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Stochastic Modeling and Uncertainty Quantification in the Operational Modal Analysis of a Honeycomb Sandwich Panel

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Abstract. The aeronautical and aerospace industries have been carried out researches to develop structures that combine cost-effectiveness with excellent mechanical properties. In this context, honeycomb sandwich panels stand out due to their high stiffness and low structural weight. In aerospace applications, these panels are often subjected to complex dynamic behavior, requiring advanced methods to analyze modal parameters under operational conditions and ensure structural integrity. Operational Modal Analysis (OMA) emerges as a robust approach that complements models based on the Finite Element Method (FEM), which are commonly used for simulating structures with dynamic behavior. OMA uses stochastic models to identify modal parameters accurately, even without knowledge of excitation forces. However, its application is subject to uncertainties associated with system variables such as nominal mechanical properties, geometric tolerances, manufacturing effects, and acquisition equipment errors, which may affect the accuracy of modal parameter estimation. Given the importance of accurately estimating modal parameters under real operational conditions, this study proposes an uncertainty analysis to quantify the influence of variability in the modal parameter estimation procedure for a honeycomb sandwich panel. The tested panel represents a structural element of SGDC 1, the first Brazilian geostationary satellite. The SSI-COV and SSI-DATA methods were used to extract modal parameters and, to quantify uncertainties, laboratory tests were conducted and the Monte Carlo method was used to generate synthetic responses with added noise, forming a randomized sample space. The SSI methods were applied to each dataset using computational routines, allowing modal parameter estimation. The goal is to quantify the impact of noise uncertainty on modal parameters estimation, identify the most sensitive variables, and support modeling strategies and the application of OMA to improve result reliability in aerospace projects. The results showed that the SSI-COV method yielded more reliable results, being less sensitive to noise and having lower computational cost. Although more sensitive to noise, the SSI-DATA method also provided reliable results and is recommended for cases using only direct structural response data.

Keywords: Uncertainty Quantification, Operational Modal Analysis, Modal Parameter Estimation, Honeycomb Sandwich Panel

1 Introduction

The growing demand for lightweight structures with high mechanical performance has driven the use of honeycomb-core sandwich panels in the aerospace industry. These components offer high specific stiffness, good energy absorption capacity, and reduced structural weight, making them widely used in satellites, aircraft, and spacecraft. However, their application in harsh operating environments requires accurate assessment of their dynamic behavior, especially regarding modal parameters, which are essential for structural integrity and reliability analyses.

Traditional modal identification methods rely on precise knowledge of excitation, which is not always feasible under real-world operating conditions. In this scenario, Operational Modal Analysis (OMA) stands out because it allows the extraction of modal parameters from only the structure's responses, assuming stochastic excitation. Among the algorithms based on this approach, the SSI-COV and SSI-DATA methods stand out, estimating state-space models based on temporal data.

Despite its robustness, the practical application of OMA is subject to several sources of uncertainty, such as variations in mechanical parameters, geometric imperfections, measurement noise, and acquisition system limitations. Such uncertainties can compromise the accuracy of modal identification[1][2], especially in complex struc-

tures such as honeycomb-core panels. Therefore, this work proposes a study of uncertainties in the operational modal analysis of a honeycomb sandwich panel, a representative element of SGDC 1, Brazil's first geostationary satellite. Through laboratory tests and stochastic simulations using the Monte Carlo method, the impact of variability on the modal results obtained with the SSI-COV and SSI-DATA methods is evaluated. The objective is to identify the effects of noise on the estimation of modal parameters, identify the most sensitive variables, and contribute to increasing the reliability of OMA application in aerospace projects.

2 Object Description and Mathematical Background

The honeycomb sandwich panel will be used to validate the methodology. The panel is a plate 620mm long, 260mm wide and 39.5mm thick. The panel is composed by two laminate plates, each one is 0.3mm thick. Between them, there is a honeycomb-like core formed by hexagonal prismatic cells. The thickness of honeycomb core is 0.0254mm, the maximum height is 38.9mm and the edge length of each hexagonal cell is 3.18mm. The laminates are composed of Aluminum 2024 (AL2024), and the honeycomb core consists entirely of Aluminum 5056 (AL5056). Figure 1 illustrates the main dimensions of the honeycomb panel used in the the procedures.

