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## A Comparative Study of OMA Techniques Using a Novel Python Library for Structural Health Monitoring

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### ABSTRACT

Operational Modal Analysis (OMA) is one of the most widely used approaches in Structural Health Monitoring (SHM) for extracting dynamic properties such as natural frequencies, mode shapes, and damping ratios from vibration data under operational conditions. The reliability of OMA outcomes is influenced by both the structural characteristics and the identification methods applied. This study investigates the efficacy of several OMA techniques, including Frequency Domain Decomposition (FDD), Enhanced Frequency Domain Decomposition (EFDD), covariance-driven and data-driven Stochastic Subspace Identification (SSI-COV, SSI-DATA), PolyMAX, and Ibrahim Time Domain (ITD), integrated within new built-on python library. The utility of this library is demonstrated on two structures: a controlled testbed of a three-story aluminium building excited by a shaker, and a real-world, multi-span bridge measuring 217 meters in length, featuring Gerber half-joints and equipped with multiple accelerometers. The bridge case study particularly highlights the library's capacity for precise modal parameter estimation in complex civil structures, alongside the practical benefits and limitations encountered. Additionally, the results obtained using the new built-on python library have been validated against ARTEMIS Modal, a widely recognized software for operational modal analysis, demonstrating consistency and reliability. This cross-validation further underscores the robustness of this library in diverse SHM applications. The findings of this research are intended to support researchers in selecting the most suitable OMA methods across diverse SHM applications, establishing this new built-on python library as a robust and versatile resource in the field of structural dynamics.

*Keywords: Operational Modal Analysis, Structural Dynamics, Python Library, Modal Identification; Bridge Monitoring, SHM.*

## 1. INTRODUCTION

### 1.1. General information

Operational Modal Analysis (OMA) has emerged as a critical tool in Structural Health Monitoring (SHM), enabling the extraction of dynamic properties such as natural frequencies, mode shapes, and damping ratios from operational vibration data[1]-[3]. Unlike Experimental Modal Analysis (EMA) [4],[5], which requires controlled excitation and input-output measurements, OMA relies solely on output responses [6],[7], making it particularly suitable for large-scale civil structures where controlled inputs are impractical. This approach has been widely applied to bridges, buildings, and other infrastructure, offering a non-invasive means of assessing structural integrity.

Several OMA techniques, including Frequency Domain Decomposition (FDD) [8], Enhanced Frequency Domain Decomposition (EFDD) [9], Stochastic Subspace Identification (SSI-COV, SSI-DATA) [10][11], PolyMAX [12], and ITD [13] have been developed to address diverse SHM challenges. However, the implementation of these methods often requires specialized, costly software, limiting their accessibility to researchers and practitioners. To bridge this gap, there are a few python libraries [14], however, this study introduces a new python-based library designed to provide a more comprehensive, extensive, and more user-friendly open-source platform for OMA, which is validated in this study with two different case studies.

The library's efficacy is demonstrated through its application to two case studies: a three-story aluminum building subjected to controlled excitation and a 217-meter multi-span bridge equipped with accelerometers. The results, validated against ARTeMIS Modal [15], a widely recognized OMA software, highlight the library's accuracy and reliability in estimating modal parameters for complex structures. This research aims to support the SHM community by offering a versatile, user-friendly tool for modal analysis, facilitating the selection of appropriate OMA methods across diverse applications.

## 2. APPROACH AND FRAMEWORK

### 2.1. Operational modal analysis: Methods and applications

Operational Modal Analysis techniques are critical for determining the dynamic properties of structures, including natural frequencies, mode shapes, and damping ratios, under operational conditions without the need for controlled excitation. These methods are primarily divided into two categories: frequency-domain and time-domain approaches. Frequency-domain methods, such as Frequency Domain Decomposition (FDD) and its enhanced variant, Enhanced Frequency Domain Decomposition (EFDD), extract modal parameters by analysing the spectral properties of system responses. FDD is valued for its simplicity and ease of use, while EFDD enhances damping ratio estimation accuracy by leveraging time-domain correlation functions derived from spectral data. Another notable frequency-domain method, PolyMAX, overcomes the limitations of traditional techniques by offering clearer stabilization diagrams and improved handling of closely spaced modes.

