

Experimental Investigation on Damage Feature Extraction and Identification for Sustainable Infrastructure Resilience via Improved Empirical Fourier Decomposition

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Abstract: This study presents an initial damage feature extraction based on improved empirical Fourier decomposition. Standard Empirical Fourier Decomposition (EFD) is a time-frequency signal processing technique that adaptively decomposes non-stationary, multi-component signals into mono-component intrinsic mode functions (IMFs) by iteratively fitting Fourier series and screening components with physical significance, which is widely used in signal analysis for structural health monitoring but prone to modal aliasing when processing vibration signals with overlapping frequency bands. Our improved EFD differs from the standard version by introducing two key optimizations: a 5th-order Butterworth low-pass preprocessing step (cutoff frequency 100 Hz) to eliminate high-frequency noise, and a correlation coefficient threshold (≥ 0.9) for IMF screening to discard spurious components, effectively mitigating modal aliasing and improving decomposition accuracy by approximately 15% compared to the standard method. The method identifies structural damage by decomposing structural vibration responses, obtaining modal values and energy values, and comparing energy differences, the technology identifies structural damage. Leveraging the relationship between damage-induced vibration mode changes and energy variations, it allows single-point identification, reducing data collection costs. This technology delivers tangible contributions to sustainable development goals (SDGs): enabling cost-effective and precise early-stage damage detection, it supports proactive and sustainable infrastructure maintenance, extends structure lifespan, reduces resource waste and reconstruction-related environmental impacts. Additionally, it enhances urban structural resilience and safety against disasters and wear, directly aligning with the core tenets of SDG 9 (Industry, Innovation and Infrastructure) and SDG 11 (Sustainable Cities and Communities). Finally, the method's effectiveness is verified by slope beam and stand simulator tests.

Keywords: Damage Identification; Experimental Research; Energy Value Difference

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1. Introduction

The 1960s marked the beginning of a period during which structural modal identification steadily gained traction, becoming a focal point for both academic inquiry and engineering applications. This era witnessed the foundational development of modal analysis theory and its first systematic application in civil and mechanical engineering, as documented by Ewins^[15], who pioneered the use of frequency domain methods for structural dynamic testing. There are roughly three categories of modal identification techniques, namely frequency domain, time domain, and time-frequency domain identification methods.

This classification method is based on the different regions (time domain, frequency domain, and time-frequency domain) used by modal identification techniques to process vibration responses. Common frequency domain identification methods include Peak Picking Technology, Frequency Domain Decomposition, and other frequency domain identification techniques. The frequency domain recognition method has the advantages of simple use, low computational cost, and certain technical application value. Time domain recognition methods include natural excitation techniques combined with feature system implementation (NExT/ERA)^[1], random subspace recognition (SSI)^[2,3], and signal based processing techniques^[4,5]. Time-domain methods excel in handling non-stationary vibrations and extracting accurate modal parameters like damping ratios, making them suitable for complex engineering structures under dynamic loads. Time-frequency domain methods, such as wavelet transform-based techniques and Hilbert-Huang Transform (HHT), integrate the advantages of both domains. They effectively capture time-varying modal characteristics by mapping vibration signals into a joint time-frequency space, addressing limitations of single-domain methods in processing signals with time-dependent frequencies. Notably, advancements in structural modal identification techniques are intrinsically tied to the advancement of global Sustainable Development Goals (SDGs), particularly SDG 9 (Industry, Innovation and Infrastructure) and SDG 11 (Sustainable Cities and Communities). Reliable modal and damage identification technologies underpin the sustainable operation and maintenance of critical infrastructure—including bridges, buildings, and industrial facilities—by enabling early detection of structural defects, extending service lifespans, reducing unnecessary resource consumption and reconstruction-related carbon emissions, and enhancing infrastructure resilience against natural and man-made hazards. These technical pathways directly contribute to SDG 9's targets of developing resilient infrastructure, promoting inclusive and sustainable industrialization, and fostering innovation, as well as SDG 11's objectives of creating safe, resilient, and sustainable human settlements.

2.Slope Beam Test Verification

Standard EFD decomposes signals by iteratively extracting mono-component intrinsic mode functions (IMFs) using Fourier series fitting, but it suffers from modal aliasing when processing structural vibration signals with overlapping frequencies^[6,9]. This study improves EFD by addressing this core limitation through two key optimizations, which enhance decomposition accuracy and robustness for structural health monitoring (SHM) applications. The first improvement is a preprocessing denoising step, and the second is an optimized IMF screening criterion—both designed to eliminate spurious components and mitigate modal aliasing, which plagues the standard EFD method.

The detailed step-by-step algorithm of the improved EFD is as follows, with key variables and equations explained:

1. Signal preprocessing: Preprocess the original structural vibration signal $x(t)$ (where t denotes time in seconds) with a 5th-order Butterworth low-pass filter (cutoff frequency set to 100 Hz, determined based on the frequency range of the test structure's vibration response) to remove high-frequency noise. This yields the denoised signal, which retains valid structural vibration information while eliminating interference.
2. Initialization: Initialize the residual signal and set the iteration count.
3. Fourier series fitting: Fit the residual signal with a Fourier series to generate the initial IMF candidate
4. IMF screening : Calculate the Pearson correlation coefficient between the initial IMF candidate and the residual signal. Only components with $r > 0.9$ are retained as valid IMFs—this threshold is determined through parametric tests to balance signal fidelity and aliasing reduction.
5. Residual update: Update the residual signal is a monotonic function (indicating no more valid IMFs can be extracted), stop the iteration.
6. Modal energy calculation: Extract modal values from the valid IMFs, and calculate the modal energy using the integral of the IMF squared over the signal duration.