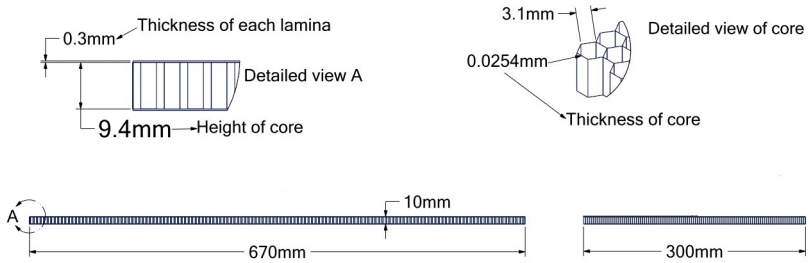


Figure 1. Honeycomb sandwich panel dimensions

2.1 Operational Modal Analysis Mathematical Background

Operational Modal Analysis (OMA) is a technique used to identify the dynamic parameters of a structure—such as natural frequencies, damping factors, and vibration modes—using only the responses measured during normal operation, without the need for controlled excitation. Unlike traditional experimental modal analysis, which relies on hammers or exciters, OMA uses ambient or operational excitation sources, such as wind, engine vibration, or traffic loads, making it especially useful for real structures in service. In the literature[3], the most applied OMA methods are SSI-COV and SSI-DATA, where these methods are based on stochastic state-space modeling of dynamical systems. Thus, instead of the traditionally studied system of ordinary differential equations, the stochastic state-space model introduces random variables into the traditionally deterministic model, in order to model the uncertainties arising from the model and the real physical experiment. The stochastic state-space modeling of a system is described by Peeters and De Rpeck [4] and shown below in Eq.(1) , where $[A]$ is the state matrix of the system and $[C]$ is the output matrix of the system. The vectors $\mathbf{x}_k$ and $\mathbf{y}_k$ are, respectively, the state vector and the response vector of the system, while $\mathbf{v}_k$ and $\mathbf{w}_k$ are the noise vectors of the system, composing the stochastic part of the modeling.

$$\begin{aligned} \mathbf{x}_{k+1} &= [A]\mathbf{x}_k + \mathbf{w}_k \\ \mathbf{y}_k &= [C]\mathbf{x}_k + \mathbf{v}_k \end{aligned} \tag{1}$$

The objective of the SSI-COV and SSI-DATA methods is to calculate the matrices $[A]$ and $[C]$ and then extract the modal parameters of the system by solving the eigenvalue problem of the matrix $[A]$, while the vibration modes are extracted from the matrix $[C]$.

2.2 Uncertainty Quantification

Modal identification using operational methods is subject to several sources of uncertainty that can affect the accuracy of the estimated parameters. These sources include measurement noise, sensor variability, structural

coupling effects, and signal preprocessing. To quantify these uncertainties, statistical approaches based on the generation of multiple response samples using the Monte Carlo Method (MCM) are commonly used.

Histogram and boxplot analyses are effective statistical tools for assessing the dispersion of modal parameters, such as natural frequencies, damping ratios, and mode shapes[5]. Histograms allow visualization of the probability distribution associated with each parameter, identifying trends, asymmetries, and possible outliers. Boxplots complement this analysis by providing a compact representation of quartiles, the median, and the presence of outliers, and are especially useful for comparing the performance of different algorithms under the influence of noise.

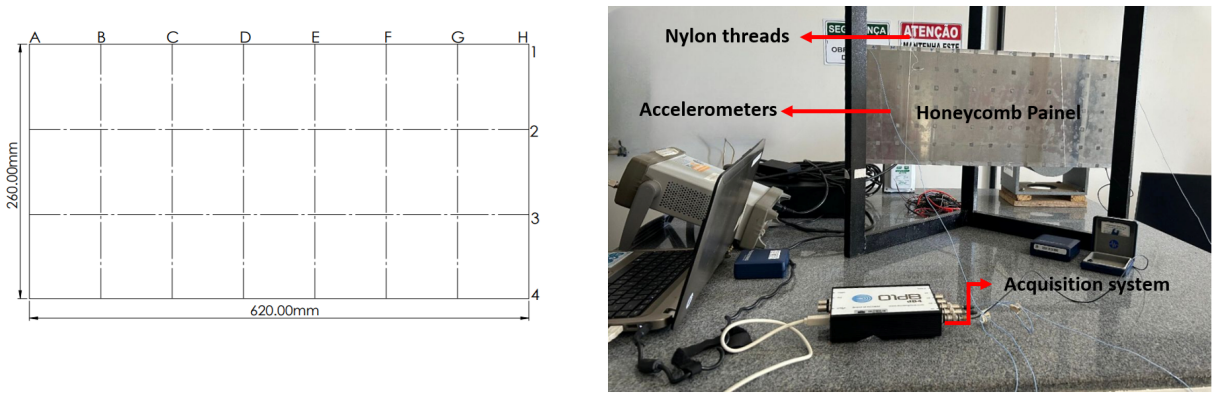
According to Zhou et al. [6], fundamental equations that support the statistical analysis of the extracted parameters are based on mean values and standard deviations. To generate multiple response samples in OMA, the Monte Carlo method operates by adding a white noise matrix $\mathcal{N}(0, \sigma_N)$ to the matrix of real structural responses Y_0 collected in the laboratory. To simulate noise levels in acquisitions, this noise matrix is typically produced with a mean of 0 and a standard deviation of σ_N, according to the Eq. (2), where α is the level of synthetic noise to be considered to be added to the original data.