In contrast, time-domain methods, such as Stochastic Subspace Identification (SSI), and Ibrahim Time Domain (ITD) focus on fitting state-space models or directly processing correlation functions in the time domain. SSI is available in two formats: covariance-based (SSI-COV) and data-driven (SSI-DATA). It is widely recognized for its computational efficiency and robustness in noisy environments. Each OMA method has distinct strengths and limitations, making its suitability dependent on factors like structural complexity, data quality, and the desired accuracy in modal parameter identification. For a detailed mathematical explanation of these methods and their underlying formulas, refer to [6]. This section provided a general overview of OMA methods and introduces a new mathematical framework, termed the Modal Similarity Criterion (MSC), to evaluate modal similarity. The following sections will discuss the efficiency and reliability of python code applied to two case studies.

### 2.2. A new criterion for modal similarity assessment: Modal similarity criterion (MSC)

To validate the reliability of the proposed python code, its results are compared with those from other implementations documented in prior research. This comparison necessitates the use of objective metrics to quantitatively evaluate the accuracy of the results. In this subsection, we introduce criteria

for assessing the similarity between two sets of modal properties, which can be derived from different OMA methods or from a combination of an OMA approach and ARTeMIS Modal outputs. Two specific metrics are employed to measure the differences in mode shapes ( $\Delta_M$ ) and natural frequencies ( $\Delta_f$ ) between the two sets of properties, as defined below:

$$\Delta_M = 1 - MAC(\phi_1, \phi_2) = 1 - \frac{(\phi_1^T \phi_2)^2}{(\phi_1^T \phi_1)(\phi_2^T \phi_2)} \quad (1)$$

$$\Delta_f = 1 - e^{-\frac{(f_1 - f_2)^2}{c^2}} \quad (2)$$

Here,  $\phi_1$  and  $\phi_2$  represent the mode shapes identified by the two methods,  $T$  denotes vector transposition, and  $MAC$  refers to the Modal Assurance Criterion. Eq. (1) defines the mode shape dissimilarity metric ( $\Delta_M$ ), which ranges from 0 (indicating perfect similarity) to 1 (indicating no similarity). Similarly,  $f_1$  and  $f_2$  are the corresponding natural frequencies. The frequency dissimilarity metric ( $\Delta_f$ ) in Eq. (2) is derived using an inverse Gaussian bell-shaped function. The parameter  $c$  is a scaling factor that governs the sensitivity of the inverse Gaussian bell-shaped function to frequency differences. It is determined based on the smallest frequency difference among the modal frequencies being compared, ensuring adaptability to the dataset. Unlike a statistical standard deviation,  $c$  is tailored to the specific modal frequency distribution, enhancing the metric's sensitivity to closely spaced modes. To create a unified criterion, the average of these two metrics is considered, as expressed in Eq. (3). This combined measure, referred to as the Modal Similarity Criterion ( $MSC$ ), is implemented in the python code:

$$\text{Modal Similarity Criterion (MSC)} = 1 - \sqrt{\frac{\Delta_M^2 + \Delta_f^2}{2}} \quad (3)$$

