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Signal Denoising for Timber Bridge Structural Health Monitoring Using Optimized Variational Mode Decomposition

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ABSTRACT: Operational and measurement noise presents a major challenge to the accuracy and reliability of structural health monitoring (SHM) systems, particularly in timber bridge applications. This study investigates the effectiveness of Variational Mode Decomposition (VMD), an advanced signal processing technique, in enhancing the quality of response measurements from a laboratory-scale pedestrian timber bridge. Acceleration and strain signals were collected under both intact and damaged conditions to perform a detailed signal analysis. VMD was applied to decompose the signals into narrowband intrinsic mode functions (IMFs), enabling the isolation of structural responses from noise. The method yielded high cross-correlation values (above 0.998) between original and reconstructed signals, confirming that critical features were preserved. Furthermore, energy retention analysis across IMFs revealed distinct patterns reflective of structural condition, with meaningful content concentrated in the lower-order modes and noise primarily captured by the final components. These findings confirm the potential of VMD as a robust preprocessing tool for noise reduction within SHM frameworks, supporting improved interpretation of structural responses in timber bridge structures.

KEYWORDS: Timber bridge, variational mode decomposition, noise reduction, structural health monitoring.

1 – INTRODUCTION

Engineering constructions such as bridges and other civil infrastructures have a significant role in the economy and serve a vital purpose in facilitating the daily activities of individuals [1]. Growing concern about the economic and societal impacts of infrastructure aging, degradation, and exposure to extreme events has led to a heightened demand for more advanced structural health monitoring (SHM) systems and effective damage detection methods [2]. Bridges play a crucial role in transportation infrastructure networks [3]. As timber is considered as a structural material [4], timber bridges have many advantageous characteristics, including cost-effectiveness, ease of construction, environmental sustainability, and the potential for an extended lifetime [5-8]. However, timber bridges may provide challenges in some scenarios due to their inability to accommodate the current or increasing traffic volume, as well as their need for costly maintenance interventions [9]. Hence, it is essential to give precedence to the preservation and extension of the longevity of timber bridges [10-12]. Conventional bridge assessment approaches often lack the capability for real-time monitoring, hindering the immediate detection of structural issues. While SHM

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systems offer continuous monitoring capabilities, extracting meaningful insights from the data collected can be challenging and requires advanced processing techniques [13]. Moreover, traditional SHM methods pose challenges in data analysis and processing [14]. Variational Mode Decomposition (VMD) has emerged as a valuable technique for analysing complex signals, especially when dealing with noise and overlapping frequency components. Its ability to break down non-stationary signals into distinct modes makes it a strong candidate for diverse fields such as medical diagnostics, machinery fault detection, and structural health evaluation [15]. In engineering applications, VMD has proven effective in pinpointing structural damage by revealing subtle shifts in system dynamics, particularly when multiple frequencies are closely spaced [16], thus offering greater clarity in identifying changes in vibrational behaviour. Therefore, practical validation methods on laboratory-scale pedestrian bridges are required. This study is aimed to evaluate the capabilities of VMD for noise reduction in timber bridge monitoring applications. This investigation involves a comprehensive experimental study on a laboratory-scale pedestrian bridge. The performance of VMD is evaluated on sensor-based structural response data. Moreover, the effectiveness of VMD in early damage detection, condition assessment, and monitoring automation are evaluated.

2– Methodology

2.1 Laboratory timber bridge

A laboratory timber bridge with dimension of 8.5 m in length, 1.2 m in width, and 0.902 m in height was constructed in the UNSW Heavy Structures Laboratory, as shown in Fig. 1. The timber bridge, consisting of four spans, was made of three glulam beams as girders and plywood panels as deck section. The timber bridge was supported by pin and roller bearings, which were mounted on concrete abutments.

