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APPLICATION OF A NON-DESTRUCTIVE APPROACH FOR STRUCTURAL HEALTH MONITORING ON REAL-WORD STRUCTURES

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Abstract

The ability to assess the integrity of real-world structures is a critical objective, particularly when it comes to cultural heritage buildings. Monitoring the condition of these buildings is essential to preserve their longevity against the gradual accumulation of damage over the years and so ensuring timely interventions. In such cases, it becomes especially important to preserve the structures' integrity throughout the monitoring process itself, making non-invasive and non-destructive methods essential for effective and sustainable maintenance. In this context, a dedicated method implemented in a software based on vibration analysis was tested to conduct Structural Health Monitoring analysis on a real-world structure made by truss elements. The analyzed structure is a lattice structure approximately 9 meters in height, monitored using 18 uniaxial accelerometers positioned in pairs across 9 different levels. The data utilized was gathered through continuous monitoring over a span of one year. The results obtained are highly significant, as all minor damages were successfully identified using the applied processing methods, which relied solely on the monitored data, without requiring any prior knowledge of the actual structure. This is particularly important, as acquiring such data for a structure built many years ago would be extremely challenging. Furthermore, the results were based on acquisitions conducted in environmental conditions, each lasting 10 minutes, providing a reasonable timeframe for obtaining immediate feedback regarding potential damage to the structure. So, the fact that this method is reference-free, requires a relatively small number of accelerometers, and involves short acquisition times, makes it an appealing approach for initial damage detection, while also paving the way for more in-depth investigations.

Keywords: Structural health monitoring, Damage detection, Vibration measurements, Stochastic subspace identification.

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1 INTRODUCTION

Structural Health Monitoring (SHM) plays a crucial role in detecting damage in aerospace, civil, and mechanical infrastructures through continuous monitoring and dynamic analysis. Unlike traditional visual inspections, SHM offers a more effective approach to ensuring long-term safety. Vibration-based SHM is particularly significant, as it extracts damage-sensitive features, such as shifts in natural frequencies [1], mode shapes, and energy dissipation, from collected data [2-3]. These parameters are then analyzed statistically to assess structural health. For long-term monitoring, periodic updates help determine whether a structure can still fulfill its intended function. Operational Modal Analysis (OMA) is a key technique in SHM, addressing the challenge of identifying modal parameters without direct measurement of excitation forces. Unlike Experimental Modal Analysis (EMA), OMA is more practical for large structures and has been widely used to track structural integrity over time.

The main advantage of OMA in SHM is its ability to assess structural integrity in operational conditions, non-destructively. While various algorithms can determine modal parameters, their sensitivity to damage depends on factors like location, severity, and data quality, often requiring filtering techniques [4]. A recent commercial software from ARTeMIS has been developed to aid damage detection, specifically addressing the first level of Rytter's classification (damage existence). This tool can identify potential structural risks solely from accelerometer data, without evaluating modal parameters, and in a non-invasive manner. Similar data-driven methods exist in the literature [5-8], though not using this specific software and algorithm. The present work explores recent results published in [9] related to a new dataset continuously acquired on a real-world structure subjected to ambient conditions to test the software SHM tool. This dataset has been acquired and made available from the Leibniz Universität Hannover research group in Germany [10].

The main novelty of the present work is the testing of a new method (named control chart) to detect damage through the acquired experimental data, comparing the data when the structure is intact and when it is damaged. This study considers different data acquisition sessions to assess the feasibility of monitoring the structural conditions. The tested method requires processing 15 data acquisition sessions under environmental conditions, each lasting 10 minutes. The 15 sessions corresponding to the intact state were randomly selected during the period when the structure was undamaged (August 1 – October 13, 2020). Conversely, the 15 sessions related to the damaged state were collected in three different ways during the period when the structure was damaged by the removal of two arms positioned in the lower area (13-27 October 2020).

The SHM method applied is demonstrated to be not sensitive to natural changes in the dynamic behavior of the structure due to fluctuations in ambient conditions and shows excellent results in determining the damage condition for all the cases considered.

The work is organized as follows: in section 2 the damage detection algorithm implemented in the software tool is described, in section 3, the specific system under examination is shown, providing an overview of its characteristics and data acquisition modalities; finally, in section 4 the results obtained from the analysis will be presented and discussed, and in section 5 conclusions are drawn.