### 3. CASE STUDIES

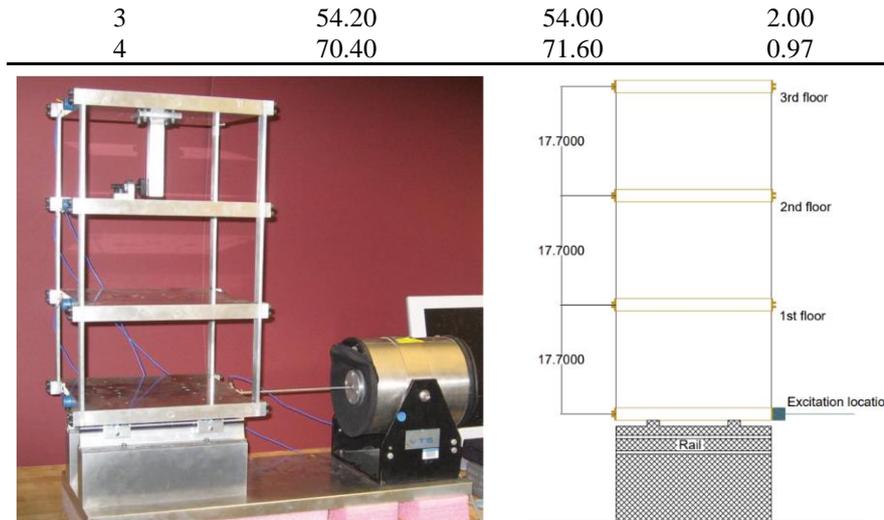
#### 3.1. Case Study 1: Three-story building structure

This experimental configuration features a four-degree-of-freedom system with aluminum components: vertical columns (177×25×6 mm) and horizontal plates (305×305×25 mm), connected via bolted joints that restrict movement to the x-axis depicted in Figure 1 [16]. This particular case study was selected for several compelling reasons. Firstly, the controlled laboratory environment allows for precise manipulation of input and environmental parameters, establishing a pristine baseline for testing. Secondly, the distinct separation of natural frequencies makes this setup ideal for evaluating the python code's ability to accurately identify modal parameters without interference from closely spaced modes. Lastly, it provides an opportunity to investigate the impact of signal filtering using a Butterworth filter. While the study employed band-limited excitation between 20 Hz and 150 Hz, the sensors possess a Nyquist frequency of 160 Hz. Therefore, implementing a band-pass filter could potentially enhance the quality of results by eliminating frequencies outside the excitation band.

To capture the structural response, four accelerometers, each with a sensitivity of 1000 mV/g, are strategically positioned along the centerline of each floor. These accelerometers are specifically chosen for their insensitivity to torsional modes, ensuring that only translational modes are measured. Data acquisition was carried out using a Dactron Spectrabook system at a sampling frequency of 320 Hz. A comparative analysis of the natural frequencies and damping ratios of a three-story aluminum structure is presented in Table 1, based on both experimental testing and numerical simulations using the finite element model (FEM). This analysis highlights the dynamic characteristics of the structure across multiple vibration modes, focusing on three specific modes: Mode 2, Mode 3, and Mode 4. Mode 1 is excluded from the analysis, as it corresponds to rigid body motion, which does not contribute to the structural dynamics [16].

**Table 1.** Comparison of experimental and numerical natural frequencies and damping ratios [16].

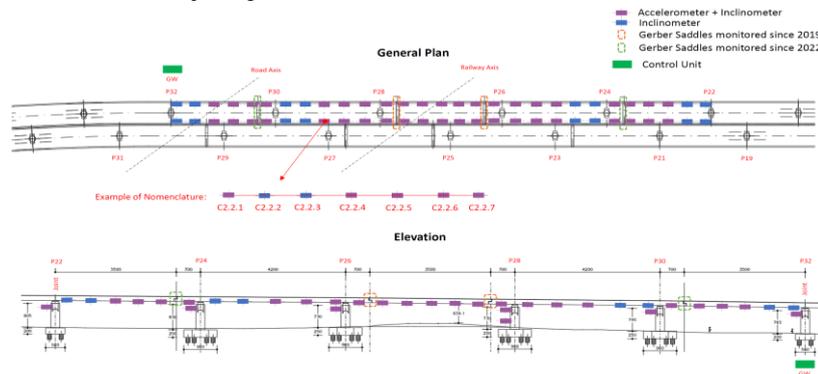
Mode number	$f$ (Hz)		$\zeta$ (%)
	Experimental	FEM	Experimental
	30.70	29.80	6.30