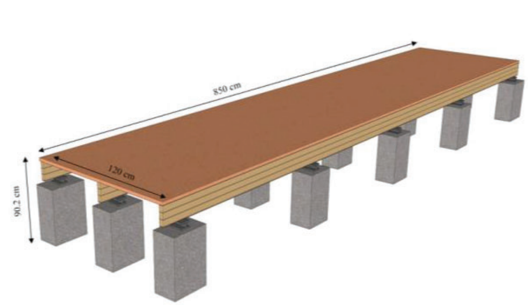


Figure 1: Schematic of the laboratory timber bridge

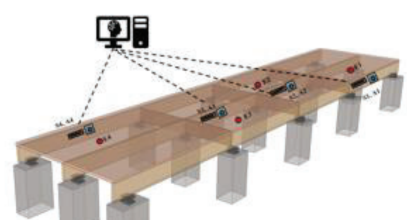
2.2 Damage Scenario

As shown in Fig. 2, adding mass (20 kg) was applied as a damage scenario. The mass was added on the one of the midspans.

Figure 2: Adding mass (20 kg) on the laboratory timber bridge

2.3 Instrumentation

To capture the structural responses, four electrical resistance strain gauges and four accelerometers, as shown in Fig. 3 (a) and (b), were positioned at different locations (midspans of girders) on the timber bridge. The laboratory-scale timber pedestrian bridge was designed in accordance with AS 5100.2 and AS 1720.1 [17, 18].



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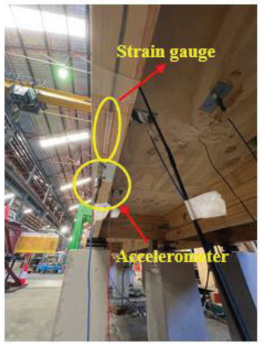

Figure 3 (a and b): Accelerometer and strain gauge sensors placed under the girder of the timber bridge

2.4 Impact Hammer Testing

As shown in Fig. 4, impact hammer testing was conducted on the timber bridge where hammer strikes were applied at four locations of the deck section (E1, E2, E3 and E4), with six repetitions at each location. The sensor recording specifications (sampling frequency and duration) are detailed in Table 1.

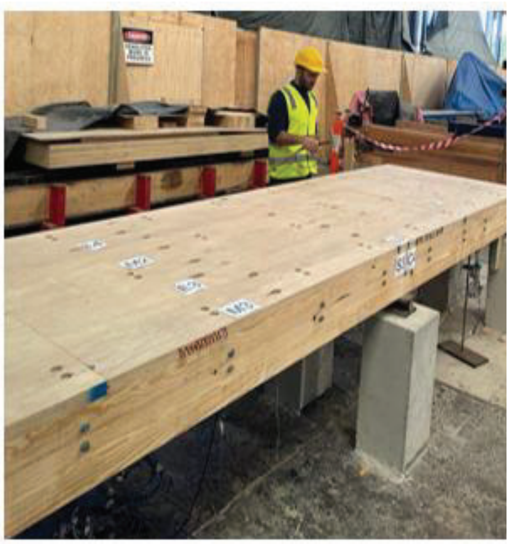

Figure 4: Impact hammer testing on the laboratory timber bridge

Table 1. Sensor specifications used for data acquisition, including sampling frequency, duration of each measurement, and number of repeated impacts per test

Sensor	Sample Frequency	Measurement Duration per Incident	Impact Repetitions per Incident
Strain gauge	4.8 kHz	30 seconds	6
Accelerometer	10 kHz	30 seconds	6

2.5 Noise Reduction using VMD

In the context of SHM for bridges, measured signals, such as strain and acceleration responses, often contain noise due to measurement errors and operational conditions. To extract meaningful structural features, it is essential to denoise these signals and decompose them into their intrinsic components. In this study, we employ VMD as a preprocessing step for denoising and mode extraction of both strain and acceleration signals collected from a laboratory bridge model.

2.5.1 Rationale for Using VMD in SHM

VMD is a data-driven signal decomposition technique that can adaptively separate a signal into a set of band-limited IMFs. Each IMF captures a distinct oscillatory component, enabling the isolation of structural responses associated with different physical phenomena (e.g., low-frequency global deformation vs. high-frequency local damage). This makes VMD particularly well-suited for SHM applications, where it is important to distinguish between meaningful structural behaviour and noise.