2 THE TOOL GENERAL SPECIFICATIONS

The Structural Health Monitoring (SHM) tool implemented in Artemis Modal [11], analysed in this study, relies on the Stochastic Subspace Identification (SSI) method [12-13], within the framework of Operational Modal Analysis (OMA) techniques, to construct a reference state model, serving as the basis for evaluating the dynamics and structural condition of the system in question.

To monitor the structural integrity of the truss tower, which will be presented in the next paragraph, the Structural Health Monitoring (SHM) tool offers various methods to detect potential damage by analyzing recorded measurement files and results obtained during periodic monitoring.

2.1 Theoretical background about the SSI and the damage detection algorithm

The SSI method, already detailed in [9] and here synthesized for clarity, begins by defining a discrete-time stochastic state-space model, where the structure is assumed to be excited by white noise. This assumption allows for the substitution of unmeasurable ambient vibration excitations, and the model is formalized as shown in Eq. 1

$$\begin{cases} x_{k+1} = Ax_k + w_k \\ y_k = Cx_k + v_k \end{cases} \tag{1}$$

Where $w_k \in \mathbb{R}^{n \times 1}$, is the noise in the process that arises from disturbance and inaccuracies in modeling; $v_k \in \mathbb{R}^{l \times 1}$, is the measurement noise due to sensor inaccuracy.
$A \in \mathbb{R}^{n \times n}$ and $C \in \mathbb{R}^{l \times n}$ are respectively the state matrix and the output matrix (with n system order equal to $2m$, m DOF, and l used sensors).
Measurements are available at discrete time instants $k\Delta t$, $k \in \mathbb{R}^n$, with Δt the sample time.
$x_k=x(k\Delta t) \in \mathbb{R}^{n \times 1}$ is the discrete-time state vector, and $y_k \in \mathbb{R}^{l \times 1}$ are the outputs.
The SSI data-driven method provides the possibility to gather the output measurements in the so-called Hankel matrix H, structured as in Eq. 2:

$$H = \left[\begin{array}{cccc} y_0 & y_1 & \cdots & y_{N-1} \\ y_1 & y_2 & \cdots & y_N \\ \cdots & \cdots & \cdots & \cdots \\ y_{i-1} & y_i & \cdots & y_{i+N-2} \\ \hline y_i & y_{i+1} & \cdots & y_{i+N-1} \\ y_{i+1} & y_{i+2} & \cdots & y_{i+N} \\ \cdots & \cdots & \cdots & \cdots \\ y_{2i-1} & y_{2i} & \cdots & y_{2i+N-2} \end{array}\right] = \left[\frac{H_p}{H_f}\right] \tag{2}$$

Here, i is a user-defined index representing the data shift, which determines the number of block rows in the matrix. Each block row consists of l rows, where l corresponds to the number of measured degrees of freedom (DOFs). Increasing i generally improves the accuracy of the estimates. N represents the total number of data samples acquired during a single accelerometer recording.
From the Hankel matrix it is obtained a projection matrix $\mathcal{P}$, through the projection of the row space of the future outputs H_f, into the ones of the past reference outputs H_p. This is then decomposed through a Singular Value Decomposition (Eq.3):

$$\mathcal{P} = U_1 S_1 V_1{}^T = \begin{bmatrix} U_1 & U_0 \end{bmatrix} \begin{bmatrix} S_1 & 0 \\ 0 & S_0 \end{bmatrix} \begin{bmatrix} V_1{}^T \\ V_0{}^T \end{bmatrix} \tag{3}$$

With $U_1 \in \mathbb{R}^{li \times n}$ and $V_1 \in \mathbb{R}^{N \times n}$ are orthonormal matrices that correspond to a collection of n left and right singular vectors related to n singular values $S_1 \in \mathbb{R}^{n \times n}$ contained in a diagonal matrix and are called, respectively, the image and the co-image of a matrix. The matrices U_0

and V_0 are called the left and right null spaces of a matrix, respectively. They contain the left and right singular vectors that correspond to the singular values in S_0, which approximate zero [12]. The projection matrix can also be factorized as a product of an observability matrix and a Kalman filter state sequence. Specifically, the observability matrix O can be described as follows:

$$O_i = U_1 {S_1}^{1/2} = \begin{bmatrix} C \\ CA \\ CA^2 \\ \vdots \\ CA^{i-1} \end{bmatrix} \tag{4}$$