**Figure 1.** Experimental setup of the three-story building structure with shaker for dynamic testing [16].

### 3.2. Case study 2: Multi-span highway bridge

This analysis focuses on a five-span, 217-meter prestressed concrete bridge under continuous monitoring since 2022. The structural monitoring system employs 26 triaxial MEMS accelerometers across spans 2-4, positioned strategically at Gerber half-joints to capture tri-directional responses (transverse X, longitudinal Y, vertical Z) depicted in Figure 2. A wired network with centralized gateway synchronization ensures coordinated 100 Hz sampling, enabling detection of nine vibration modes spanning 1.5-6.96 Hz through operational modal analysis [17]. Table 2 specifically details these identified frequencies, including first nine modes, cross-validated using SACERTIS company OMA software and commercial solutions as referenced [17]. Three principal motivations guided this selection: 1) operational complexity of full-scale infrastructure for realistic modal identification challenges, 2) high sensor density configuration testing measurement resolution requirements, and 3) availability of longitudinal datasets for lifecycle performance evaluation .



**Figure 2.** Overview and sensor layout of a multi-span prestressed concrete bridge with Gerber half joints [17].

**Table 2.** Natural frequencies identified by the SACERTIS company through internal OMA software [17].

Mode numbers	1	2	3	4	5	6	7	8	9
$f$ (Hz)	1.50	1.70	2.10	2.46	2.70	4.60	5.41	5.95	6.96

## 4. RESULTS: COMPARISON AND VALIDATION

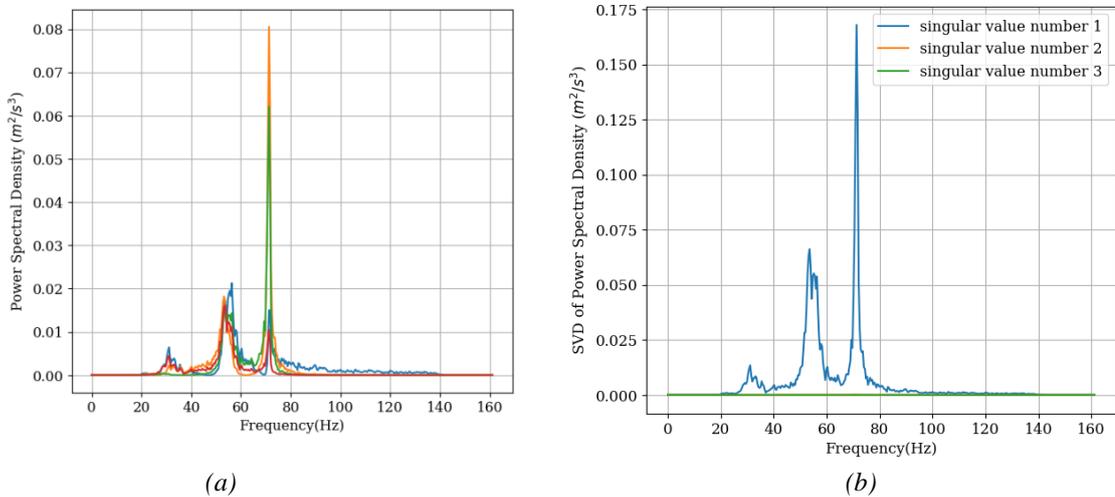
### 4.1. Case Study 1: Three-story building structure

The initial case study is analyzed in Table 3, which illustrates a comprehensive comparison of natural frequencies and damping ratios derived through various Operational Modal Analysis techniques. These techniques were executed using python and ARTeMIS Modal software. When the results are juxtaposed with those in Table 1, a remarkable alignment is observed, with ARTeMIS Modal acting as a reliable validation benchmark. This validation process confirms the efficacy of all python-based methods in

accurately identifying natural frequencies and damping ratios for this case study. The consistency in natural frequencies across all methods highlights their dependability, a result of the straightforward nature of the three-story laboratory frame, characterized by well-separated vibration modes. Although slight discrepancies in damping ratios reveal the sensitivity of different algorithms, the overall consistency across methods underscores the robustness of the newly developed python code. Figure 3 showcases the Power Spectral Density and its corresponding Singular Value Decomposition, presented on a linear scale. These visualizations enable users to pinpoint the dominant frequencies within the system and differentiate significant modal frequencies from background noise. The SVD of the PSD proves particularly effective in isolating primary frequency components, facilitating a more precise interpretation of the data for subsequent modal analysis.