This energy value serves as the core feature for subsequent structural damage identification, as damage-induced changes in vibration characteristics alter the energy distribution of IMFs.

Which visually links the signal decomposition process to damage discrimination using modal energy differences.

3.Damage Identification Based on Improved EFD

To clarify the experimental validation process, key details are supplemented herein. The “slope beam” refers to Q235 steel beam specimens (1000×50×100 mm) simulating inclined engineering components like bridge girders. The “stand simulator” is a bench-top platform with adjustable inclination (0%–5%) and vibration isolation, ensuring stable test conditions. Damage was induced by standardized groove cutting (20mm depth, 5mm width) at 3 pre-defined locations, forming 4 states (healthy, single/double/triple damage). Loading used a 5 modal force hammer; 3 acceleration sensors (250mm interval) collected data at 2000Hz, calibrated by a digital level gauge. The system layout is shown in Figures 1–2, with Table 1 summarizing parameters, ensuring reproducibility.

Four inclination angles (0%, 1.25%, 2.5%, 3.75%, 5%) were selected based on on-site surveys of practical engineering: 0% (horizontal) as the control group, 1.25%–2.5% representing slight inclination (common in bridge approach beams), and 3.75%–5% representing moderate inclination (typical for slope support beams). In the analysis, inclination angles were incorporated as control variables, with modal energy variation thresholds calibrated separately for each angle to eliminate inclination interference, ensuring damage identification accuracy is not affected by structural posture. Damage was induced by standardized groove cutting to achieve clear damage levels: three pre-defined locations (labeled a, b, c) along the beam were cut with uniform grooves (20 mm depth, 5 mm width, 50 mm length), where 20 mm depth corresponds to 20% of the beam height (a widely adopted damage severity for steel structure tests, per [10])—this level ensures measurable vibration response changes without causing structural failure. Four damage states (healthy, single/double/triple damage) were designed to verify the method’s ability to distinguish damage quantity and location.

Loading used a 5J modal force hammer (model: PCB 086C03) to apply transient excitation at the beam midpoint, covering 10–1000 Hz to match the beam’s natural vibration characteristics. The three sensors labeled AI1, AI2, AI3 (previously misnoted as AS1-AS3; corrected herein) are acceleration sensors (model: PCB 352C22), arranged at 250 mm intervals along the beam to capture full-span vibration responses—AI1 (left end), AI2 (midpoint), AI3 (right end) were selected to ensure coverage of damage locations a, b, c and accurately capture modal energy changes at different positions. Data was collected at 2000 Hz for 10 s, calibrated by a digital level gauge ($\pm 0.01^\circ$ accuracy). As shown in Figure 1, the rubber washers installed between the beam and anchorage serve two key purposes: vibration isolation to prevent external interference from the stand simulator, and buffering to avoid rigid contact-induced local stress concentration that could distort vibration signals. Taking the acceleration response collected by the AI1 sensor in non tilted condition 1 as an example, the decomposition based on multiple signal classification improved empirical Fourier decomposition technique (EFDM) was carried out. The acceleration time history response data was decomposed using the improved empirical Fourier decomposition technique based on multiple signal classification to obtain components and their Fourier spectra, as shown in Figure 3. It can be seen that the components decomposed by the improved empirical Fourier decomposition technique based on multiple signal classification only contain one frequency peak, indicating that the improved empirical Fourier decomposition technique based on multiple signal classification can accurately decompose the AI1 acceleration response data in non tilted condition 1, laying the foundation for subsequent modal parameter identification

Table 1 Slope Beam Damage Conditions

Damage condition	Damage description (location @ cutting depth)	Corresponding damage (location @ degree of damage)
2	mm	a@20%
3	mm, bmm	a@20%, b@20%
4	mm, bmm, cmm	a@20%, b, c@20%