$$Y_i = Y_0 + \alpha\mathcal{N}(0, \sigma_N) \tag{2}$$

3 Methodology

The adopted methodology consists of three main steps, namely 1) Carrying out experimental tests in the laboratory for processing OMA analyses, 2) Comparison of the OMA modal parameters with the EMA results from the literature to validate the results and 3) Insert synthetic noise into the collected data to construct a sample set of modal parameters extracted from these synthetic data.

For the experimental tests on the panel, a support with nylon threads was used to simulate the free-free condition. To facilitate data acquisition, the structure was discretized as shown in Fig. 2a. For OMA impact hammer excitation was used with a sampling frequency of 4096Hz, and the excitation point was kept fixed at A4, where the responses were acquired at 32 different points of Fig. 2a, separately. During the tests, the aim was to maintain the peak impact force constant at 1.10N, aiming to preserve the uniformity of the excitation energy throughout the measurements. This was done to preserve the physical coherence of signal simultaneity because instead of acquiring 32 points simultaneously, the acquisitions were made individually and then concatenated to simulate a single simultaneous experiment. To validate the values extracted by OMA, the extracted modal parameters were



(a) Point discretization

(b) Experimental setup

Figure 2. Experimental setup for acquiring responses to performing OMA analysis

compared with the respective values extracted by Domingues [7], which extracted the same parameters through an EMA conducted with an impact hammer. To analyze uncertainty in modal parameters, the objective is to determine how noise levels and measurement uncertainties affect the performance of OMA methods. Four case studies were simulated, each one incorporating noise into the laboratory-collected responses according to Eq. (2), varying only the α and σ_N parameters. The case studies are: 1)$\alpha = 0.15$ and $\sigma_N = \overline{RMS}$ and 2)$\alpha = 0.15$ and $\sigma_N = RMS_i$, where $\overline{RMS}$ is the RMS value of the signals from all 32 acquisition points and RMS_i represents the RMS value of the signal from the respective acquisition point at which noise is being inserted. For each case, the histograms of natural frequencies and damping of the first four modes were extracted, in addition to the standard deviations and means of each parameter, considering both the SSI-COV and SSI-DATA methods. In all cases, 1000 response matrix samples were generated, and the results are analyzed and discussed.

4 Results

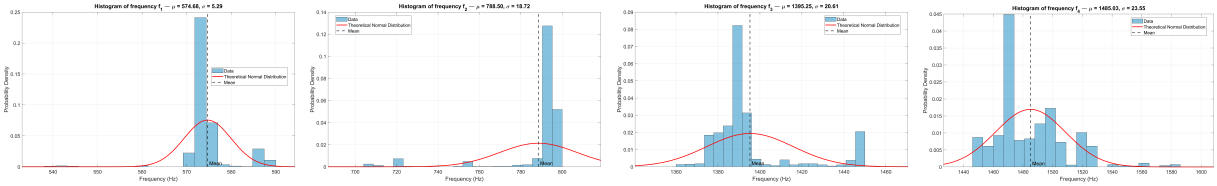
To validate the OMA methods,Table 1 presents the comparison of values between the modal parameters extracted by the OMA methods in comparison with the respective values extracted by EMA in the literature.