2.5.2 Theoretical Background of VMD

The goal of VMD [19] is to decompose a signal into a predefined number of IMFs by solving a constrained optimization problem in the frequency domain. The main properties of VMD include:

• Variational formulation: VMD is posed as an optimization problem, ensuring a well-defined mathematical foundation for decomposition.

• Mode separation: It produces modes that are compact around their centre frequencies, which helps in separating structural responses from noise and other dynamic influences.

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• Adaptability: Unlike traditional methods such as Empirical Mode Decomposition (EMD), VMD avoids mode mixing and is less sensitive to endpoint effects, making it more reliable for real-world SHM applications.

Each IMF$\mathbf{u}_k(t)$ resulting from VMD can be represented as:

$$\mathbf{u}_k(t) = \mathbf{A}_k(t)\cos(\phi_k(t)) \tag{1}$$

where $\mathbf{A}_k(t)$ and $\phi_k(t)$ denote the instantaneous amplitude and phase, respectively. These parameters are particularly useful in SHM because variations in amplitude and frequency may indicate structural changes or damage over time.

The instantaneous frequency (IF) is computed as:

$$\omega(t) = \frac{\partial \phi(t)}{\partial t} \tag{2}$$

To obtain both IF and instantaneous amplitude (IA), the analytic signal is formed using the Hilbert transform:

$$\mathbf{u}_a(t) = \mathbf{u}(t) + j\hat{\mathbf{u}}(t) \tag{3}$$

where $\hat{\mathbf{u}}(t)$ is the Hilbert transform of $\mathbf{u}(t)$. From this, IA and IF are derived:

$$\mathrm{IA}(t) = \sqrt{u^2(t) + \hat{u}^2(t)} \tag{4}$$

$$\mathrm{IF}(t) = \frac{d}{dt}\left(\tan^{-1}\left(\frac{\hat{u}(t)}{u(t)}\right)\right) \tag{5}$$

These quantities provide valuable information for damage detection. For example, sudden spikes in IA or shifts in IF over time may correspond to stiffness changes in the bridge structure.

VMD solves the following augmented Lagrangian optimisation problem:

$$\mathcal{L}(\mathbf{u}_k, \omega_k, \lambda) = \alpha \sum_k \left\| \partial_t \left(\delta(t) + \frac{j}{\pi t} * \mathbf{u}_k(t) \right) e^{-j\omega_k t} \right\|_2^2 + \left\| \mathbf{f}(t) - \sum_k \mathbf{u}_k(t) \right\|_2^2 + \left\langle \lambda(t), \mathbf{f}(t) - \sum_k \mathbf{u}_k(t) \right\rangle \tag{6}$$

where $\mathbf{f}(t)$ is the original signal, $\mathbf{u}_k(t)$ are the IMFs, ω_k are their center frequencies, and $\lambda(t)$ is the Lagrange multiplier. The parameter α controls the trade-off between bandwidth constraint and data fidelity.

In the context of SHM, this optimisation ensures that each extracted IMF represents a physically meaningful structural response mode, facilitating subsequent analysis like damage localisation or health indexing.

VMD requires the specification of several parameters. The selection of these parameters directly affects the quality of the decomposition and the interpretability of the modes. In SHM applications for bridges, where data is often limited due to logistical or economic constraints, parameter tuning is typically informed by prior knowledge rather than extensive search algorithms.

In this study, the parameters were chosen based on empirical studies and prior SHM literature [15, 16, 20]. Table 2 lists the parameter values used for decomposing strain and acceleration signals collected from the timber laboratory bridge.

Table 2. Selected parameters for VMD applied to signals .