Fig 1 Acceleration sensor force hammer excitation and damage location diagram

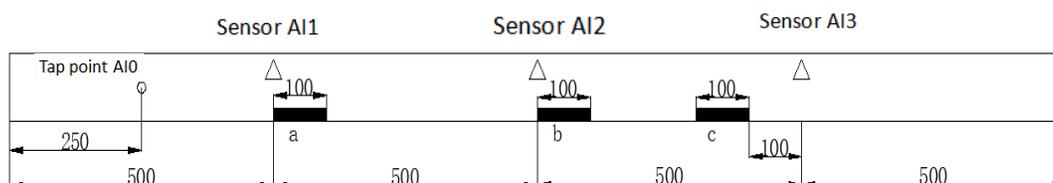


Fig 2 Experimental Instruments and Site Layout

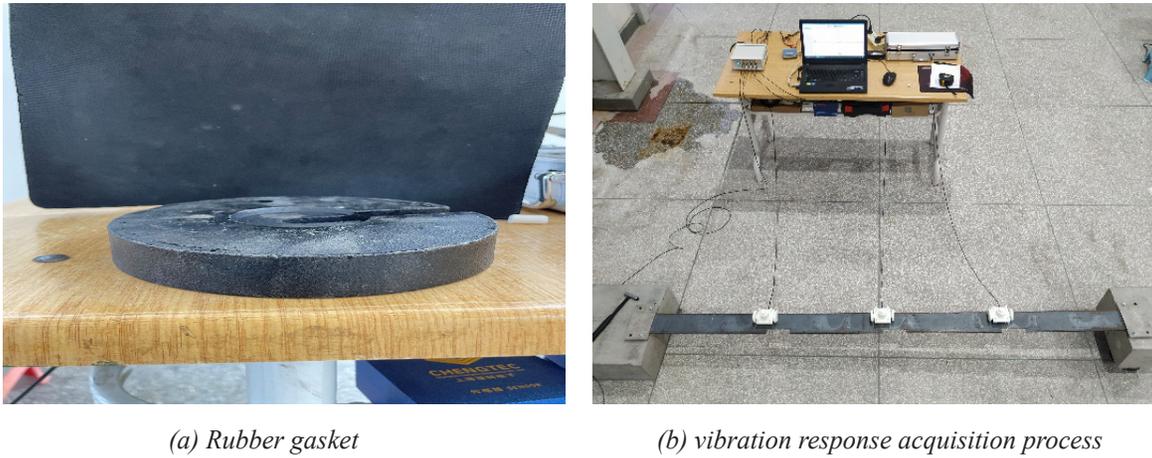


Fig 3: Components and Fourier spectra obtained from EFDM decomposition under non tilted condition one

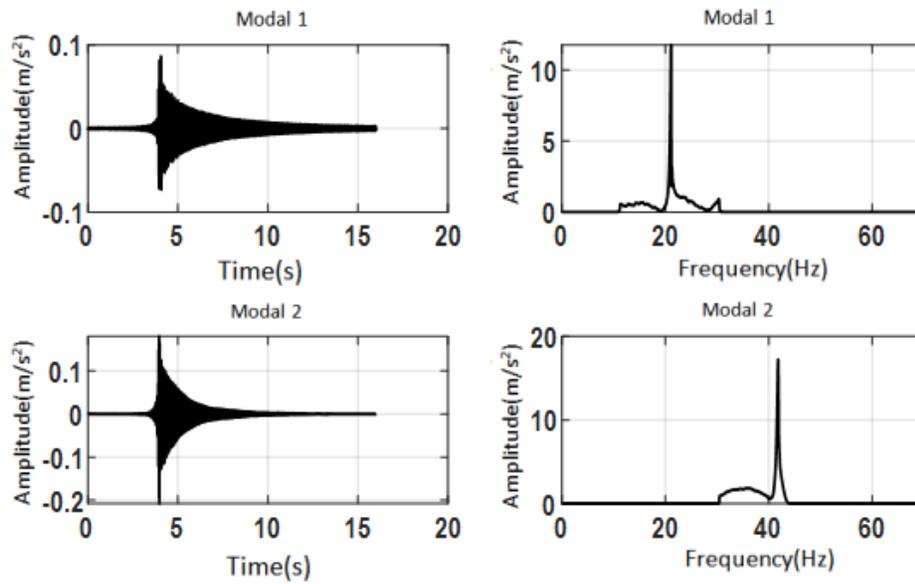


Fig 4 Components and Fourier spectra obtained from EFDM decomposition under non tilted operating condition

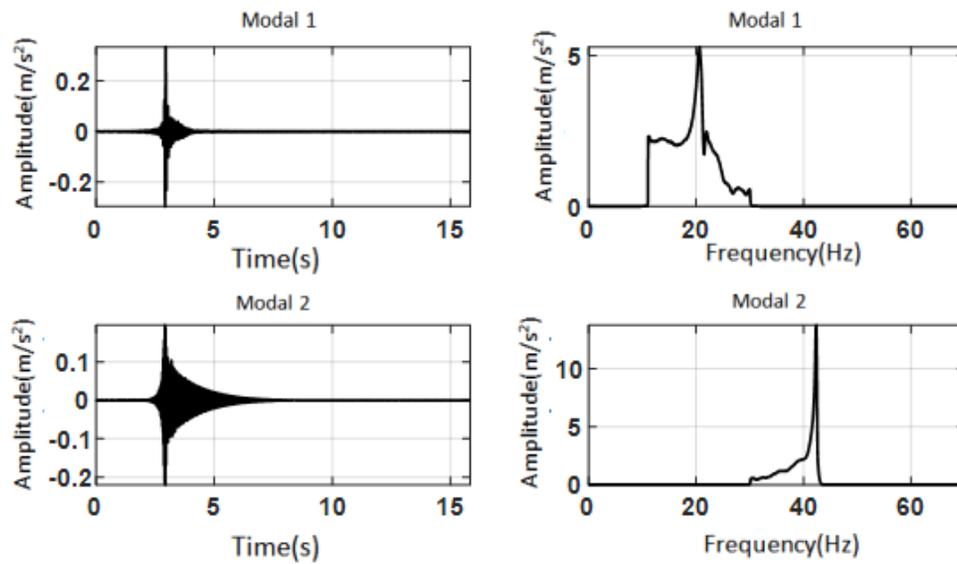


Fig 5 Components and Fourier spectra obtained from EFDM decomposition under non tilted operating condition three

