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Reviving the I-40 Structural Deficit Paradigm: An Online Computational Behavioural Study Under Imposed Traffic Loads

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ABSTRACT

Bridges are constructed with decades-long serviceability expectations for facilitating connectivity, economical routing of goods, accessibility to remote areas, and emergency response to disasters. In recent years, the rapid increase in the number of bridges has not only enhanced convenience for people but also inadvertently increased potential risks arising from various deficiencies, such as structural flaws or functional obsolescence. This research specifically addresses the deteriorating condition of the I-40 Bridge in New Mexico, US, with a particular focus on crack formation observed in one of its plate girders. While prior studies have primarily concentrated on the pre-rehabilitation phase of the bridge, this current investigation shifts its attention to the critical assessment of the bridge condition under varying traffic loads which provides more comprehensive understanding of its structural performance. To achieve this objective, the behaviour of various bridge components, especially in areas experiencing extreme stresses, is thoroughly examined using advanced finite element modelling techniques. This approach allows for a detailed analysis of how the bridge behaves under different load conditions, providing insights into its capacity and potential vulnerabilities. The study goes further by exploring variations in structural behaviour across different scenarios and conducting comprehensive strength assessments under a wide range of steady and transient loading conditions. These assessments are complemented by modal identification techniques, which help to understand the dynamic characteristics of the bridge. Furthermore, the results of these analyses were validated through the application of Empirical Mode Decomposition (EMD) and Variational Mode Decomposition (VMD) methods, both of which offer valuable insights into bridge health. These techniques are employed to decompose complex signals into simpler components referred to as Intrinsic Mode Functions (IMF). EMD is an adaptive time-frequency analysis method, comparatively easy to implement but prone to mode mixing in complex signals. VMD is an entirely non-recursive and quasi-orthogonal multi-scale signal decomposition method based on the frequency domain and uses an optimized approach for signal processing that decomposes the signal into a predefined number of modes. In addition to analysing structural behaviour and dynamic characteristics, the

research extends to important aspects such as damping estimation and damage quantification utilising these methodologies. The findings of this study not only explain the condition of the I-40 Bridge but also yield insights regarding the computational efficiency of the methods employed in the analysis and compared on computational time, energy distribution in IMFs, and sensitivity for structural damage under random loading. A key conclusion drawn from this research is that VMD is more consistent in mode separation than EMD, but it has a higher computational cost than EMD, which could have implications for future studies focusing on similar assessments. Overall, this research contributes to a deeper understanding of bridge health and safety, highlighting the importance of ongoing structural assessments to ensure the longevity and safety of critical infrastructure.

Keywords: I-40 Bridge, EMD, VMD, Finite element, Damage detection, Operational modal analysis

1. INTRODUCTION

Bridges serve as critical links in regional and national transportation networks, facilitating economic activity and emergency response capabilities. The increasing number of aging bridges worldwide has directly correlated to the demand for advanced structural health monitoring (SHM) techniques that can provide accurate, real-time assessments of structural integrity [1]. Structural deficiencies, including fatigue-induced cracks and localized material degradation [2], can significantly impact bridge safety and performance, sometimes leading to catastrophic failures, if not properly monitored and maintained [3]. The I-40 Bridge in New Mexico, USA, has become a case of particular interest due to the emergence of crack formations in one of its plate girders (Fig.1), thereby raising concerns about its long-term serviceability. Previous studies have largely focused on conditions prior to rehabilitation efforts, leaving a critical gap in understanding its *post-rehabilitation* behavior under critical traffic loads. Addressing this gap is crucial for evaluating the effectiveness of maintenance interventions and ensuring reliability. This study aims to investigate the structural performance of the I-40 Bridge under varying traffic loads through an advanced computational approach, offering deeper insights into its stress distribution, dynamic response, and potential vulnerabilities. To achieve this, the research employed advanced Finite Element Methods (FEM) to simulate the stress distribution across different components, particularly in regions experiencing extreme loading conditions. Furthermore, signal decomposition methods are used to analyse structural behavior and damage patterns by breaking down complex response signals into Intrinsic Mode Functions (IMFs), specifically using Empirical Mode Decomposition (EMD) and Variational Mode Decomposition (VMD). EMD, recognized for its adaptive, data-driven approach to time-frequency analysis, offers computational efficiency but can encounter challenges with mode mixing [5]. In contrast, VMD provides enhanced mode separation through a non-recursive, frequency-domain approach, though it experience higher computational costs [6]. The findings emphasise the critical need