Parameter	**Description and Relevance to SHM**	**Value**
p	Number of IMFs: Determines how many distinct frequency bands (structural modes) are extracted.	5
α	Bandwidth constraint: Controls the smoothness of each mode; higher values yield narrower bands, aiding noise suppression.	100
τ	Time-step for dual ascent: Affects convergence and noise handling. Set to zero to improve noise robustness.	0
ϵ	Convergence threshold: Determines when the algorithm stops. Small values ensure stable and accurate decomposition.	10^{-5}
init	Centre frequency initialization method: Affects how initial guesses are distributed. Uniform initialization (0) is used for reproducibility.	0
DC	Inclusion of DC mode: If enabled, retains constant (mean) component; disabled (0) to remove slow drift in strain data.	0

3 – RESULTS

Operational and measurement noise remains a challenge in SHM, often masking the true dynamic behaviour of civil structures. To address this, VMD was employed in this study as a preprocessing step to enhance signal quality by isolating meaningful modal content from high-frequency noise in both strain and acceleration measurements. The raw data collected from various sensor locations exhibited pronounced high-frequency components and overlapping modal characteristics,

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particularly under excitations applied near the mid-span of the structure. VMD was applied to each signal using the parameter settings summarised in Table 2, with the objective of decomposing each measurement into five narrowband IMFs. The efficacy of this decomposition is visually demonstrated in Fig. 5 through 10, where a clear distinction emerges between informative oscillatory modes (IMFs 1–3) and higher-order components (IMFs 4 and 5), which primarily capture residual noise and non-structural content. Complementary quantitative results are provided in Table 3 for strain gauges and Table 4 for accelerometers. These tables report cross-correlation values between the original and reconstructed signals, along with the percentage of signal energy retained in each IMF, offering a direct comparison between intact and damaged states. Collectively, these results validate the utility of VMD as a robust signal conditioning tool in SHM, facilitating more accurate modal analysis and reliable damage detection by preserving the essential features of the structural response while suppressing non-informative disturbances.

3.1 Analysis of Extracted IMFs

The application of VMD to acceleration (A1–A3) and strain (S1–S3) signals under excitation E1 provided valuable insights into the distribution of structural dynamics across different frequency bands in both damaged and intact conditions. As shown in Figs 5 through 10, each decomposed IMF represents a distinct oscillatory mode. In general, IMF1 and IMF2 capture high-frequency noise and local transient effects, while IMFs 3 to 5 contain more physically meaningful structural responses associated with global and modal behaviour. This decomposition makes it possible to distinguish between informative and spurious signal components. In strain signals, IMF1 alone accounted for over 80% of the total energy in the intact state, suggesting that global structural response is largely concentrated at low frequencies. However, in damaged conditions, the energy becomes more evenly distributed across IMF2 and IMF3, indicating the presence of additional mid-frequency content potentially due to local damage or stiffness loss. A similar trend is observed in acceleration signals, where broadband energy is spread across the first three IMFs in both structural states, with greater variability under damaged conditions. To ensure that only structurally relevant content is retained, the first three IMFs were used to reconstruct the denoised signals, while IMFs 4 and 5 were excluded from further analysis. These final two components consistently exhibited low energy and irregular, high-frequency content, confirming their association with measurement noise or non-structural artifacts. The reconstructed signals based on IMFs 1 to 3 preserved the dominant dynamic behaviour of the system and achieved high cross-correlation with the original signals—often exceeding 0.998 for strain data and 0.85 for acceleration measurements. These results confirm the utility of VMD as a reliable preprocessing tool for SHM, offering an effective balance between denoising and preservation of key modal characteristics necessary for downstream feature extraction and damage detection tasks.

3.2 Evaluation of VMD-Based Denoising

To assess the effectiveness of VMD for preprocessing structural signals, we analysed both strain gauge (S1–S4) and accelerometer (A1–A4) measurements under damaged and intact conditions. Two key metrics were used:

1) Cross-correlation between the original and denoised signals, and
2) Energy retention across the first five IMFs.