Thus, this approach is employed to derive the matrices A and C, from which the system's eigenvalues and eigenvectors are computed via eigenvalue decomposition. This enables the extraction of the natural frequencies that characterize the analyzed structure.
For what concern the damage detection methodology, it is based on the definition of a novel parameter [14]: the residual vector. This residual vector allows for the identification of potential damage without requiring the estimation of modal parameters.
Let ζ represent a damage detection residual derived from damage-sensitive features extracted from measurement data in both the reference (healthy) and the currently tested states, with Σ_ζ denoting its asymptotic covariance matrix. Comparing measurements between the healthy and tested states involves modeling the residual as following a Gaussian distribution.
In the non-parametric version of the damage detection test (i.e., without relying on modal parameters) and assuming a constant covariance excitation, this residual can be defined based on the selected damage detection method as follows:

$$\zeta_N{}^Q = \sqrt{N} vec(S^T \hat{H}) \tag{5}$$

for the classic subspace-based residual, or as:

$$\xi_N{}^Q = \sqrt{N} vec(S^T \hat{U}_1) \tag{6}$$

for the robust subspace-based residual.
Where N is the number of samples acquired, $\hat{H}$ is the estimated Hankel matrix of the reference state computed on data corresponding to the covariance Q, S is the null space ($S=U_0$ in Eq. (3)), and $\hat{U}_1$ is the estimate of the left singular vector obtained from the SVD.
Once the residual reference vector is determined, it must be computed for every state under evaluation. Each new residual vector is obtained by iteratively replacing the null space value S of the reference state in Eqs. 5 and 6 with that of the tested states while maintaining multiplication by the estimated Hankel matrix or the estimated singular vector of the reference state.
When the test data statistically corresponds to the baseline data, the mean value of the residual is zero, indicating that the currently tested dataset represents a healthy state. Conversely, if the residual deviates significantly from zero, it suggests that the tested data originates from a damaged structure.
To determine whether the residual is significantly different from zero, a non-parametric test is performed as described in Eqs. 7 and 8, corresponding to the classical and robust methodologies, respectively.

$$\chi^2 = (\zeta_N)^T (\hat{\Sigma}_\zeta)^{-1} \zeta_N \tag{7}$$

$$\gamma^2 = (\xi_N)^T(\hat{\Sigma}_\xi)^{-1}\xi_N \tag{8}$$

where $\hat{\Sigma}_\zeta$ is a consistent estimate of Σ_ζ computed on data in the currently tested state in Eq.7, and analogously in Eq. 8.
These values obtained from this $\chi^2 - test$ should be compared to an appropriate threshold to define if the structure is in a healthy or damaged state. In this study, the thresholds are set at the 95th percentile to define a critical structural state and the 99th percentile to indicate an unsafe condition. These thresholds are determined based on the analysis of the reference state model, against which data from each damaged state is compared.
Furthermore, the information obtained from multiple algorithms can be integrated by the software into a "control chart." This approach helps minimize the probability of false alarms and enhances the reliability of damage detection, ensuring more accurate assessments of the structure's condition. Given the greater reliability of the combined 'Control Chart' algorithm, already verified by the authors in [9], this study will analyze and present only the results of this algorithm.

3 CASE STUDY

The huge dataset provided by the University of Leibniz University Hannover in Germany has been considered [10] to analyze the software's performance. To obtain a structure exposed to natural sources of excitation, which exhibits damages of various intensities and at multiple locations throughout its lifetime, while also enabling long-term measurements, the Hannover research group has developed and installed the Leibniz University Test Structure for Monitoring (LUMO). This is a lattice mast structure standing at around 9 meters tall, positioned outdoors, and equipped with accelerometers, strain gauges, and a temperature sensor, ensuring continuous monitoring (Fig.1). All collected data, from August 2020 to July 2021, are available online through an open-access repository.

3.1 Structure's description and damage mechanism

As detailed in [10], and also depicted in Fig. 1, the steel lattice analysed structure consists of three identical segments, each measuring 3 m in length, resulting in a total height of 9 m. Its overall weight, excluding sensors, is approximately 90 kg. Each segment features three tubular legs arranged to form a cross-section resembling an isosceles triangle. Additionally, they consist of seven bracing levels, along with short connecting sections at the ends. The sections terminate in an elliptical flange, facilitating the assembly of segments in any order using standard M10 steel bolts. The primary characteristic of the test structure revolves around localized reversible damage, which is evident through changes in stiffness and mass. Activation of the damage mechanisms involves loosening the screw sockets and potentially removing the connecting pieces, resulting in the complete separation of the corresponding bracings. The damage considered in this analysis is positioned at a low level of the structure, as illustrated in Fig. 1. The structure was damaged by removing the arms during the period from October 13 to October 27, 2020. During this time, it was monitored using 18 uniaxial accelerometers, arranged in pairs (along with the x and y directions) at 9 positions labeled ML1, ML2...ML9, placed at different heights of the structure, as illustrated in Figure 1 with separate sessions of acquisition, each acquisition 10 minutes in length, with a sampling frequency of 1651.6 Hz. The structure was also monitored before the damage, in the period 1/8-13/10/2020, in healthy state, with the same acquisition setup.