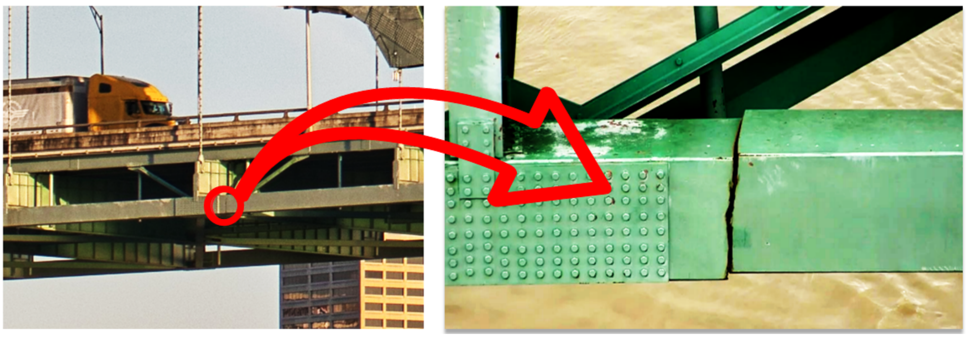

Figure 1: A crack detected in one of two 900-foot horizontal steel tension tie girders of the I-40 Bridge which was recorded (a) in 2019 and later (b) on May 11, 2021, fracture was detected ([4]).

for ongoing structural assessments and explore the computational trade-offs inherent in signal decomposition methodologies.

2. EMD AND VMD – THE ”WHAT”, ”WHY”, & ”HOW” ?

Table 1: Algorithms for EMD and VMD

Algorithm 1 Empirical Mode Decomposition (EMD)

Require: Signals $x_1(t) = x_2(t) = x(t)$, $i = 1$

1: Find the locations of all extrema of $x_1(t)$;
2: Interpolate all the maxima (minima) using cubic spline interpolation to obtain the upper (lower) envelope, ($e_{\text{max}}(t)$), ($e_{\text{min}}(t)$);
3: Compute the local mean,

$$m(t) = \frac{e_{\text{min}}(t) + e_{\text{max}}(t)}{2};$$

4: Subtract the mean from the signal to obtain the oscillatory mode,

$$s(t) = x_1(t) - m(t);$$

5: **if** $s(t)$ obeys the stoppage criterion **then**
6: Set $d_i(t) = s(t)$, go to 10;
7: **else**
8: Set $x_1(t) = s(t)$ and repeat from 1;
9: **end if**
10: Subtract the derived IMF $d_i(t)$ from $x_2(t)$ so that $x_2(t) = x_2(t) - d_i(t)$
11: **if** $x_2(t)$ becomes monotonic or lacks sufficient extrema for forming an envelope **then**
12: $r(t) = x_2(t)$;
13: **else**
14: Set $x_1(t) = x_2(t)$, $i = i + 1$, and return to 1;
15: **end if**
16: **Return** IMFs $\{d_i(t)\}_{i=1}^{M}$ and the residual $r(t)$;

Algorithm 2 Variational Mode Decomposition (VMD)

Require: Input signal $x(t)$, number of modes K, penalty parameter α, Lagrange multiplier λ, convergence tolerance ϵ

1: Initialize: $\{u_k^0\}_{k=1}^{K}$, $\{\omega_k^0\}_{k=1}^{K}$, and λ^0 in the frequency domain
2: Compute the Fourier transform $\hat{x}(\omega)$ of the input signal $x(t)$
3: **while** not converged **do**
4: **for** each mode $k = 1, 2, \ldots, K$ **do**
5: Update mode u_k in the frequency domain:

$$\hat{u}_k(\omega) = \frac{\hat{x}(\omega) - \sum_{i \neq k} \hat{u}_i(\omega) + \frac{\lambda(\omega)}{2}}{1 + \alpha(\omega - \omega_k)^2}$$

6: Update center frequency ω_k:

$$\omega_k = \frac{\int_0^\infty \omega |\hat{u}_k(\omega)|^2 d\omega}{\int_0^\infty |\hat{u}_k(\omega)|^2 d\omega}$$