Importantly, only the first three IMFs were used to reconstruct the denoised signal, while IMF4 and IMF5 were considered residual noise and excluded from reconstruction. This decomposition strategy allows preservation of essential low-to-mid-frequency structural information while discarding high-frequency artifacts. The results, shown in Tables 3 and 4 demonstrate that VMD preserves signal morphology with high accuracy. For strain gauges, cross-correlation between the original and reconstructed signals remained extremely high in both structural states. For example, Sensor S1 yielded correlations of 0.9984 (damaged) and 0.9988 (intact), confirming that VMD-denoised strain signals remain nearly indistinguishable from the originals. Sensors S2 to S4 also maintained correlations above 0.89, even under damaged conditions, underscoring the method's robustness. In comparison, acceleration signals exhibited slightly lower cross-correlation, with values ranging from 0.7322 to 0.8476 in the damaged state and 0.7530 to 0.8516 in the intact state. This is expected due to the inherently noisier nature of acceleration measurements and the presence of higher-frequency dynamics. However, VMD still achieved strong agreement between original and reconstructed signals, particularly in Sensors A1, A2, and A4, where correlation exceeded 0.84 in at least one condition.

1) The energy retention patterns across IMFs further reveal how VMD isolates dominant structural behaviour. In both sensor types, the first IMF consistently contains the majority of the signal energy, particularly in signals from

the intact structure, where global structural responses dominate. For instance:

2) Strain Sensor S1 showed 84.17% of its intact energy in IMF1 versus 91.29% in the damaged case.
3) Acceleration Sensor A4 showed 75.89% (intact) vs. 78.46% (damaged) in IMF1, confirming stability across structural states.

A comparison between intact and damaged signals reveals that damaged cases tend to exhibit more balanced energy across IMF1–IMF3, suggesting an increase in mid-frequency content, potentially due to damage-induced changes in dynamic response. This is especially evident in S4 and A3, where the energy in IMF2 and IMF3 increased in the damaged condition. Cross-correlation and energy retention analyses jointly confirm that VMD is an effective preprocessing tool for SHM. It isolates meaningful frequency content while maintaining signal fidelity under both damaged and intact conditions. This consistency across sensor types and structural states supports its application in feature extraction and damage detection frameworks.

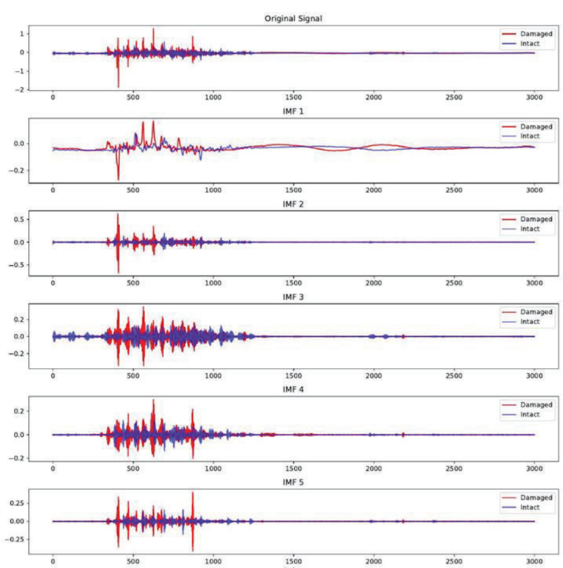

Figure 5. Comparison of raw and denoised signals for Sensor A1 under excitation E1

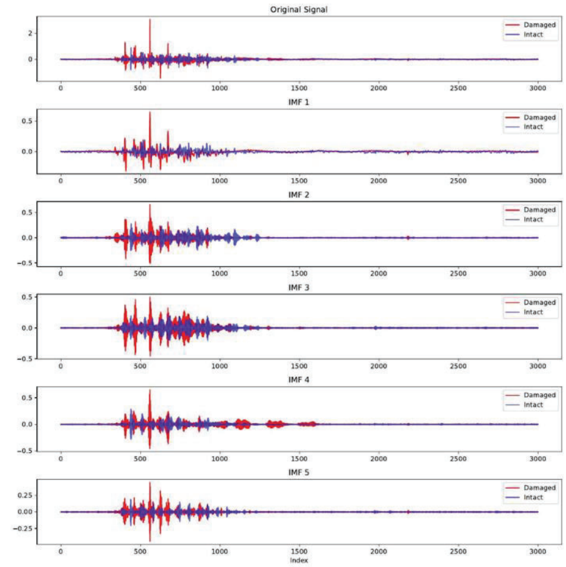

Figure 6. Comparison of raw and denoised signals for Sensor A2 under excitation E1