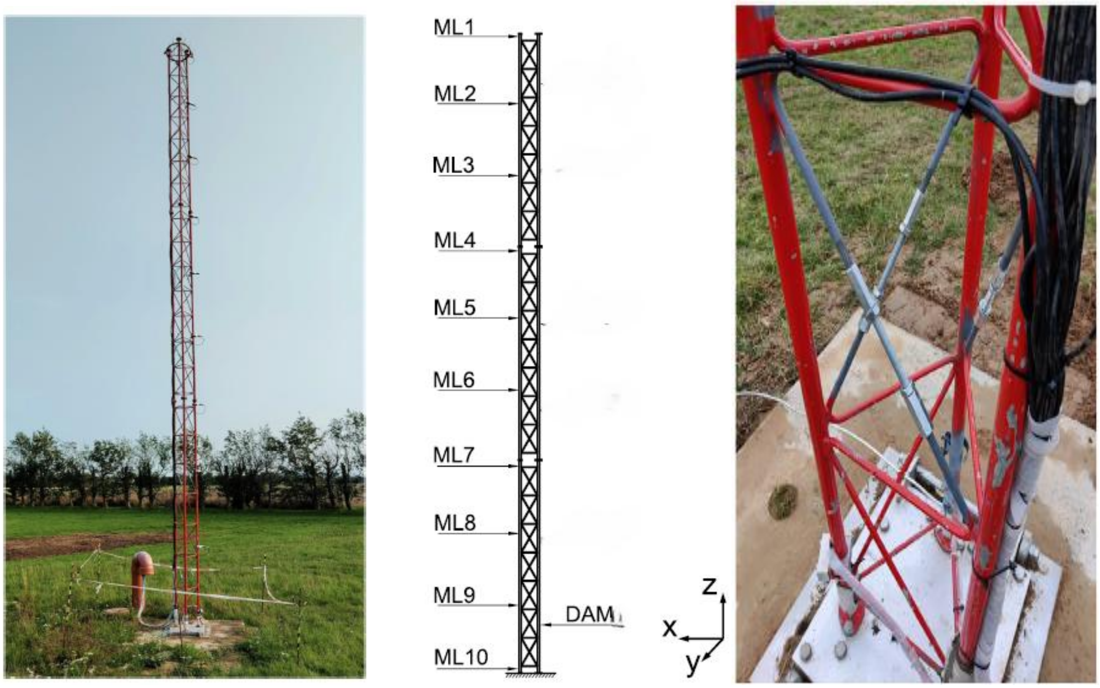


Figure 1: Structure under test and damage localization.

Out of all the data sessions recorded during the period of structural integrity, 15 were randomly selected and distributed throughout the entire period. The selected 15 sessions, along with their start time (each lasting 10 minutes) and the corresponding temperature, calculated as the mean value recorded by a temperature sensor during each session, are presented in Table 1.

Day	Time	Temp. [°C]	Day	Time	Temp. [°C]
01/08/2020	00:02	17.51	25/09/2020	01:37	14.66
02/08/2020	00:01	18.24	27/09/2020	01:46	8.33
05/08/2020	00:29	9.34	01/10/2020	00:04	9.83
15/08/2020	01:05	18.83	03/10/2020	00:03	14.39
30/08/2020	10:16	10.33	05/10/2020	00:12	7.14
01/09/2020	00:05	11.25	06/10/2020	00:12	8.77
09/09/2020	01:11	16.07	09/10/2020	00:40	12.39
17/09/2020	01:22	10.31			

Table 1: Details of the 15 acquisition sessions (10 minutes) considered in the integer state

Regarding the data sessions recorded during the period when the structure was damaged (October 13–27, 2020), the selected sessions were considered using three different methods. These sessions are presented in Tables 2, 3, and 4, following the same format as those from the intact period. The three data collection methods were designed to simulate different monitoring approaches:

Modality 1: All 15 sessions were conducted on the same day.