7: **end for**
8: Update Lagrange multiplier:

$$\lambda(\omega) = \lambda(\omega) + \tau \left(\hat{x}(\omega) - \sum_{k=1}^{K} \hat{u}_k(\omega) \right)$$

9: Check for convergence:

$$\sum_{k=1}^{K} ||u_k^n - u_k^{n-1}||_2^2 < \epsilon$$

10: **end while**
11: Compute the inverse Fourier transform of $\hat{u}_k(\omega)$ to obtain time-domain modes $u_k(t)$
12: **Return** decomposed modes $\{u_k(t)\}_{k=1}^{K}$

In modern structural engineering, FEM has become a powerful computational tool used for simulating complex structures under various loading conditions. By discretising a structure into smaller, manageable elements, FEM enables detailed analysis of stress distributions, modal properties, and dynamic responses. This technique has been widely adopted for predicting system behavior and identifying critical structural regions susceptible to damage. Complementary to FEM approaches, data-driven techniques such as EMD and VMD have emerged as effective methods for processing and analyzing structural response signals [7].

In this context, EMD is a time-frequency domain signal decomposition technique that has gained significant popularity in the field of *output-only modal identification of structures*. The standard EMD aims to adaptively decompose a signal into a finite set of oscillatory components known as *IMFs*. For a real-valued p-dimensional signal $x(t)$, the application of EMD yields a set of IMFs $\{d_i(t)\}_{i=1}^{M}$ and a monotonic residue $r(t)$, as represented as $x(t) = \sum_{i=1}^{M} d_i(t) + r(t)$. The decomposition process is outlined in Algorithm 1 (presented in Table1). On the other hand, VMD is an advanced signal decomposition technique that extends EMD by formulating the problem as a *constrained variational optimization process*. Unlike EMD – which adaptively extracts IMFs based on local extrema – VMD decomposes a signal into a predefined number of band-limited modes, each with distinct frequency characteristics. The method iteratively determines each mode by minimizing a cost function that balances *data fidelity and spectral separation*, enforced through a quadratic penalty and a Lagrange multiplier. Given a real-valued input signal $x(t)$, VMD produces a set of modes $\{u_k(t)\}_{k=1}^{K}$, where K is the predefined number of modes. The decomposition process is outlined in Algorithm 2 (presented in Table1).

3. PROPOSED APPROACH

The proposed methodology illustrated in Fig.2, integrates a *model-based approach* using **FEM** and a *data-driven approach* utilizing **EMD** and **VMD** for structural identification and damping estimation. First, an FE Model is developed to simulate the I-40 Bridge response under various loading conditions, including a severe damage scenario. The generated response signals are then processed using signal decomposition techniques to extract meaningful modal characteristics. The adopted methodology is explained stepwise for an easy comprehension in the following subsections.