**Table 3.** Comparison of natural frequencies and damping ratios identified by different OMA Techniques.

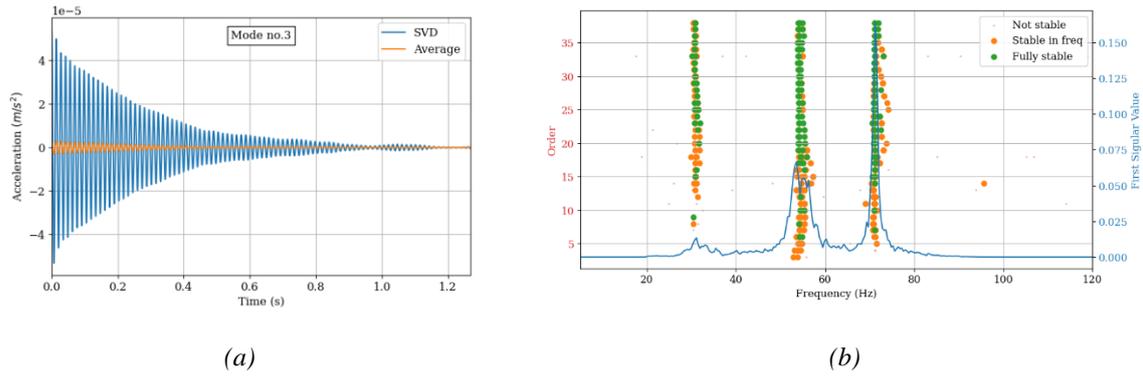
Number of modes	ARTeMIS Modal				Python									
	EFDD		SSI-UPCX		EFDD		SSI-COV		SSI-Data		PolyMax		ITD	
	$f$ (Hz)	$\zeta$ (%)	$f$ (Hz)	$\zeta$ (%)	$f$ (Hz)	$\zeta$ (%)	$f$ (Hz)	$\zeta$ (%)	$f$ (Hz)	$\zeta$ (%)	$f$ (Hz)	$\zeta$ (%)	$f$ (Hz)	$\zeta$ (%)
2	31.37	4.81	30.42	7.41	31.77	5.20	30.03	7.06	29.40	7.33	31.21	5.22	30.32	8.21
3	54.37	4.15	54.40	4.20	54.26	3.05	54.36	3.68	54.35	3.54	54.48	3.42	54.40	3.60
4	71.19	1.19	71.19	0.92	71.35	0.91	71.15	1.09	71.22	1.07	71.16	1.14	71.19	1.07



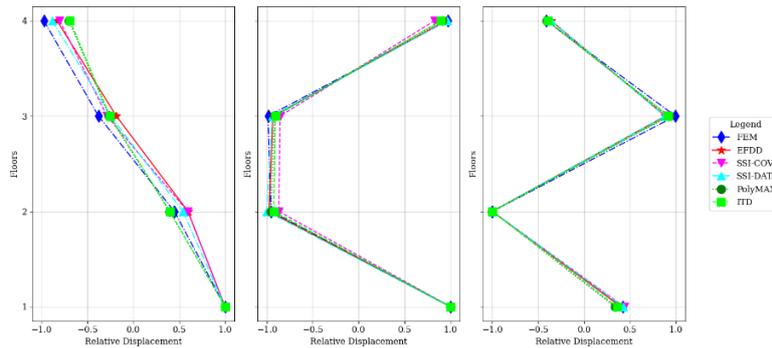
**Figure 3.** (a) PSD analysis in linear scale (b) SVD of PSD in linear scale.