Modality 2: The sessions were conducted on different days but at the same time of day.

Modality 3: The sessions were conducted on different days but at the same time of night.

Modality 1 refers to data acquisitions conducted on the same day (October 26, 2020) at different times and under varying temperatures following the daily trend (see Table 2). This approach can be considered a methodology for rapid structural monitoring, as all acquisitions were completed in less than a day.

Day	Time	Temp. [°C]	Day	Time	Temp. [°C]
26/10/2020	00:03	10.99	26/10/2020	12:03	12.19
26/10/2020	02:03	9.96	26/10/2020	14:03	12.62
26/10/2020	03:03	9.91	26/10/2020	15:03	11.27
26/10/2020	05:03	9.69	26/10/2020	17:03	8.76
26/10/2020	06:03	10.27	26/10/2020	18:03	8.10
26/10/2020	08:03	11.24	26/10/2020	20:03	7.79
26/10/2020	09:03	12.35	26/10/2020	22:03	6.00
26/10/2020	11:03	11.41			

Table 2: Details of the 15 acquisition sessions (10 minutes) considered in modality 1.

In contrast, modalities 2 and 3 can be considered representative of a systematic monitoring approach, with a single acquisition per day at the same time, daytime for modality 2 and nighttime for modality 3. The temperatures of the different sessions also vary, as expected for different days (even if consecutive). However, the temperatures recorded in modality 2 sessions are consistently higher than those in modality 3 sessions, as shown in Tables 3 and 4.

Day	Time	Temp. [°C]	Day	Time	Temp. [°C]
16/10/2020	13:38	12.11	23/10/2020	13:04	14.65
17/10/2020	13:47	20.13	23/10/2020	14:04	14.69
18/10/2020	13:47	12.37	24/10/2020	13:04	19.08
19/10/2020	13:46	12.69	24/10/2020	14:04	16.50
20/10/2020	13:46	12.42	25/10/2020	13:03	15.19
21/10/2020	13:05	17.25	26/10/2020	13:03	11.56
22/10/2020	13:05	19.53	26/10/2020	14:03	12.62
22/10/2020	14:05	19.24			

Table 3: Details of the 15 acquisition sessions (10 minutes) considered in modality 2.

Day	Time	Temp. [°C]	Day	Time	Temp. [°C]
16/10/2020	02:38	8.30	23/10/2020	02:04	10.30
17/10/2020	02:48	7.12	23/10/2020	03:04	10.12
18/10/2020	02:47	3.41	24/10/2020	02:04	10.31
19/10/2020	02:47	6.99	24/10/2020	03:04	11.76
20/10/2020	02:46	3.34	25/10/2020	02:03	12.37
21/10/2020	02:56	10.89	25/10/2020	03:03	11.92
22/10/2020	02:05	15.92	26/10/2020	02:03	9.96
22/10/2020	03:05	14.68			

Table 4: Details of the 15 acquisition sessions (10 minutes) considered in modality 3.

4 RESULTS OF STRUCTURAL HEALTH MONITORING

The previously described SHM tool was used with the data from the sessions listed in Table 1 (intact state), comparing them with the sessions from the three modalities considered for the damaged structure. For each investigation, the 15 sessions of the intact state are compared with the 15 sessions of the damaged state. It is specified that only accelerometric data under environmental conditions are considered in the comparison.

The tool used not only identifies frequencies through different OMA techniques (for example, Figure 2 shows the identification result obtained using the SSI_UPCX technique in the first analyzed session) but also evaluates critical conditions using different assessment methods. For each session, the obtained values are compared against a safety threshold.