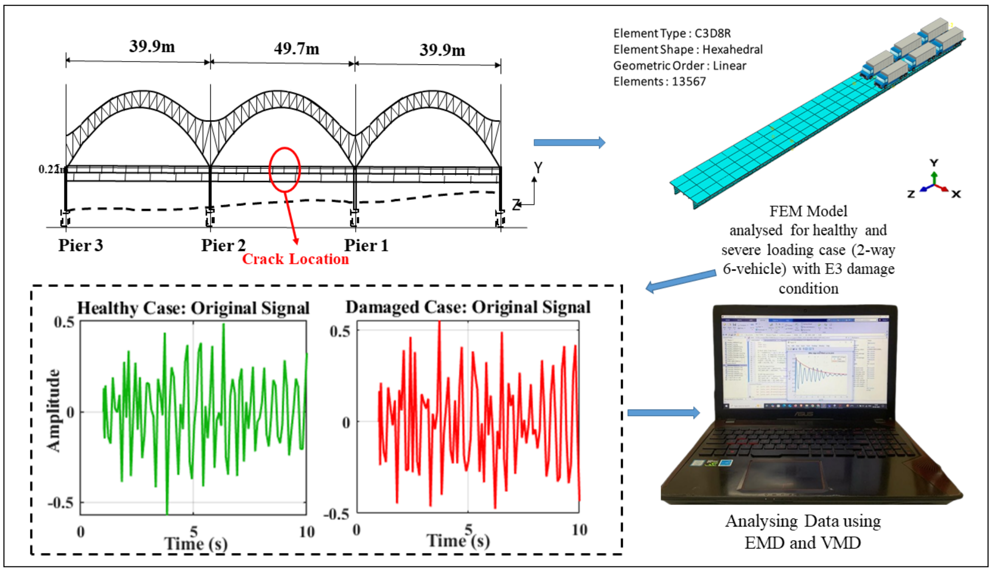

Figure 2: Overview of data aquisition and analysis

3.1. Model-Based Approach using FEM

To assess the structural condition of the I-40 Bridge before and after rehabilitation, a detailed FEM study was conducted. This model-based approach enables the evaluation of stress and strain distributions under various loading conditions, allowing for the identification of critical regions susceptible to damage. The I-40 Bridge is modeled as a three-span structure with span lengths of $39.9m$, $49.7m$, and $39.9m$. The bridge geometry and material properties were incorporated into the ABAQUS software for numerical simulation. To simplify the modeling process while maintaining structural equivalency, the bridge deck slab is represented as a uniform $220mm$ thick slab, ensuring an equivalent cross-sectional area to the actual non-uniform slab. The floor beams and stringers are assigned 36 WF 150 and 21 WF 62 sections, respectively, with appropriate Young's modulus and Poisson's ratio values. The loading conditions applied in the FEM simulations follow the AASHTO HL-93 classification, considering traffic scenario as 6-vehicle configurations for two-way traffic. To investigate the impact of structural degradation, three levels of **damage (E-1, E-2, E-3)** were induced in the north plate girder at the mid-span, near the seat supporting the floor beam:

- E-1: A 0.6 m (2 ft) long, 10 mm (3/8 in) wide cut through the web, centered at mid-height.
- E-2: Extension of the cut to the bottom of the web.
- E-3: A full flange incision, leaving only the top 1.2 m (4 ft) of the web and the top flange to carry the load.

The progression from E-1 to E-3 represents increasing levels of damage severity, enabling a comprehensive evaluation of the bridge's behavior under extreme conditions. For the purpose of this study, the most severe damage scenario (E3) is considered, where a crack propagates through the web and flange of the north plate girder. Structural response data is collected by subjecting the FEM model to dynamic loading with a two-way traffic scenario (6 vehicles), and time-domain response signals (**acceleration response data**) are extracted for both healthy and damaged conditions. This data obtained from FEM analysis serves as the input for subsequent **structural identification and damping estimation** using EMD and VMD.

3.2. Data-driven approach using EMD & VMD

The data-driven module of the proposed methodology employs the acceleration responses – generated from the FEM module – as inputs to the EMD & VMD approaches. EMD decomposes the inherently nonlinear and non-stationary signals into a set of IMFs through an iterative sifting process that identifies local extrema and constructs upper and lower envelopes. However, due to the susceptibility of EMD to mode mixing, VMD is simultaneously employed. It decomposes the signal into a predetermined number of band-limited modes by solving a constrained variational optimization problem that minimizes the sum of estimated bandwidths while ensuring data fidelity. This dual-decomposition strategy enables the precise isolation of modal components corresponding to the system natural frequencies and damping ratios. By analyzing shifts in these modal parameters – particularly when comparing the healthy state to the damage case – the approach facilitates the detection of subtle damage-induced changes [8].

4. RESULTS AND DISCUSSIONS

The modal characteristics, including modal frequencies and damping ratios, are analysed for both healthy and damaged cases. The extracted IMFs are used to evaluate the effectiveness of EMD and VMD. The following subsections discuss the detailed inferences drawn from the obtained results. All data, models, and code generated or used during the study appear in the submitted article. The metadata can be readily accessed at oscarlab-SHM.

4.1. Spectral Analysis for Healthy and Damaged Cases of the I-40 Bridge

Fig.3 and 4, illustrate the time-domain IMFs and their frequency spectra obtained using EMD and VMD for the healthy structure. The EMD-based decomposition shows mode mixing in lower IMFs, whereas VMD produces more distinct and well-separated frequency components. The first few IMFs in both cases represent higher frequency content, while lower IMFs correspond to fundamental structural modes. The frequency spectrum of IMFs obtained using VMD aligns better with the expected modal frequencies than EMD, ensuring accurate feature extraction.