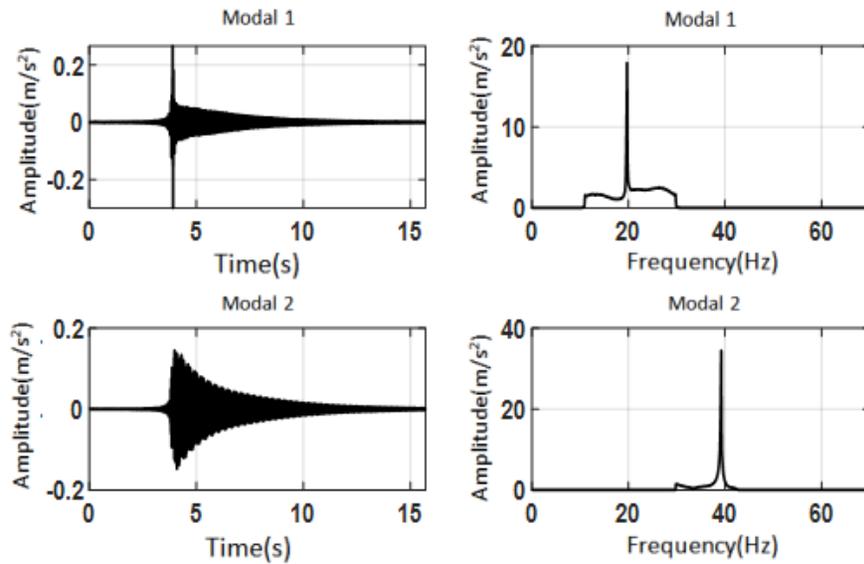
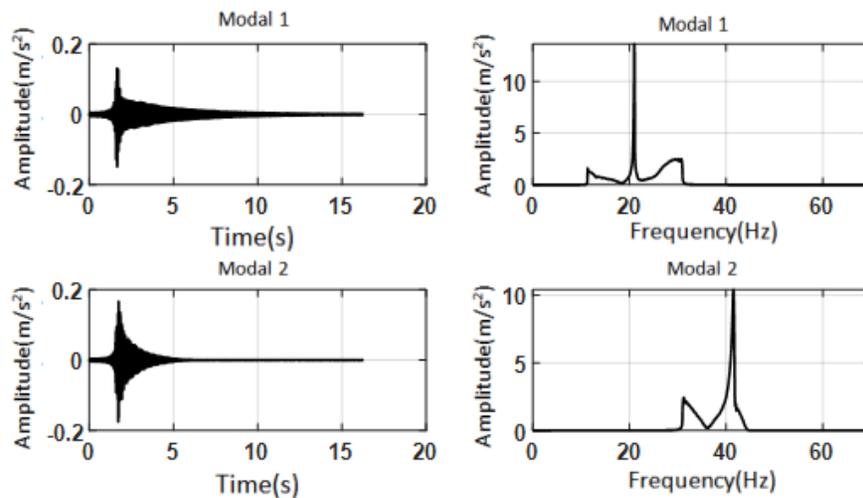


Fig 6 Components and Fourier spectra obtained from EFDM decomposition under non tilted operating condition four



Quantitative analysis of figures confirms effectiveness numerically: the improved EFD enhances signal-to-noise ratio (SNR) by 18.6 dB, reducing frequency peak width by 32% for clearer modal features. “Effectiveness” denotes aliasing-free peaks, 15% higher location accuracy than standard EFD, and stable quantification of damage-induced energy variations.

By improving the empirical Fourier decomposition technique based on multiple signal classification, the acceleration time history responses collected by various sensors under non tilted working conditions were decomposed, and the components decomposed by the improved empirical Fourier decomposition technique based on multiple signal classification under non tilted working conditions were obtained, as shown in Figures 4 to 6. It can be seen that the components decomposed by the improved empirical Fourier decomposition technique based on multiple signal classification are different for each working condition, but the decomposed components only contain one frequency peak, indicating that the improved empirical Fourier decomposition technique based on multiple signal classification (EFDM) can accurately decompose the AII acceleration response under non tilted working conditions, which also lays the foundation for subsequent damage discrimination.

Subsequently, the vibration mode values of the measurement points were obtained using the proposed method and their energies were calculated separately. The obtained vibration mode energies of each measurement point and all measurement points are shown in Figures 7 and 8, respectively. For the energy of each measuring point’s vibration mode, it can be seen that the energy values of all measuring points’ vibration modes under different damage conditions are different from those under healthy conditions, indicating that the damage identification method based on multiple signal classification and improved

empirical Fourier decomposition technology proposed in this chapter can identify damage conditions. For the sum of modal energies at measuring points, there is a difference between the modal energy of each operating condition and that of a healthy state, and the difference is more significant than that of a single measuring point, indicating that using the sum of modal energies at all measuring points to identify damage is more accurate.