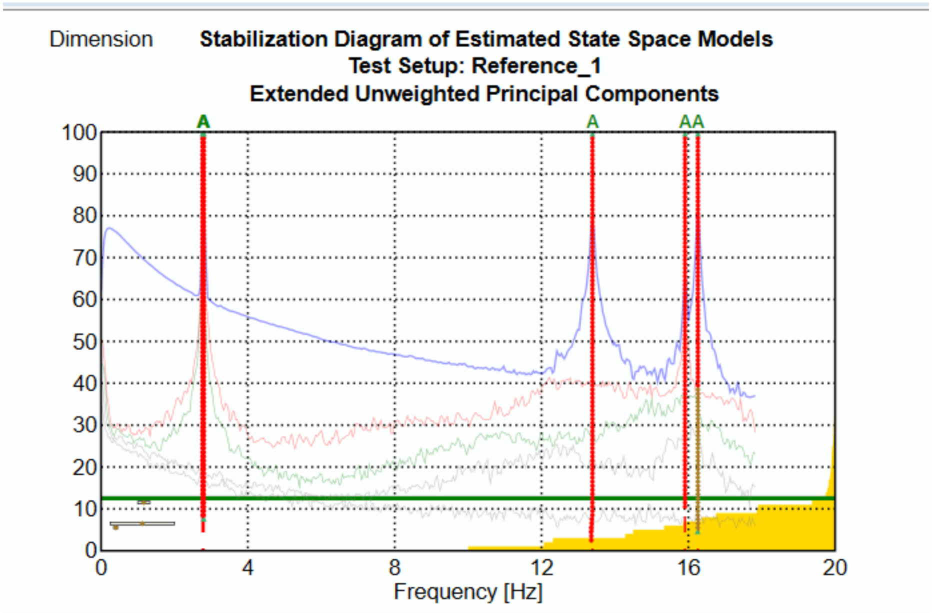


Figure 2: Identification results through SSI-UPCX for the first session considered.

All implemented algorithms (Classic and Robust) [9] and the algorithm derived from their combination (called Control Chart) produced similar and highly reassuring results. They demonstrated an excellent ability to detect damage in the real structure using only accelerometric data obtained under environmental conditions.

Figures 3, 4, and 5 show the results obtained by applying the Control Chart algorithm considering a threshold significance level of 0.99%. The analysis considers 15 sessions with the intact structure (sessions 1 to 15) and 15 sessions with the damaged structure (sessions 16 to 30), using the damaged sessions from modality 1 (Figure 3), modality 2 (Figure 4), and modality 3 (Figure 5).

Figure 3: damage state acquisition modality 1.

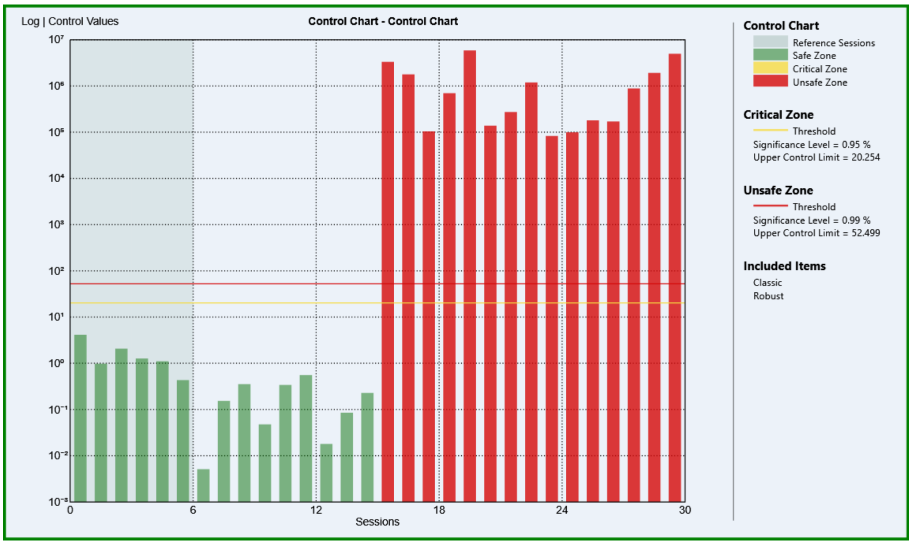


Figure 4: damage state acquisition modality 2.