To determine damping ratios, single-degree-of-freedom systems are isolated from the power spectral density, and the autocorrelation function is derived through an inverse Fourier transform, as illustrated in Figure 4(a) for the third mode. However, due to imperfections in the isolation process, the autocorrelation function exhibits a combination of closely spaced frequencies, leading to irregularities and a non-uniform decay pattern. Nevertheless, the damping ratio can still be effectively extracted from these SDOF systems. A practical approach involves taking the absolute value of each data point, identifying the peaks, and fitting an exponential curve to them, which can subsequently be linearized. The slope of this linear fit is directly proportional to the damping ratio. Figure 4(b) displays the stabilization diagrams generated using the PolyMAX method, which include stable poles representing natural frequencies and damping ratios. These poles are annotated and categorized based on the similarity of frequencies and damping ratios across consecutive orders.

Figure 5 presents a comparison of the mode shapes identified by various operational modal analysis (OMA) techniques with those obtained from the finite element model (FEM) as reported by Figueiredo et al. [16]. The mode shapes identified by each technique demonstrate a high degree of consistency, thereby validating the reliability and accuracy of the python-implemented methods.

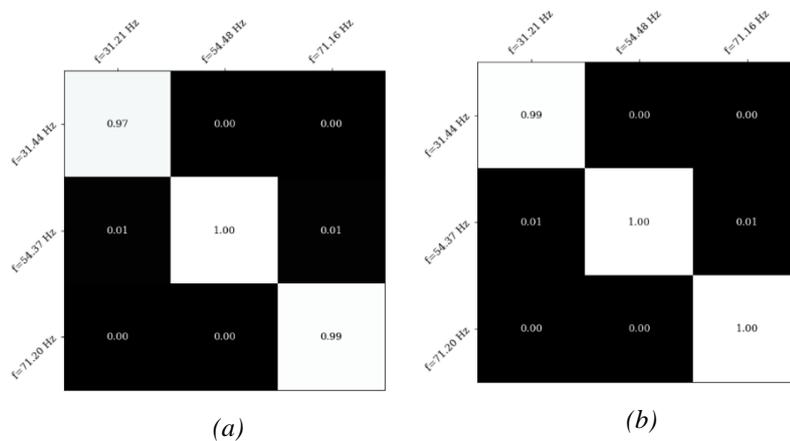


**Figure 4.** (a) Autocorrelation function of the SDOF system for mode 3. (b) Stabilization diagram using (PolyMAX).



**Figure 5.** Comparison of mode shapes identified by different python methods and by FEM.

The findings illustrated in Figure 6 demonstrate the efficacy of the PolyMAX technique when contrasted with the EFDD method employed in ARTeMIS Modal, showing full alignment for the laboratory test structure. This verification is supported by the MAC matrix, which emphasizes strong correlations among mode shapes, and the MSC matrix, which combines both mode shape and frequency alignment to provide a comprehensive measure of agreement. Within the new python library, other methods such as EFDD, SSI (both covariance-driven (SSI-COV) and data-driven (SSI-DATA) approaches), and ITD have likewise displayed robust validation against ARTeMIS Modal, with PolyMAX presented as a representative example to avoid redundancy. While this validation on a simple three-story testbed highlights the reliability and robustness of the python code, the structure’s simplicity ensures well-separated modes, making it an ideal initial benchmark. Next case study will extend this validation to complex real-world structure, showcasing its capability to address challenging scenarios involving closely spaced frequencies and coupled modes.