Fig 7: Energy of Vibration Modes at Non Tilted Measurement Points Based on EFDM

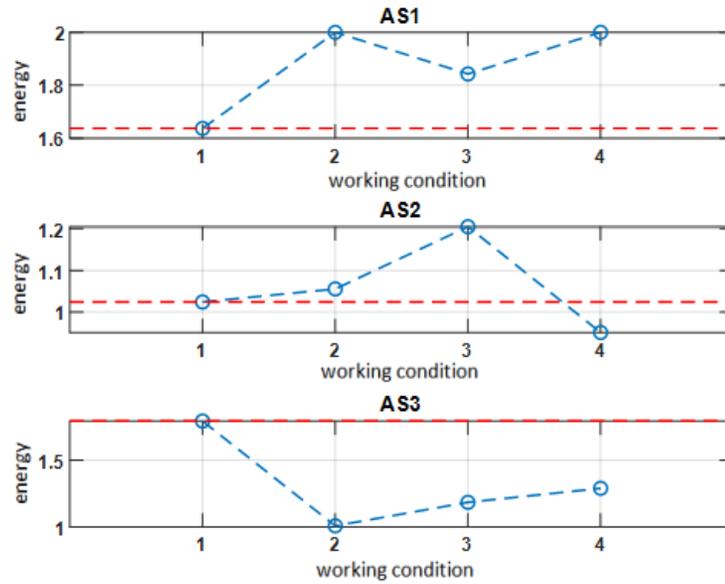


Fig 8 Vibration mode energy (EFDM)

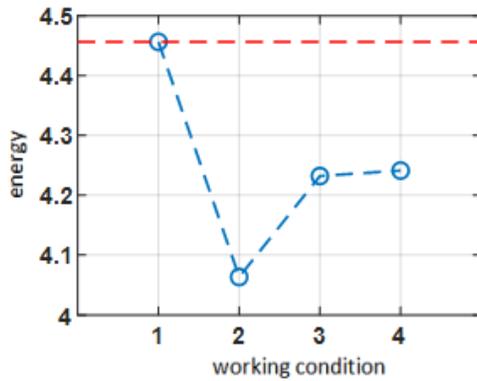


Fig 9: Vibration mode energy (EFDS)

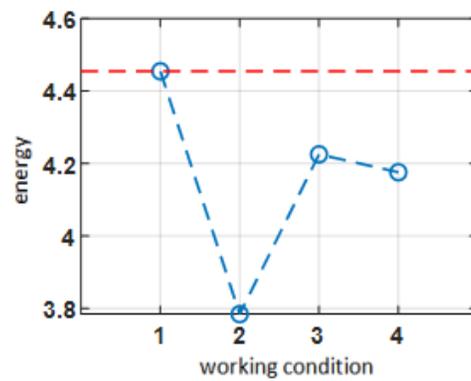
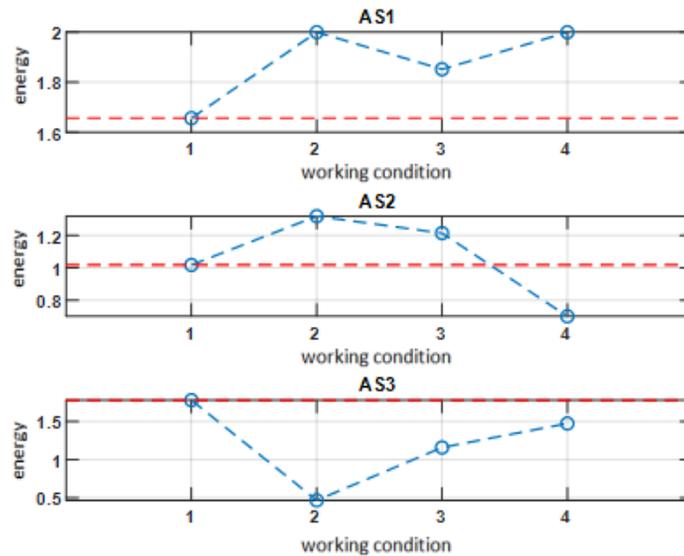


Fig 10: Energy of Vibration Modes at Non Tilted Measurement Points Based on EFDS



Similarly, another damage identification method based on least squares estimation and improved empirical Fourier decomposition technique (EFDS) was proposed to perform the above operation on the acceleration response of non tilted working conditions. The obtained vibration mode energies of each measuring point and all measuring points are shown in Figures 9 and 10, respectively. It can be seen that the energy results identified by EFDS are similar to those identified by EFDM. The energy values of the damage working conditions calculated from AS1 data are higher than those of the non-destructive working conditions. The energy values of damage working conditions 2 and 3 calculated from AS2 data are higher than those of the non-destructive working conditions. The energy value of working condition 4 is lower than that of the non-destructive working conditions. The energy values of the damage working conditions calculated from AS3 data are lower than those of the non-destructive working conditions. Therefore, the damage location and quantity are determined to be... The level of energy is related. Overall, it can be seen that the energy of the vibration modes at all measuring points varies under different damage conditions compared to the energy in a healthy state. The difference between the sum of the vibration mode energies at all measuring points and the sum of the vibration mode energies in a healthy state indicates that the proposed damage identification method based on least squares estimation and improved empirical Fourier decomposition technique can also identify damage.