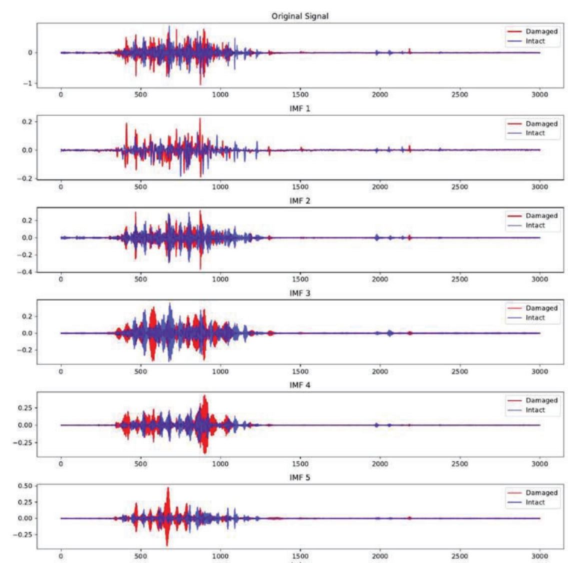

Figure 7. Comparison of raw and denoised signals for Sensor A3 under excitation E1

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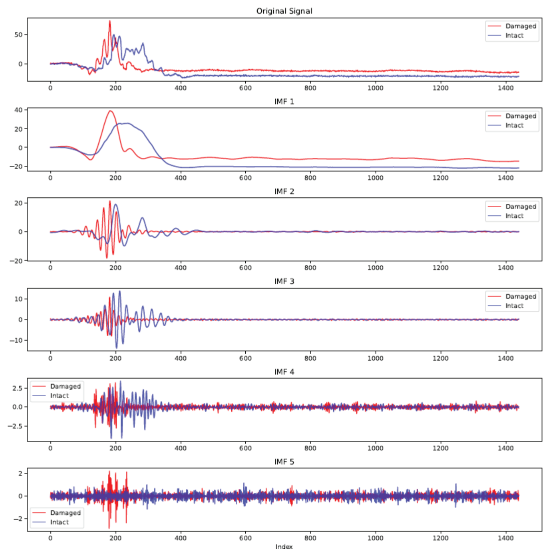

Figure 8. Comparison of raw and denoised signals for Sensor S1 under excitation E1

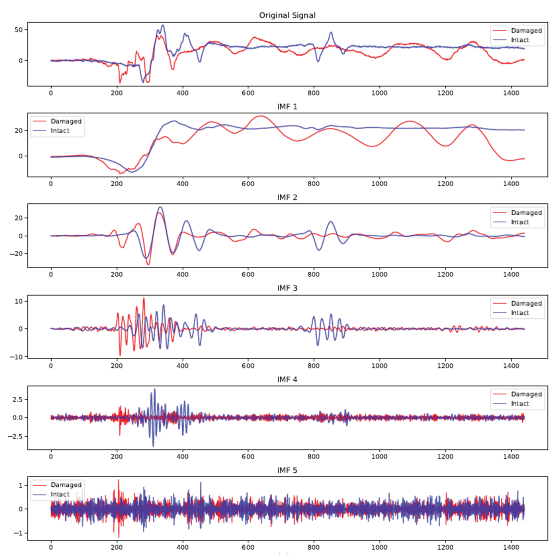

Figure 9. Comparison of raw and denoised signals for Sensor S2 under excitation E1