**Figure 6.** (a) MAC & (b) MSC matrices obtained by python (PolyMAX) and ARTeMIS Modal (EFDD).

## 4.2. Case study 2: Multi-span highway bridge

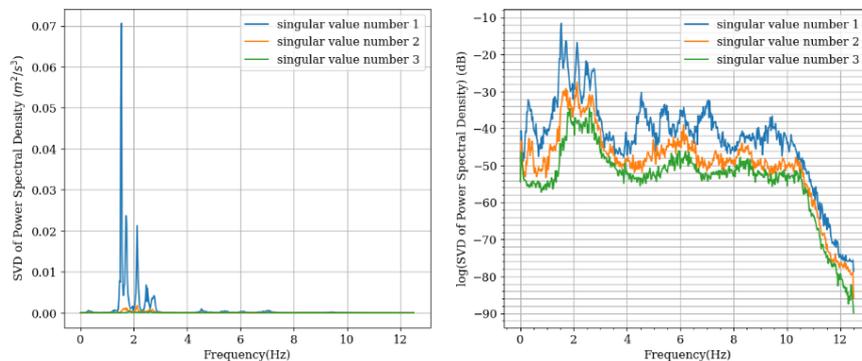
The second case study focuses on a real-world bridge analysed under in-situ conditions, aiming to showcase the capabilities of the preprocessing tools embedded in the python code for managing, filtering, and refining raw data obtained from field tests. These data often contain inherent noise and disturbances. Through the application of multiple Operational Modal Analysis (OMA) techniques, the study successfully extracted and analysed natural frequencies, damping ratios.

Table 2 displays only the frequencies, whereas Table 4 offers a detailed comparison of natural frequencies and damping ratios derived from various OMA methods implemented in the python library. The first nine modes, crucial for assessing the bridge's structural behaviour—especially concerning flexural and torsional vibrations during operation—show consistent agreement across methods. The natural frequencies demonstrate high consistency across all techniques and align closely with the values in Table 2. In contrast, damping ratios exhibit greater variability, which is anticipated due to their sensitivity to mathematical approaches and noise filtering strategies. Among the methods, EFDD and SSI-COV stand out as particularly reliable for all modes. It is worth mentioning that ARTeMIS Modal's SSI-UPCX method can find the nine modes in the highest possible order selection, but with a high computational time of approximately 30 minutes. In contrast, python implemented methods achieves this with significantly lower computational times, around 4.9 seconds for SSI-COV and 35.4 seconds for SSI-DATA, demonstrating its superior efficiency.

To highlight the dominant frequency components of the multi-span bridge, the Singular Value Decomposition of the Power Spectral Density is illustrated in both linear and semi-logarithmic scales in Figure 6. Despite the proximity of some modes (e.g., the first five modes are within a 1 Hz range), none are overshadowed, as each mode is distinctly represented in the first singular value diagram. This ensures clarity and precision in the analysis of the bridge's dynamic behaviour.