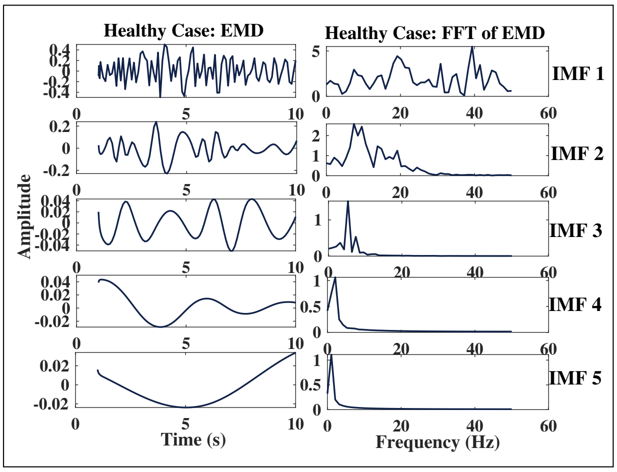

Figure 3: Healthy case: The left panel shows the IMFs and their corresponding FFTs obtained using EMD in right panel

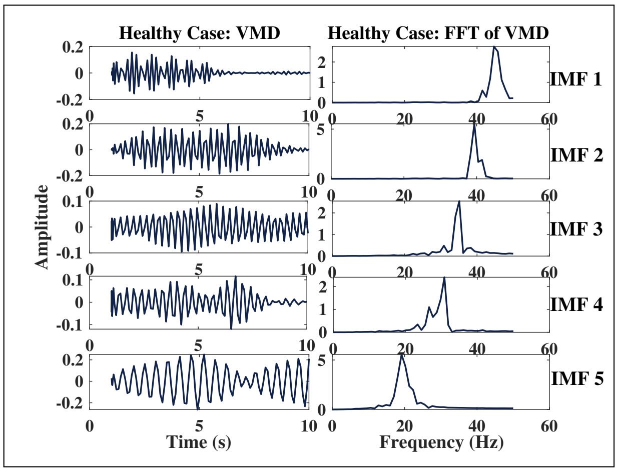

Figure 4: Healthy case: The IMFs (left) and their corresponding FFTs (right) obtained using VMD

For the damaged structure, Fig.5 and 6 present the extracted IMFs and their frequency spectra using EMD and VMD, respectively. A *significant shift in modal frequencies* is observed in the IMFs of the damaged case, indicating structural degradation. The energy distribution among the IMFs also changes, with lower frequency components now becoming more dominant. Comparatively VMD effectively isolates the frequency components, making it more suitable for detecting damage-induced changes in structural response.

The IMFs obtained from the damaged case exhibit a shift in dominant frequencies, consistent with the observations in Table 2. This table represents a comparative analysis of the modal frequencies obtained from the IMFs of EMD and VMD for both healthy and damaged cases. It is easily observed that the modal frequencies extracted using VMD show higher consistency compared to those obtained through EMD. Notably, IMF 1 from VMD exhibits a modal frequency of 44.6809 Hz in the healthy case, whereas in the damaged case, it reduces to 41.4894 Hz. A reduction in modal frequencies is similarly observed across all IMFs, confirming structural damage. The results suggest that VMD provides a more stable frequency extraction mechanism compared to EMD.

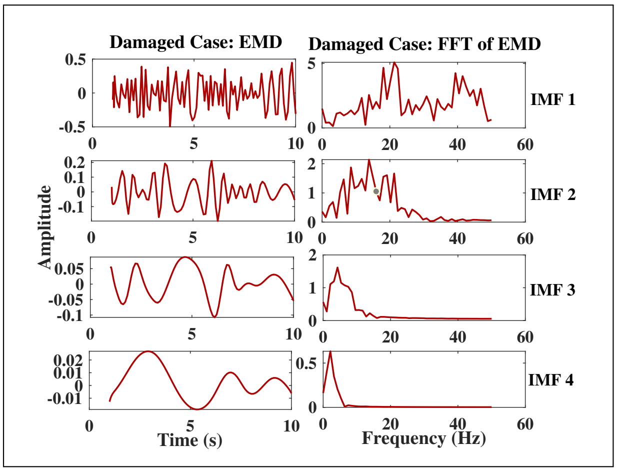

Figure 5: Damage case: The left panel shows the IMFs and their corresponding FFTs obtained using EMD in right panel