Table 1. Comparison between the modal parameters extracted by OMA with the values from the literature

	OMA				**EMA**	
	SSI-COV		**SSI-DATA**		**Literature**[7]	
Mode	f(Hz)	ζ(%)	f(Hz)	ζ(%)	f(Hz)	ζ(%)
1	576.66	0.43	563.43	0.30	566.946	0.40
2	720.19	0.62	727.27	0.34	728.42	0.89
3	1478.70	1.73	1477.96	0.08	1419.48	1.39
4	1515.98	0.31	1503.94	0.09	1466.67	1.10

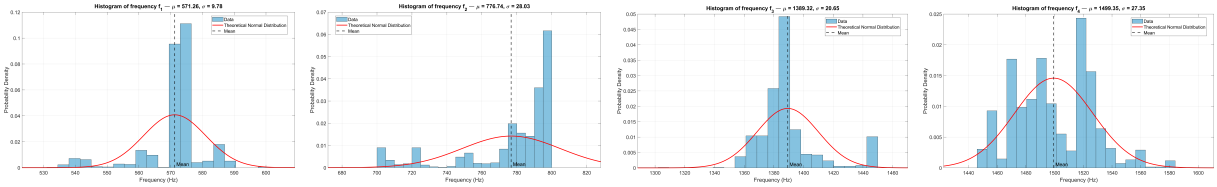
The values presented show that in all vibration modes presented, the frequencies identified by OMA presented good values compared to EMA, with slight variations in modes 3 and 4. Furthermore, it is noted that the damping of modes 1 and 2 of OMA presented values very close to the respective values of EMA, with more significant damping variations in modes 3 and 4. Even so, all parameters extracted by OMA were quite consistent and close to the modal parameters calculated by EMA, evidencing and validating the efficiency of OMA methods in the cases analyzed.

Figures 3 and 4 present the frequency histograms for cases I and II, respectively, for the SSI-COV method, while Figures 5 and 6 present the results of the same cases for the SSI-DATA method.



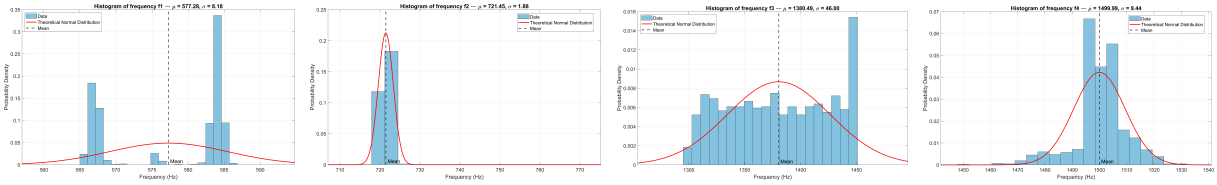
(a) Mode 1 (b) Mode 2 (c) Mode 3 (d) Mode 4

Figure 3. Histogram of frequencies extracted by the SSI-COV method - Case I



(a) Mode 1 (b) Mode 2 (c) Mode 3 (d) Mode 4

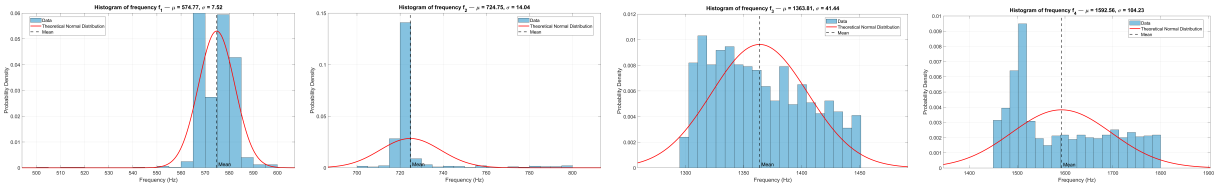
Figure 4. Histogram of frequencies extracted by the SSI-COV method - Case II



(a) Mode 1 (b) Mode 2 (c) Mode 3 (d) Mode 4

Figure 5. Histogram of frequencies extracted by the SSI-DATA method - Case I

The analysis of the frequency histograms obtained by the SSI-COV (Figures 3 and 4) method showed that the way the noise standard deviation is defined influences the stability of the modal estimate. In Case I, the noise