**Table 4.** Comparison of natural frequencies and damping ratios identified by OMA techniques for case study 2.

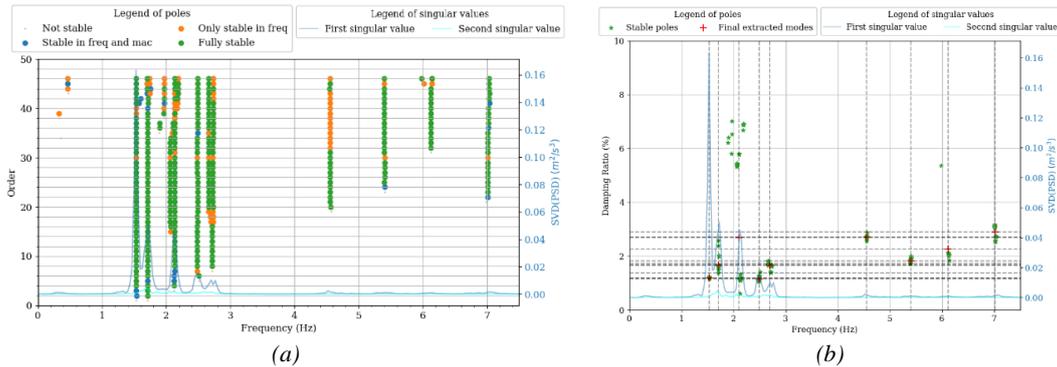
Number of modes	ARTeMIS Modal				Python									
	(EFDD)		SSI-UPCX		EFDD		SSI-COV		SSI-DATA		PolyMAX		ITD	
	$f$ (Hz)	$\zeta$ (%)	$f$ (Hz)	$\zeta$ (%)	$f$ (Hz)	$\zeta$ (%)	$f$ (Hz)	$\zeta$ (%)	$f$ (Hz)	$\zeta$ (%)	$f$ (Hz)	$\zeta$ (%)	$f$ (Hz)	$\zeta$ (%)
1	1.53	2.24	1.52	1.32	1.52	1.58	1.53	1.20	1.52	1.31	1.55	1.54	1.55	1.16
2	1.73	2.37	1.69	2.26	1.72	1.46	1.71	1.71	1.70	2.53	1.67	1.95	-	-
3	2.13	1.94	2.12	1.22	2.12	0.71	2.12	1.42	2.11	1.01	2.12	0.27	2.10	2.46
4	2.52	1.09	2.46	1.51	2.51	0.86	2.49	1.79	2.44	1.32	2.12	3.65	2.52	3.38
5	2.71	1.00	2.73	2.00	2.67	0.45	2.74	1.88	2.72	1.94	2.48	1.51	2.67	2.20
6	4.57	3.13	4.56	2.86	4.54	1.60	4.54	2.49	4.59	1.41	4.55	1.27	4.59	1.61
7	5.42	0.76	5.38	2.13	5.42	0.60	5.40	1.72	5.40	1.37	5.41	1.33	5.41	0.67
8	6.15	0.64	6.12	2.24	6.12	0.62	6.12	2.46	6.01	1.28	6.07	2.51	6.01	2.44
9	6.95	1.35	7.09	3.39	7.05	0.56	7.01	2.45	6.98	1.25	7.04	2.30	6.98	2.88



**Figure 6.** SVD of PSD in linear & semi-logarithmic scale for case study 2.

Figure 7 presents the stabilization diagram obtained through the SSI-COV technique for the multi-span bridge. This visualization highlights the progressive convergence of natural frequencies, damping ratios, and mode shapes with increasing model order, enabling the differentiation of genuine physical modes from spurious computational ones. The SSI-COV stabilization diagrams exhibit distinct pole stabilization for the identified modes, reinforcing their dependability. Additionally, the singular value

decomposition of the power spectral density plot reveals prominent frequencies via singular peaks, further corroborating the stable poles derived from the SSI-COV analysis.



**Figure 7.** Stabilization diagram using SSI-COV method (a) stable poles, (b) damping ratios for case study 2.

## 5. DISCUSSION AND CONCLUSIONS

This study evaluated various Operational Modal Analysis (OMA) techniques using a newly developed python library, validated through two case studies: a three-story aluminum building in a controlled laboratory setting and a multi-span highway bridge under operational conditions. The first case study demonstrated the library’s reliability in identifying natural frequencies and damping ratios for a simple structure with well-separated modes. Results showed strong agreement between the python methods and ARTeMIS Modal, with minor discrepancies in damping ratios due to algorithmic sensitivities. Visualization tools like Power Spectral Density analysis and stabilization diagrams enhanced the clarity of modal identification, while preprocessing techniques, such as Butterworth filtering, improved data quality. This controlled setup highlighted the library’s robustness and accuracy as a benchmark for modal analysis.

The second case study showcased the library’s capability to handle complex real-world structures, accurately identifying nine closely spaced modes in the bridge’s vibration response. python-based methods, particularly EFDD and SSI-COV, provided consistent results for natural frequencies and reliable stabilization diagrams, even under noisy conditions. The Modal Similarity Criterion (MSC) effectively quantified the agreement between methods, further validating the library’s performance. Overall, the python library offers a versatile and accessible tool for SHM applications, with strong alignment to commercial software like ARTeMIS Modal. By integrating advanced OMA techniques into an open-source platform, this library supports accurate and efficient modal parameter identification across diverse structural systems.

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