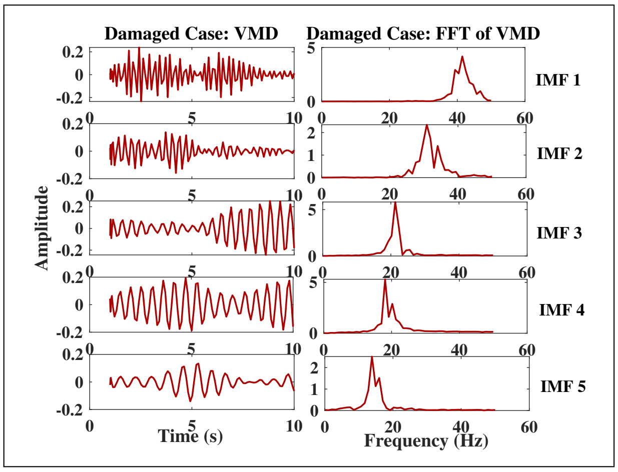

Figure 6: Damage case: The left panel shows the IMFs and their corresponding FFTs obtained using VMD in right panel

Table 2: Comparison of modal frequencies obtained from IMFs of EMD and VMD for healthy and damaged cases

IMFs	Modal frequencies (H_z)			
	Healthy Case		Damaged Case	
	EMD	VMD	EMD	VMD
IMF 1	39.3617	44.6809	21.2766	41.4894
IMF 2	7.4468	39.3617	13.8298	30.8511
IMF 3	5.3191	30.8511	4.2553	21.2766
IMF 4	2.1276	20.2128	2.1276	18.0851
IMF 5	1.0638	19.149	-	13.8298

Table 3: Comparison of theoretical damping ratio with the damping ratio obtained from IMFs of EMD and VMD

IMFs	Damping ratio (ζ) obtained	
	EMD	VMD
IMF 1	0.0090	0.0090
IMF 2	0.0091	0.0090
IMF 3	0	0.0084
IMF 4	0	0.0090
IMF 5	-	0.0104
Theoretical damping ratio (ζ) 0.0094	0.004525	0.00916

4.2. Structural Damping Estimation using Logarithmic Decrement

Table 3 compares the theoretical damping ratio with those obtained from the IMFs of EMD and VMD. The damping ratio extracted from VMD aligns closely with the theoretical damping ratio, indicating exact mode separation. For instance, IMF 3 obtained from VMD has a damping ratio of 0.0084, whereas EMD fails to extract any damping information. Similarly, the damping ratio for IMF 5 is 0.0104, highlighting the advantage of VMD in preserving damping information for low and high modes.

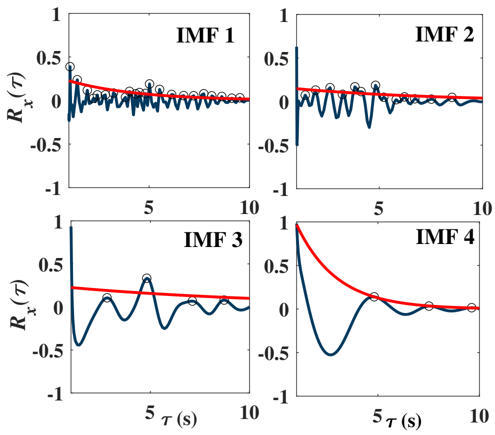

Figure 7: Auto correlation result and expo fitting for damping estimation using EMD

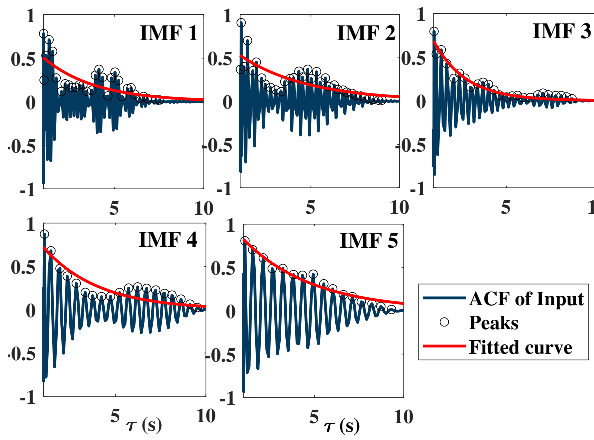

Figure 8: Auto correlation result and expo fitting for damping estimation using VMD