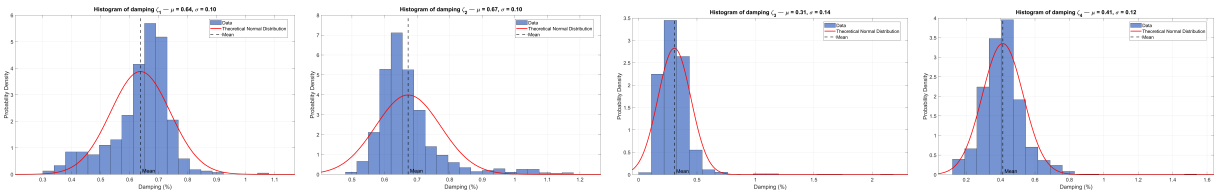
(a) Mode 1 (b) Mode 2 (c) Mode 3 (d) Mode 4

Figure 6. Histogram of frequencies extracted by the SSI-DATA method - Case II

was proportional to the mean RMS of the original matrix, resulting in more homogeneous distributions. In Case II, the noise was proportional to the individual RMS of each channel, generating greater variability between samples. Mode 1 showed high robustness in both cases, with low dispersion and good symmetry, being insensitive to the type of noise. Mode 2, on the other hand, was more affected, with a significant increase in dispersion and asymmetry in Case II. Mode 3 had the worst overall performance, with wide variability and the presence of outliers in both cases, indicating intrinsic instability. Mode 4 maintained a relatively stable distribution, with a slight increase in dispersion in Case II.

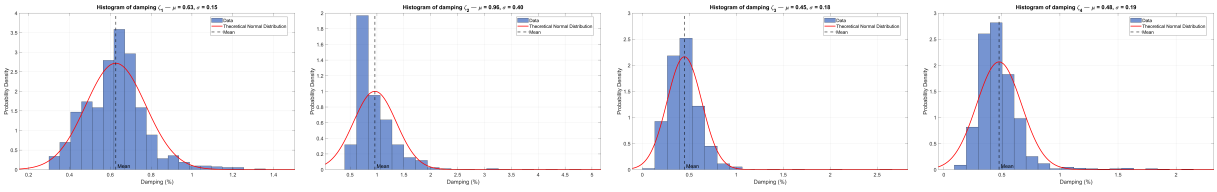
Analyzing SSI-DATA based on Figures 5 and 6, it can be seen that the sensitivity of the SSI-DATA method to noise is significant and noticeable in the form of the histograms. In Case I, the histograms remain concentrated around the mean for all modes. The peaks remain well-defined, with low dispersion, especially in modes 1 and 2, indicating that the SSI-DATA method can preserve the consistency of modal identification even under noisy excitation. On the other hand, in Case II, there is a visible increase in the dispersion of the extracted values, especially in the higher modes (modes 3 and 4). The asymmetry of the histograms and the greater variability suggest that this approach amplifies the effects of noise, impacting the algorithm's robustness in accurately identifying frequencies. These results indicate that SSI-DATA is sensitive to noise level variations and that its performance can be significantly degraded by non-uniform disturbances. Nevertheless, under moderate conditions and with balanced noise, the method exhibits good stability.

Figures 7 and 8 present the frequency histograms for cases I and II, respectively, for the SSI-COV method, while Figures 9 and 10 present the results of the same cases for the SSI-DATA method.



