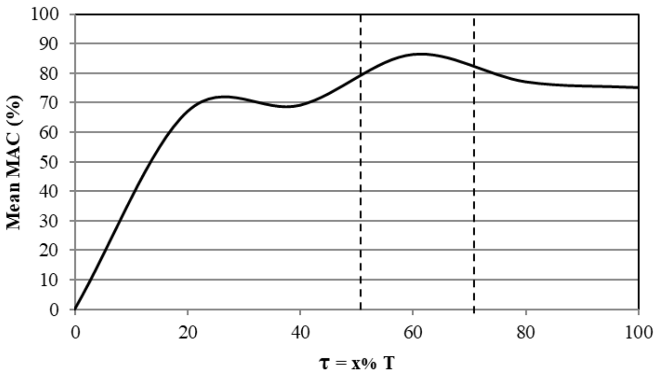
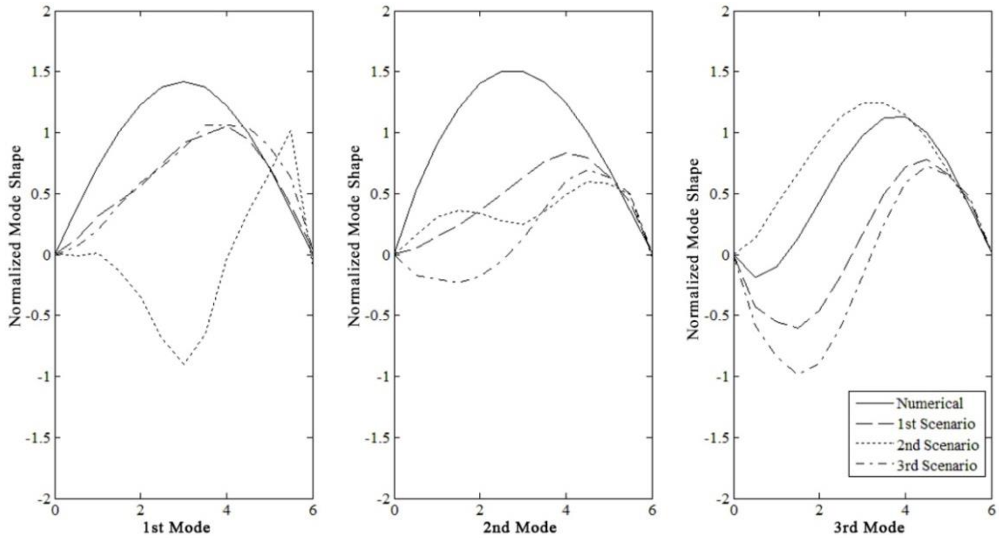


Fig. 6. Effect of τ on ERF accuracy in 2D model.

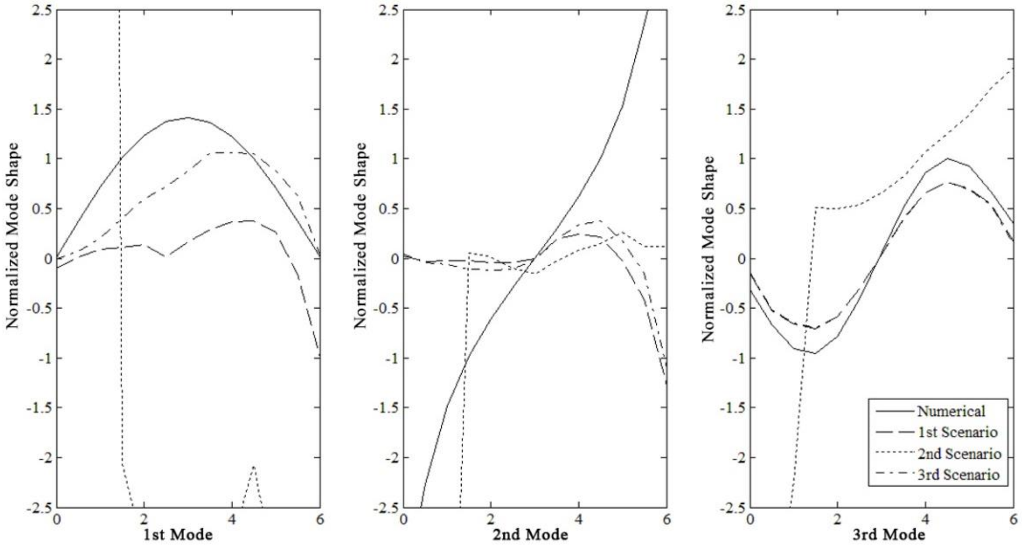
Table 3. Natural frequencies and MAC of different mode shapes for $\tau = 0.6T$ in 2D model**.**

Loading Scenario	1st Mode		2nd Mode		3rd Mode		4th Mode	
	ω	MAC (%)	ω	MAC (%)	ω	MAC (%)	ω	MAC (%)
1	3.80	99.92	16.00	99.95	33.00	12.3	55.00	0.08
2	3.80	99.97	16.00	98.01	33.00	1.87	55.00	0.06
3	3.80	99.97	16.00	97.69	32.00	0.12	-	0
4	4.00	100	14.00	2.52	-	0	-	0
5	4.00	99.99	16.00	99.47	30.00	0.03	-	0
6	4.00	99.99	16.00	97.85	-	0	-	0
7	3.90	99.93	16.00	91.48	32.00	4.22	45	0.02
8	4.00	99.99	16.00	97	33.00	82.13	-	0
9	4.00	99.95	16.00	100	34.00	91.92	52.00	0.01