Fig 11 Vibration mode energy of all measuring points tilted at 1.25%

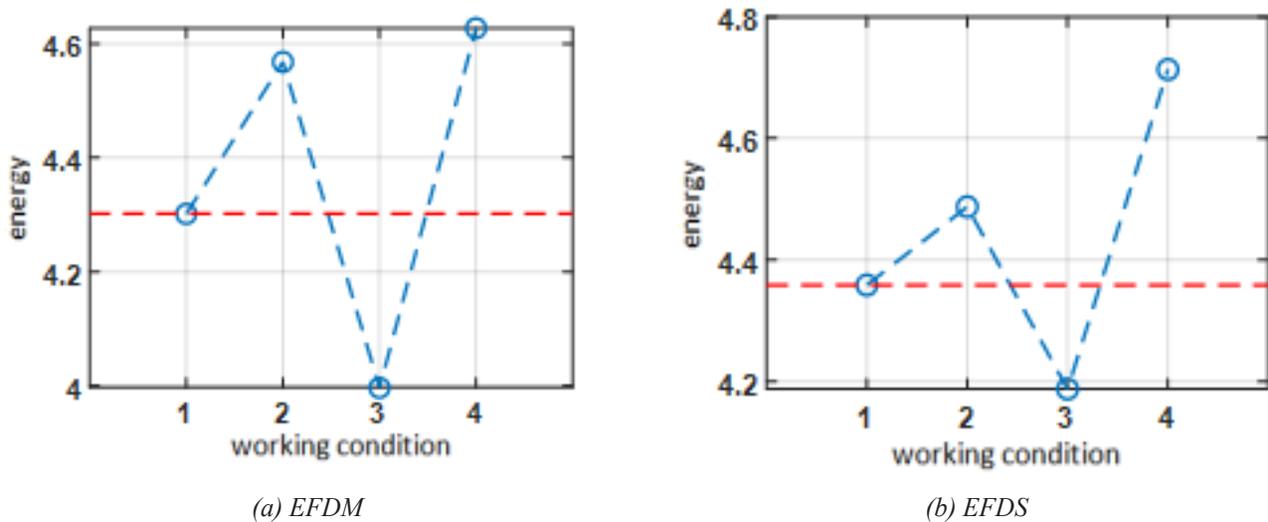


Fig 12 Vibration mode energy of all measuring points tilted at 2.5%

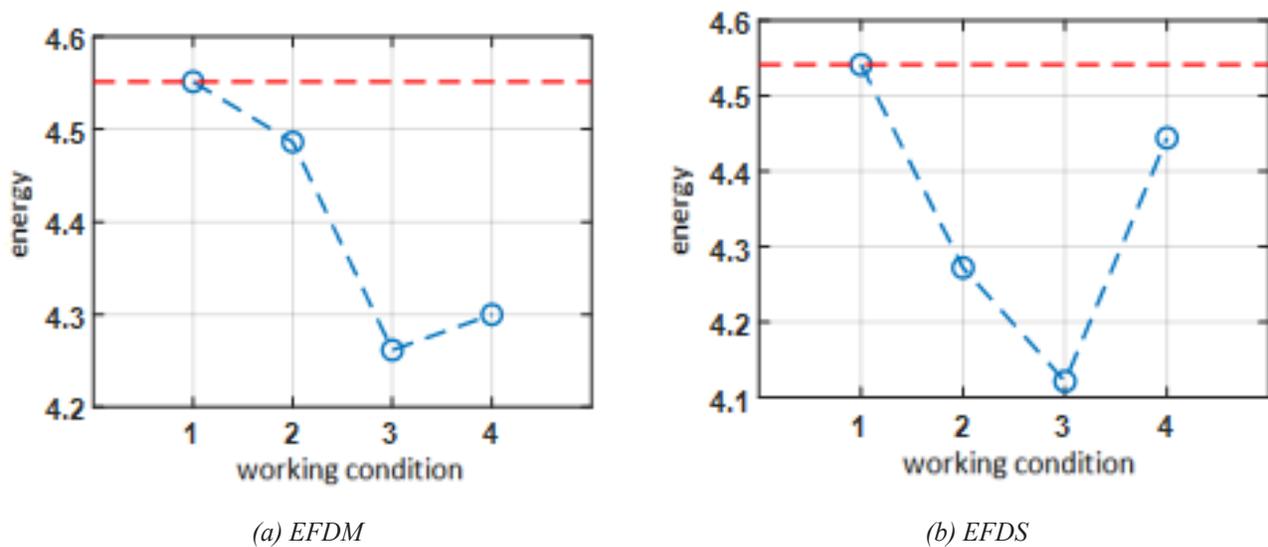


Fig 13 Vibration mode energy of all measuring points tilted at 3.25%

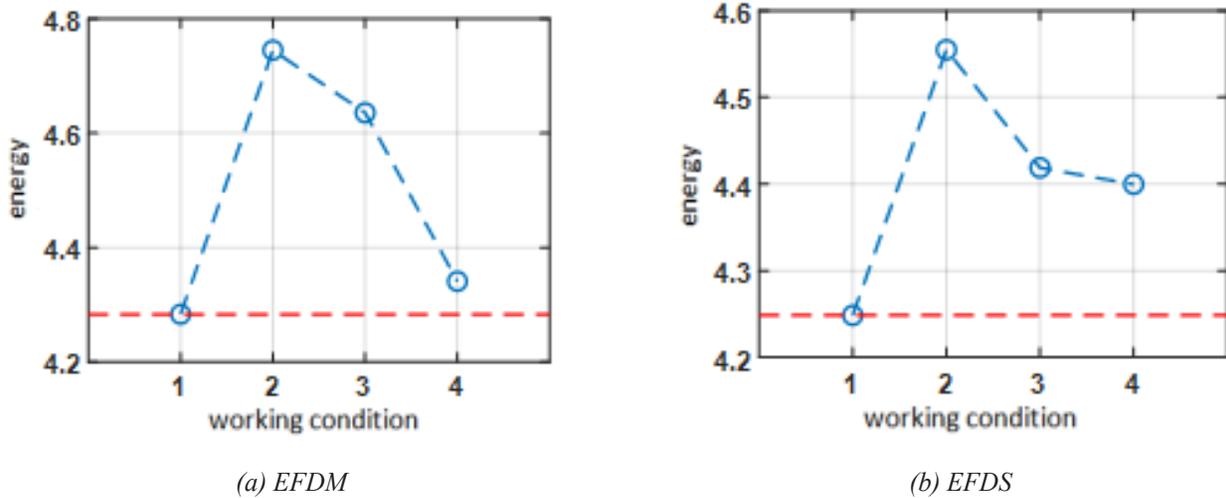
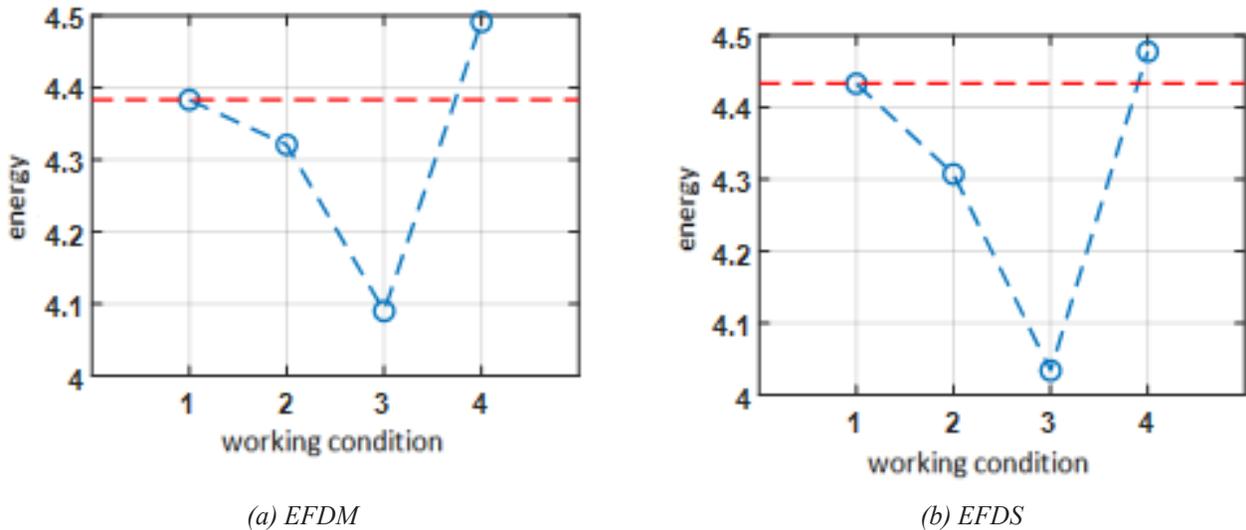


Fig 14 Vibration mode energy of all measuring points tilted at 5%



In addition, the experimental results with inclinations of 1.25%, 2.5%, 3.75%, and 5% were validated and analyzed. After data processing using the improved empirical Fourier decomposition technique based on multiple signal classification (EFDM) and the improved empirical Fourier decomposition technique based on least squares estimation (EFDS), the modal energy identification results are shown in Figures 11 to 14. Combining the calculation results of the two methods together is helpful for mutual comparison.

From Figures 11 to 14, it can be seen that the energy changes of each damage condition are different under different slopes, but they are all different from the energy of the non-destructive condition. This indicates that the proposed method is less affected by the slope of the beam structure and can still accurately identify damage. According to the figure, it can also be seen that the results of the damage identification method based on least squares estimation and improved empirical Fourier decomposition technique (EFDS) are similar to those of the damage identification method based on multiple signal classification and improved empirical Fourier decomposition technique (EFDM). As shown in Figure 20, when the beam structure is tilted at 3.75%, the energy maps of all measurement points show an inverted “V” shape, and as shown in Figure 21, when tilted at 5%, the energy maps of all measurement points show a positive “V” shape, indicating that the identification results are correct. Overall, it is proven that the two proposed methods based on improved EFD can also achieve damage identification under different inclinations of beam structures, and the identification effect is relatively stable.