(a) Mode 1 (b) Mode 2 (c) Mode 3 (d) Mode 4

Figure 7. Histogram of dampings extracted by the SSI-COV method - Case I

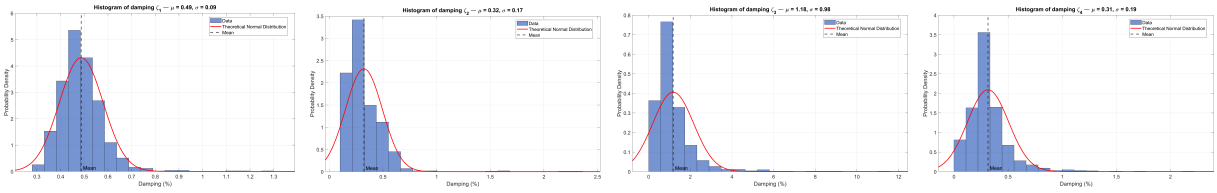


(a) Mode 1 (b) Mode 2 (c) Mode 3 (d) Mode 4

Figure 8. Histogram of dampings extracted by the SSI-COV method - Case II

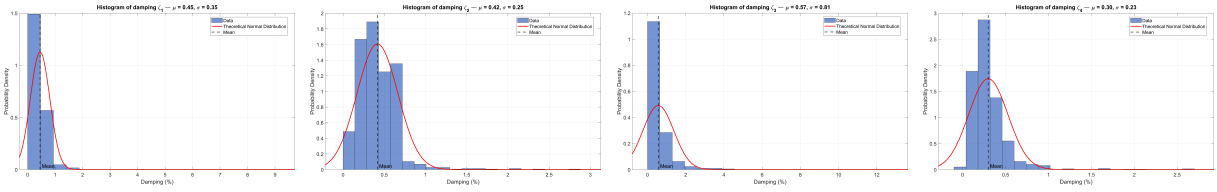
The damping analysis shows that the SSI-COV method is sensitive to the noise level and distribution, especially in the lower-order modes. In Case I, with uniform noise based on the mean RMS, the damping exhibits low variability and a well-defined distribution, indicating good robustness of the method. In Case II, with noise varying from channel to channel, greater dispersion and asymmetries are observed in the histograms, reflecting increased uncertainty and a greater impact of noise on the estimation of the most sensitive modes. This shows that, although the method is robust under controlled conditions, its accuracy decreases as the noise becomes more irregular.

Analysis of the damping histograms obtained by the SSI-DATA method shows that it is also sensitive to the presence and variation of noise in the data. In Case I, the modes exhibit narrow, well-centered distributions



(a) Mode 1 (b) Mode 2 (c) Mode 3 (d) Mode 4

Figure 9. Histogram of dampings extracted by the SSI-DATA method - Case I



(a) Mode 1 (b) Mode 2 (c) Mode 3 (d) Mode 4

Figure 10. Histogram of dampings extracted by the SSI-DATA method - Case II

with low variability, indicating good repeatability of the estimates. However, in Case II, a significant increase in dispersion is observed, as well as asymmetry in the distributions, especially in modes 2 and 4. This highlights that, although SSI-DATA performs well with controlled noise, its accuracy is compromised when the noise becomes more heterogeneous across channels.

When comparing the SSI-COV and SSI-DATA methods in the two cases analyzed, it is observed that both are affected by noise, but to different degrees. SSI-COV demonstrated greater robustness, maintaining more concentrated distributions with less scattering even in Case II, where the noise is more intense and asymmetric. SSI-DATA, on the other hand, proved to be more sensitive to noise variations, with greater scattering and asymmetry in the damping distributions, especially in modes with low signal-to-noise ratios. Thus, although both methods perform well under favorable conditions, SSI-COV tends to generate more stable estimates that are less affected by noise-induced uncertainties. Similar conclusions about modal parameters can be found in the work of Silva et al. [8] and Mao et al. [9], who obtained similar histogram results but followed different approaches. Silva et al. [8] studied uncertainties in SSI methods using bootstrapping techniques, while Mao et al. [9] addressed modal parameter uncertainties using Bayesian Operational Modal Analysis.

5 Conclusions

This comparative study between the SSI-COV and SSI-DATA methods allowed us to evaluate the influence of noise on the variability of damping estimates in different vibration modes. From the analysis of the histograms extracted for Cases I and II, several important observations were drawn.

In Case I, characterized by cleaner excitation and less noise, both methods demonstrated consistent behavior, with distributions concentrated around the mean values and relatively low standard deviations. However, even in this scenario, the SSI-COV method presented slightly more symmetrical distributions with less asymmetry compared to SSI-DATA, which already indicates a trend toward greater robustness.

In Case II, where a scenario with greater noise intensity and asymmetric disturbances was introduced, the differences between the methods became more evident. SSI-DATA showed greater sensitivity to noise, resulting in more spread-out distributions with steep tails and, in some modes, evidence of outliers. In contrast, SSI-COV maintained narrower and more concentrated distributions, with less statistical dispersion, even in the most affected modes.

These results indicate that, although both algorithms are capable of extracting modal parameters effectively under ideal conditions, SSI-COV demonstrates superior performance in terms of stability and reliability of estimates under noise. This characteristic makes SSI-COV particularly advantageous in practical applications where control of the excitation environment is not guaranteed, such as in field measurements or in structures subject to operational noise.

Therefore, it is concluded that, for studies involving the quantification of uncertainties and reliability of modal parameters, the use of the SSI-COV method is more recommended, especially in noisy or operational scenarios. SSI-DATA, while useful and with good estimates in controlled environments, requires greater caution regarding the quality of the input data.

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