Damping estimation for the transformed data is conducted through the popular time-domain method – the logarithmic decrement approach – and then a comparative assessment is carried out. The selection of this technique is considered as representative due to its fundamental and straightforward nature, which helps obscure any source of nonlinearity in the signal. The auto correlation of the physical signatures obtained from the bridge model are considered for estimating the damping ratio corresponding to each mode as shown in Fig.7 and 8. The auto correlation function (ACF) of the input signal is shown in blue, while the detected peaks and fitted curve used for damping estimation are overlaid in red (colour available in the online version). The damping estimation using EMD shows inconsistencies in certain IMFs – particularly IMF 3 and IMF 4 – where the oscillations are not well-defined. The fitted curves for some modes exhibit deviations due to mode mixing, which affects the accurate extraction of damping characteristics. The peaks are not uniformly distributed, suggesting that the decomposition does not entirely separate structural modes. In contrast, the VMD-based damping estimation provides more distinct oscillatory patterns for all IMFs, with better peak alignment and a more consistent exponential decay. The fitted curves closely follow the envelope of the ACF, indicating a more reliable damping estimation process. The damping characteristics are better preserved, highlighting the superior performance of VMD in capturing structural damping behavior. VMD outperforms EMD in damping estimation by effectively isolating the structural modes and reducing interference from other frequency components. This makes VMD a more robust, reliable, and feasible approach for analyzing damping characteristics.

5. CONCLUSIONS

The observed shifts in frequency and variations in damping between healthy and damaged states affirm the effectiveness of this approach in detecting structural damage. This research offers a detailed understanding of the modal characteristics of the structure in both healthy and damaged conditions. The results reveal that dominant modal frequencies shift as a result of structural damage, with lower frequency components becoming more pronounced. In the course of this research, a thorough distinction of damping estimation performance through EMD & VMD portrayed. VMD emerged as the clear winner – with accurate damping estimations throughout the frequency spectrum of the I-40 bridge. Overall, the findings suggest that VMD is a superior signal decomposition technique for structural health monitoring applications, enhancing damage detection capabilities and providing better characterization of dynamic structural behavior.

Although VMD promises to be a certainly very exciting prospect, the skepticism regarding its usage emanates from the trade-off in the context of its *computational expense*. When such situations are not satisfactorily addressed, the conclusion for some is that the whole idea is over-hyped, leading to skepticism becoming cynicism; which is a fallacy as proven through this research.

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REFERENCES

[1] C.R. Farrar, T.A. Duffey, P.A. Goldman, D.V. Jauregui, and J.S. Vigil. Finite element analysis of the i-40 bridge over the rio grande. Technical report, Los Alamos National Lab. (LANL), Los Alamos, NM (United States), 1996.

[2] A. Sharma and B. Bhowmik. When fire attacks: How does concrete stand up to heat? *arXiv preprint arXiv:2408.15756*, 2024.

[3] S. A. Wani, R. Pani, A.and Mohan, and B. Bhowmik. Digital payment adoption in public transportation: Mediating role of mode choice segments in developing cities. *Transportation Research Part A: Policy and Practice*, 191:104319, 2025.

[4] S. Pezeshk, C. V. Camp, A. Kashani, M. Akhani, et al. Data analyses from seismic instrumentation installed on the i-40 bridge. 2021.

[5] M. Wang, C. Xiong, and Z. Shang. Predictive evaluation of dynamic responses and frequencies of bridge using optimized vmd and genetic algorithm-back propagation approach. *Journal of Civil Structural Health Monitoring*, pages 1–18, 2024.

[6] P. Lu, L. Yang, T. Jin, Y. Wu, and M. Cai. Bridge modal identification method based on adaptive vmd-ht algorithm. *Nondestructive Testing and Evaluation*, pages 1–21, 2024.

[7] M. Civera and C. Surace. A comparative analysis of signal decomposition techniques for structural health monitoring on an experimental benchmark. *Sensors*, 21(5):1825, 2021.

[8] B. Bhowmik, B. Hazra, and V. Pakrashi. *Real-time structural health monitoring of vibrating systems*. CRC Press, 2022.