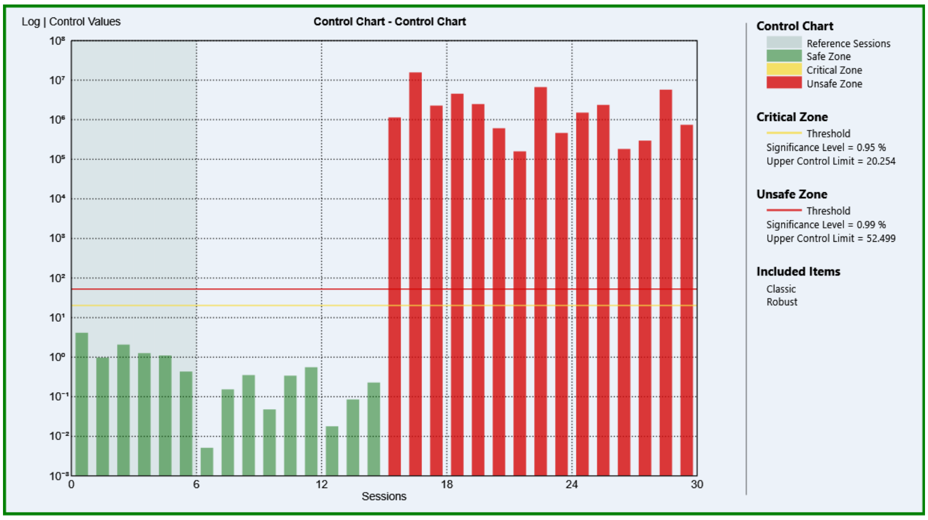


Figure 5: damage state acquisition modality 3

It is evident that the algorithm detects the presence of damage, and this result is not dependent on the chosen threshold values. Even when using different reasonable values, the results consistently demonstrate the tool's effectiveness.

To complete the analysis of the considered acquisitions, Tables 5 and 6 present the first five frequencies (in Hz) identified using the SSI-UPCX method for all the analyzed data sessions.

The results in Tables 5 and 6 show that the first two identified frequencies are very similar across all analyzed sessions, both for the intact structure and the damaged structure in all analysis methods (modality 1 to 3). However, the third frequency becomes difficult to determine in all acquisitions performed on the damaged structure. In contrast, the fourth and fifth frequencies, corresponding to secondary bending modes, are much more sensitive. For the damaged structure, these frequencies show a clear reduction in value across all considered sessions.

	Integer state					Damage state (modality 1)				
Sessions	1st fr.	2nd fr.	3rd fr.	4th fr.	5th fr.	1st fr.	2nd fr.	3rd fr.	4th fr.	5th fr.
1	2.76	2.80	13.39	15.91	16.26	2.75	2.79	/	14.32	14.71
2	2.76	2.81	13.42	15.91	16.28	2.75	2.79	/	14.31	14.71
3	2.77	2.81	13.43	15.94	16.31	2.75	2.79	/	14.31	14.71
4	2.76	2.81	13.43	15.94	16.29	2.75	2.79	/	14.32	14.71
5	2.75	2.81	13.38	15.90	16.23	2.75	2.79	/	14.30	14.71
6	2.77	2.82	13.43	15.98	16.31	2.75	2.79	/	14.31	14.69
7	2.81	/	13.42	15.98	16.31	2.75	2.79	/	14.31	14.69
8	2.77	2.82	13.45	15.99	16.32	2.75	2.79	11.64	14.30	14.70
9	2.77	2.81	13.41	15.97	16.30	2.74	2.79	/	14.30	14.70
10	2.77	2.81	13.44	15.96	16.28	2.75	2.79	/	14.31	14.70
11	2.78	2.82	13.44	16.00	16.31	2.75	2.79	/	14.32	14.71
12	2.77	2.81	13.38	15.98	16.30	2.75	2.79	/	14.31	14.71
13	2.78	2.82	13.40	15.99	16.32	2.75	2.79	/	14.31	14.72
14	2.77	2.82	13.41	15.99	16.31	2.75	2.79	11.65	14.32	14.71
15	2.77	2.81	13.43	15.97	16.30	2.75	2.79	/	14.32	14.71

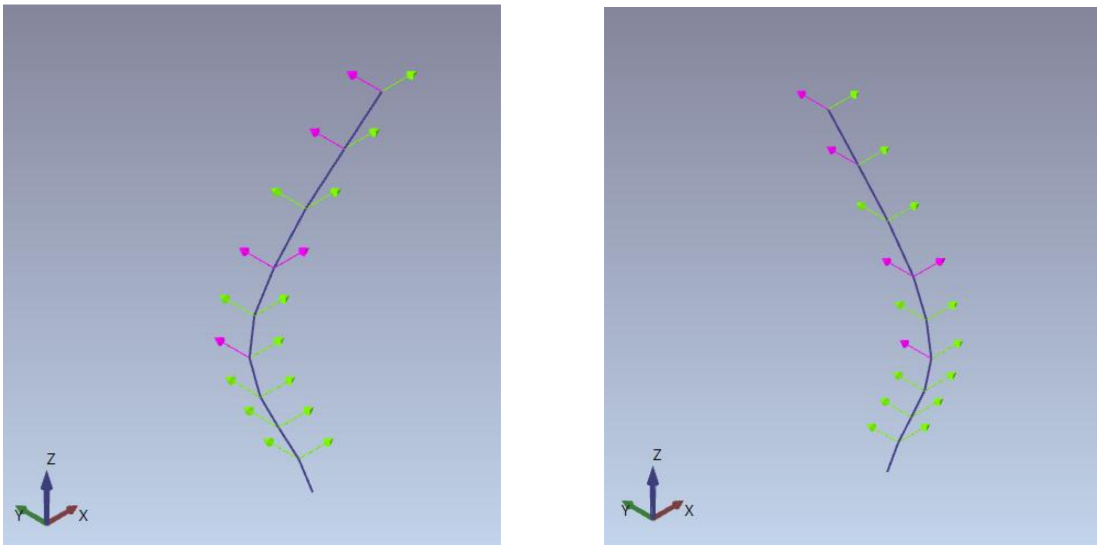
Table 5: Identified frequencies [Hz] integer state/damage state (modality 1)