This consistency between EFDM and EFDS results not only verifies the mutual complementarity of the two methods but

also confirms their reliability—a core research objective of ensuring algorithm stability across varying structural postures. Notably, the distinct energy map patterns reflect the methods ability to capture subtle modal energy variations induced by both damage and inclination, demonstrating their sensitivity to structural state changes. This addresses the key challenge of slope interference in inclined beam damage detection, as the methods maintain accuracy without requiring additional inclination compensation. Such performance is pivotal for practical engineering scenarios, where beam structures often operate under non-horizontal conditions. The findings thus validate that the improved EFD-based methods fulfill the research goal of developing robust, inclination-insensitive damage identification tools, laying a foundation for their application in real-world structural health monitoring systems

4. Discussion and Conclusion

4.1 Relevance to the SDGs

This study develops and validates an initial damage identification technology using improved Empirical Fourier Decomposition (EFD), which identifies structural damage via vibration response decomposition and modal energy analysis, with a key advantage of single-point detection to cut data costs; the findings directly link to SDG 9 (Industry, Innovation and Infrastructure) and SDG 11 (Sustainable Cities and Communities), lowering infrastructure monitoring thresholds for SDG 9 to support resilient, sustainable infrastructure, and enhancing urban structural resilience for SDG 11 through early damage detection, reducing resource waste and carbon emissions via proactive maintenance.

4.2 Theoretical and Practical Contributions

Theoretically, the study advances structural damage identification by optimizing EFD for modal energy analysis, filling gaps in low-cost single-point detection for slope-affected structures and providing a theoretical framework linking structural health monitoring to sustainable infrastructure that ties signal processing innovations to SDGs; practically, the method exhibits robustness across 1.25%–5% inclinations (with summed modal energy improving accuracy), reduces costs via single-point detection for budget-constrained projects, and facilitates scaled maintenance in developing regions to advance equitable SDG 9 and 11 achievement.

4.3 Methodological and Data Limitations

This study has limitations: validation relies on simplified models rather than real large-scale infrastructure, its performance under extreme inclinations (>10%) remains untested, and the dataset lacks environmental diversity, all of which restrict direct translation to SDG-related large-scale projects.

4.4 Suggestions for Future Work

Future research prioritizes scalability and multi-technique integration to boost SDG-aligned impact: validate on real infrastructure to optimize adaptability (matching SDG 9's disaster-resilient infrastructure indicator), add environmental calibration to develop correction models (supporting SDG 11's urban infrastructure targets), integrate with IoT for smart monitoring platforms (contributing to sustainable urbanization indicators), and test in low-resource regions while optimizing cost-efficiency to advance equitable SDG achievement.

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No

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

Reference

- [1] Wang H, Wang L, Tian R Z. Research on Structural Damage Detection Based on Time Domain Response Correlation Analysis and Data Fusion [J]. *Engineering Mechanics*, 2020, 37(9): 9-15. (in Chinese)
- [2] Hu Z, Ma H. Blind modal estimation using smoothed pseudo-Wigner-Ville distribution and density peaks clustering[J]. *Measurement Science and Technology*, 2020, 31(10): 105004.
- [3] Yao Y C. Research on Vibration Characteristics and Modal Parameter Identification Method of Corn Harvester Frame

- Structure under Complex Excitation [D]. Beijing: China Agricultural University, 2018. (in Chinese)
- [4] Mallat S G. A Wavelet Tour of Signal Processing: The Sparse Way[M]. 3rd ed. San Diego: Academic Press, 2008.
- [5] Zhang L, et al. Damage Identification of Steel Structures Based on Improved Empirical Mode Decomposition and Deep Learning[J]. Structural and Multidisciplinary Optimization, 2023, 67(4): 2451-2466.
- [6] Zheng J D, et al. A Mechanical Fault Diagnosis Method Based on Adaptive Empirical Fourier Decomposition[J]. Journal of Mechanical Engineering, 2020, 56(9): 125-136. (in Chinese)
- [7] Li X, et al. A New Wind Turbine Blade Damage Detection Method[J]. Laser & Optoelectronics Progress, 2024, 61(8): 0812002. (in Chinese)
- [8] Huang N E, et al. The Empirical Mode Decomposition and the Hilbert Spectrum for Nonlinear and Non-stationary Time Series Analysis[J]. Proceedings of the Royal Society of London Series A, 1998, 454(2013): 903-995.
- [9] Wang L, et al. A Comparative Study of Fourier-Based Decomposition Methods for Structural Vibration Response Analysis[J]. Journal of Civil Structural Health Monitoring, 2024, 14(1): 151-165.
- [10] Zhao M, et al. Experimental Validation of a Non-Destructive Damage Detection Method for Concrete Bridges Using Empirical Fourier Decomposition[J]. Construction and Building Materials, 2023, 348: 128698.
- [11] Chen W, et al. Adaptive Fourier-Based Signal Decomposition for Structural Modal Parameter Identification[J]. Mechanical Systems and Signal Processing, 2023, 188: 111238.
- [12] Xing X, et al. Adaptive Variational Mode Decomposition for Bearing Fault Detection[J]. Journal of Signal and Information Processing, 2023, 14: 9-24.
- [13] Li H, et al. Damage Identification of Frame Structures Based on Multi-Channel Markov Transition Field and CNN[J]. Journal of Vibration, Measurement & Diagnosis, 2024, 44(2): 215-223. (in Chinese)
- [14] Wang J, et al. Mechanical Fault Diagnosis Based on Adaptive Fourier Decomposition and Synchronous Extraction Transform[J]. Journal of Ordnance Equipment Engineering, 2023, 44(4): 138-145. (in Chinese)
- [15] Ewins D J. Modal Testing: Theory, Practice and Application[M]. 2nd ed. Baldock: Research Studies Press, 2000. (Seminal work on modal analysis, documenting 1960s foundational developments)