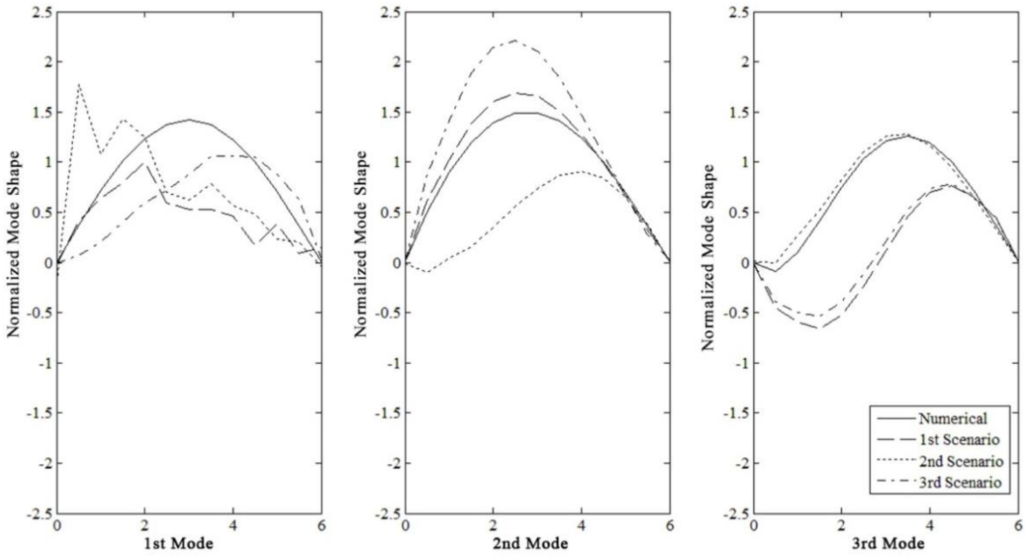
Table 4 provides the natural frequencies and mode shape similarities for the 3D model, obtained using the ERF method across different loading scenarios for τ=0.6T. The first three mode shapes were compared with the analytical mode shapes for each measuring line, as shown in Fig. 7. Different parts of this figure, illustrate the effects of various loading scenarios. As observed, for the 3D model, the estimated frequencies and mode shapes were closer to the analytical values when the loading scenario was more complex.



a) first measuring line.



b) second measuring line.



c) third measuring line.

Fig. 7. First three mode shapes with analytical mode shape.

Table 4. Natural frequencies and MAC of different mode shapes for $\tau = 0.6T$ in 3D model.

Load scenario	Acquiring Line	1st Mode		2nd Mode		3rd Mode	
		ω	MAC (%)	ω	MAC (%)	ω	MAC (%)
1	1st	7.5	88	16.7	70	24.8	95
	2nd	7.1	85	16.5	50	24	95
	3rd	7.8	55	16.9	95	25	91
2	1st	7.3	35	19.1	50	26.8	70
	2nd	6.9	35	18.9	20	25	35
	3rd	7.4	40	19.2	70	27.7	90
3	1st	7.3	85	16.7	65	25	91
	2nd	7.1	70	16.1	50	24.5	95
	3rd	7.46	80	16.8	90	25	95

5. Conclusions

This study presents a novel method for the identification of modal parameters of a bridge deck using its acceleration response to traffic loading. The key steps of the method involve:

1. **EMD-based RD technique:** This technique is employed to estimate the bridge's free-vibration response from its acceleration data under operational loads.
2. **FDD:** The natural frequencies and mode shapes are then predicted using the Frequency Domain Decomposition method.

The proposed method was validated using both 2D and 3D numerical bridge models, with various loading conditions applied and Key Findings from the Study are as follow:

- **Effect of Load Pattern:** The results demonstrated that more complex load patterns, resembling real traffic conditions, produced the most accurate modal parameters. This finding highlights the importance of considering realistic loading scenarios when using operational data for structural health monitoring (SHM).
- **Accuracy by Location:** Modal parameters, especially natural frequencies and mode shapes, were found to be most accurately identified when measuring degrees of freedom (DOFs) adjacent to the load path. This suggests that the positioning of sensors is crucial for optimal results.
- **Higher-Mode Accuracy:** For loading patterns that are more realistic and intricate, higher-mode information proved to be more accurate. This underscores the value of capturing higher modes for comprehensive structural analysis.
- **Reference Sensor Placement:** The study also touches on the importance of selecting a reference sensor for mode shape estimation. It suggests that the reference sensor should not be placed near the beginning, middle, or end of the bridge span, but rather at a more optimal location. The study indicates that further research is needed to determine the best placement for reference sensors and to identify the optimal number of data acquisition points for improved accuracy.

This method shows great promise for practical SHM applications, as it provides a way to estimate modal parameters under operational loading, which is critical for ongoing monitoring and maintenance of bridges and similar structures.

Funding

This research did not receive any specific funding from public, commercial, or not-for-profit sectors. The authors declare no financial support for the research, authorship, and/or publication of this article.

Conflicts of 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.

Authors contribution statement

Meisam Talebi: Conceptualization, Modeling, Data Curation, Formal Analysis, Investigation, Writing – Original Draft.

Zahra Tabrizian: Project Administration, Writing – Review & Editing.

Gholamreza Ghodrati Amiri: Validation, Supervision.

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