	Damage state (modality 2)					Damage state (modality 3)				
Sessions	1st fr.	2nd fr.	3rd fr.	4th fr.	5th fr.	1st fr.	2nd fr.	3rd fr.	4th fr.	5th fr.
1	2.76	2.80	11.65	14.31	14.70	2.74	2.79	11.65	14.31	14.71
2	2.74	2.78	11.63	14.29	14.68	2.76	2.79	/	14.32	14.72
3	2.74	2.78	11.64	14.30	14.69	2.75	2.79	/	14.31	14.72
4	2.75	2.78	11.64	14.31	14.70	2.75	2.79	/	14.32	14.72
5	2.75	2.79	/	14.31	14.70	2.75	2.79	/	14.32	14.71
6	2.74	2.78	11.63	14.29	14.69	2.75	2.79	/	14.31	14.70
7	2.74	2.78	11.63	14.30	14.69	2.74	2.78	11.63	14.30	14.68
8	2.75	2.79	11.63	14.30	14.70	2.74	2.79	/	14.31	14.70
9	2.73	2.79	11.63	14.28	14.69	2.75	2.79	/	14.31	14.72
10	2.75	2.78	11.63	14.30	14.69	2.79	/	/	14.31	14.71
11	2.74	2.78	11.63	14.28	14.67	2.75	2.79	/	14.31	14.71

12	2.74	2.78	11.63	14.29	14.68	2.74	2.79	11.64	14.30	14.70
13	2.75	2.78	11.64	14.30	14.69	2.74	2.79	/	14.30	14.70
14	2.75	2.79	/	14.31	14.70	2.74	2.79	11.64	14.30	14.70
15	2.75	2.79	/	14.31	14.70	2.75	2.79	/	14.31	14.71

Table 6: Identified frequencies [Hz] damage state (modality 2)/damage state (modality 3)

To provide an insight into the modes corresponding to the fourth and fifth frequencies, they are shown in Figure 6. It is clearly evident that these modes correspond to a second bending mode along the y (4th frequency) and the x (5th frequency) axes.



a) b)

Figure 6: Identified modes related to 4th (a) and 5th (b) frequencies

5 CONCLUSIONS

This study investigates the feasibility of detecting the health status of a real structure by monitoring its dynamic behavior using accelerometers and advanced data processing methodologies. Evaluating damage detection performance in real-life conditions is challenging due to the rarity of such tests, short monitoring campaigns, and the frequent demolition of tested structures. To overcome these issues, this study utilizes a database from Leibniz University Hannover, which serves as a real-world benchmark for vibration-based SHM. The database features a lattice mast structure exposed to varying environmental conditions and allows for the assessment of damage. The ARTeMIS Modal SHM tool, specifically the complete Control Chart tool based on subspace decomposition and residual evaluation, was applied to this database, considering different sessions of acquisition, almost simulating a real monitoring condition. The results confirm the algorithm's ability to detect damage conditions for any choice of monitoring modality, both in a very strict time frame and in a regular way for a long period. A key advantage of this algorithm, besides its insensitivity to environmental changes, is its ability to reliably detect damage with only a few measurement sessions lasting just minutes. Compared to using only identified frequencies, the tested methodology appears more robust, as it is not affected by the fact that specific damage may only impact certain frequencies, which might not be detectable in the damaged structure.

It is important to highlight that the tested methodology relies solely on measurements from the real structure, without the need for any reference model. The evaluation of identified frequencies and their variations could serve as a complementary element rather than a replacement for the tested methodology.

Actual researches focus on localizing damage in addition to detecting its position by considering experimental data in environmental conditions.

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