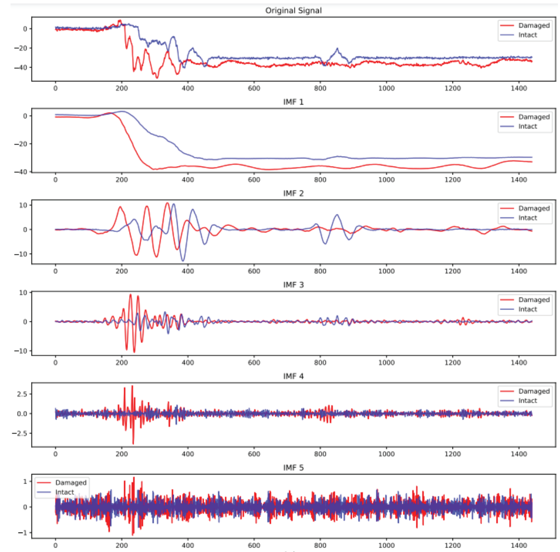

Figure 10. Comparison of raw and denoised signals for Sensor S3 under excitation E1

Table 3. Cross-correlation and energy retention results for acceleration sensors (A1-A4) under intact and damaged conditions

Sensor	Cross-Correlation (Intact)	Cross-Correlation (Damaged)	Energy Retention (Intact)	Energy Retention (Damaged)
S1	0.9988	0.9984	84.17%, 13.54%, 1.57%, 0.47%, 0.25%	91.29%, 6.96%, 0.97%, 0.25%, 0.53%
S2	0.9433	0.9800	75.52%, 15.63%, 6.47%, 0.23%, 2.15%	85.59%, 11.34%, 2.59%, 0.52%, 0.46%
S3	0.9140	0.8386	83.32%, 9.11%, 5.24%, 1.16%, 1.17%	86.44%, 5.18%, 6.38%, 1.51%, 0.49%
S4	0.8993	0.8347	69.04%, 15.48%, 12.42%, 2.40%, 0.66%	67.67%, 14.02%, 15.26%, 1.84%, 1.21%

Table 4. Cross-correlation and energy retention results for strain sensors (S1–S4) under intact and damaged conditions

Sensor	Cross-correlation (Intact)	Cross-correlation (Damaged)	Energy Retention (Intact)	Energy Retention (Damaged)
A1	0.8277	0.8476	74.01%, 9.03%, 7.12%, 6.07%, 3.77%	73.23%, 8.14%, 7.04%, 6.49%, 5.10%
A2	0.8516	0.8428	76.34%, 6.53%, 6.53%, 5.01%, 5.59%	71.85%, 8.49%, 7.48%, 6.09%, 6.09%
A3	0.7530	0.7322	71.23%, 10.02%, 9.02%, 5.96%, 3.77%	70.00%, 9.21%, 8.19%, 7.68%, 4.92%
A4	0.8175	0.8466	75.89%, 6.93%, 6.06%, 5.98%, 5.14%	78.46%, 6.04%, 5.53%, 4.97%, 5.00%

4 – CONCLUSIONS AND RECOMMENDATIONS

This study demonstrates that VMD significantly improves the quality and interpretability of SHM data in timber bridge applications by effectively separating meaningful structural responses from high-frequency environmental noise. By decomposing acceleration and strain signals into five IMFs, VMD enables the isolation of dominant modal content within the first three IMFs, while filtering out noise-dominated components typically captured in IMFs 4 and 5. Quantitative results across multiple sensor locations reinforce VMD's denoising capability. For example, cross-correlation values between the original and reconstructed signals reached as high as 0.9988 for strain and 0.8755 for acceleration in intact conditions, confirming the preservation of signal morphology. In damaged states, the energy distribution shifted from a dominant single-IMF concentration (e.g., 91.29% in IMF1 for strain sensor S1) to a more balanced spread across multiple IMFs—indicating changes in dynamic behaviour consistent with structural degradation. These findings underscore VMD's potential not only as a denoising tool but also as a feature extraction technique for damage detection. The consistent trends observed across both damaged and intact scenarios suggest that integrating VMD into SHM workflows can enhance the sensitivity of damage identification. Ultimately, the use of VMD in timber bridge monitoring enables more accurate interpretation of structural responses, supports informed maintenance strategies, and contributes to improved safety under variable environmental and operational conditions.

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